Essays in Energy Economics: A global empirical examination of decarbonization policies and of trade in energy technology materials

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This dissertation is submitted for the degree of Doctor of Philosophy

This dissertation is the result of my own work and includes nothing which is the outcome of work done in collaboration except as declared in the Preface and specified in the text.

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Deep reductions in CO2 emissions are needed in energy production and use, which constitute two-thirds of the emissions responsible for climate change. Achieving such reductions requires concerted government policy in all countries, with attention to interrelated challenges like inclusive and sustainable growth.

Introductory Chapter 1 of this dissertation on the economics of decarbonization proposes that the four stand-alone analytical chapters can be understood together along the cross-disciplinary technology innovation process: (1) the evolution public energy research, development, and demonstration (ERD&D) across technologies and countries (Chapter 2); (2) the effects of policies aimed at creating markets for low carbon energy on decarbonization (Chapter 3); and, (3) the changes in trade of materials used in energy technologies (energy technology materials, ETMs) for technologies in early adoption and diffusion (Chapters 4 – 5).

Existing statistical and econometric studies on these topics tend to focus on high-income (World Bank classification) OECD countries, which we define as "developed." Instead, this dissertation takes a broad geographical view by creating new datasets, using existing ones in new ways, and proposing changes to established methodologies to better understand the developments and challenges of the energy transition in a wider set of countries.

Chapter 2 ascertains that the evolution of global ERD&D is several times too small compared to existing estimates of what is needed to meet climate goals, even when accounting for previously unavailable data on China and India. Volatility of funding by country and technology groups (fossil fuels, nuclear, and clean plus (CP)) points towards innovation systems patterns over the United States/United Kingdom, continental Europe, and Asia. With some caveats, the years after two windows of opportunity for changes in funding patterns were not associated with significant changes in funding allocation towards CP.

Chapter 3 finds that the policies with the most immediate positive impact on energy decarbonization in developing countries from 1980-2018 dealt with counterparty risk, referring to the bankability of private participation. The impacts on decarbonization of other policy instrument categories (e.g. legal frameworks for renewable energy) are low but tend to increase with time, and we discuss possible reasons why.

Chapter 4 identifies 30 traded products related to ETMs. It finds that over the two decades between 1998-2018, trade trends (such as growth, volatility, importer concentration, and exporter concentration) in two groups, clean and refined products, display relatively beneficial changes for exporters than traditional and unrefined products do. In accordance with existing literature, however, developing countries are underrepresented as exporters of clean and refined products. The results make a case for enhancing clean and refined ETM trade and capabilities in developing countries.

Chapter 5 proposes a methodological modification to the estimation of existing structural trade demand price elasticities (defined as a change in quantity traded due to change in price). The modification allows for a comparison of the trade demand price elasticities for exporter-ETM pairs in almost 30 traded products and 20 major developing and developed country exporters over the two decades between 1998-2018. We find, amongst other things, a convergence between developing and developed countries over the past two decades and discuss possible reasons for this pattern.

Chapter 6 considers the implications of the results and reflects on directions for future research.

"The Population Reference Bureau predicts that the world's total population will double to 7,000,000,000 before the year 2000.

'I suppose they will all want dignity,' I said.

'I suppose,' said O'Hare."

Slaughterhouse-Five, or, The Children's Crusade: A Duty-Dance with Death, 1969

Kurt Vonnegut

PREFACE

Some or most of the content of the following dissertation chapters has evolved into papers that are under review, accepted for publication, or about to be submitted for publication.

Chapter 2

Under review:

Meckling, Jonas; Galeazzi, Clara; Shears, Esther; Xu, Tong; Anadón, Laura Díaz. "The Evolution of Energy Innovation Governance for Decarbonization". 2021. Resubmitting to *Nature Energy*.

Related work or publications:

Extension of the analysis is part of the accepted research proposal for a 2021-2022 postdoctoral fellowship at the Belfer Center, Harvard Kennedy School.

I am a contributing author in Chapter 16 on *Innovation, technology development and transfer* in Working Group III of the IPCC Sixth Assessment Report.

Chapter 3

Under review:

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Chapter 4

Preparing for submission:

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Chapter 5

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Related publication:

Galeazzi, Clara, Jevgenijs Steinbuks, and James Cust. 2020. "Africa's Resource Export Opportunities and the Global Energy Transition." 111. *Live Wire*. Washington, DC: World Bank, Washington, DC. https://openknowledge.worldbank.org/handle/10986/34946.

I was solely responsible for the methodology, investigation, analysis, visualization, and writing of the work in the papers or proposals for which I am first-author.

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CONTENTS

List of acronyms **12**

List of tables **14**

List of figures **18**

1 Chapter 1: Introduction **22**

1.1 Motivation *22*

1.2 Background *25*

1.2.1 Climate change as a market failure 25

1.2.2 Competing policy priorities 26

1.2.3 Energy technology innovation systems (ETIS) 28

1.3 Dissertation research questions, methods, and data *29*

1.3.1 Dissertation structure 29

1.3.2 Research questions organized by ETIS stages 31

1.3.3 Methods and data 34

1.4 Summary *36*

1.4.1 Chapter summaries 36

1.4.2 Contributions 39

2 Chapter 2: Characterizing and assessing public ERD&D investments in eight major economies, including China and India **41**

2.1 Introduction *41*

2.2 Literature review *43*

2.2.1 Optimal ERD&D investment and technological allocation 44

2.2.2 Funding volatility and systems of innovation 46

2.2.3 Windows of opportunity 48

2.3 Methods *49*

2.3.1 Compiling public ERD&D data for the Government of India 50

2.3.2 Measuring volatility 54

2.3.3 Identifying structural change through regression analysis 55

2.4 Data *56*

2.5 Results *57*
2.5.1 Funding amounts and allocation over time 57
2.5.2 Funding volatility by country and technology 62
2.5.3 Impact of crisis and cooperation on funding 65

2.6 Discussion *66*

2.7 Conclusion *69*

Appendix 2.1. Example of Government of India Union Budget data *70*

Appendix 2.2. Web of Science method details *71*

Appendix 2.3. Country samples in regression analysis *75*

Appendix 2.4. Funding in China according to MI *76*

Appendix 2.5. Discussion of increases in US unallocated funding *77*

Appendix 2.6. Growth rates by technology and country *78*

Appendix 2.7. Detailed regression input *79*

Appendix 2.8. Detailed discussion of regression results *80*

3 Chapter 3: Comparing the causal effects of seven energy policy instrument categories on energy decarbonization in 100+ developing countries 3-7 years after implementation **82**

3.1 Introduction *82*

3.2 Literature Review *85*
3.2.1 Energy decarbonization policy review 85
3.2.2 Evolving prescriptions for power sector regulation 89
3.2.3 Studies that discuss or use the RISE dataset 94

3.3 Model and methods *95*
3.3.1 Addressing omitted variables (Challenge 1) 95
3.3.2 Addressing simultaneity and reverse causation (Challenge 2) 96
3.3.3 Addressing degree of reform and policy collinearity (Challenges 3 and 4) 98

3.4 Data *99*
3.4.1 Outcome (dependent) variables 99
3.4.2 RISE dataset 100
3.4.3 PICs indices (independent variables) 108
3.4.4 Instrumental variables 111
3.4.5 Country coverage 113

3.5 Results *116*

3.6 Discussion *124*

3.7 Conclusion *126*

Appendix 3.1. Outcome variables, descriptive statistics *127*

Appendix 3.2. Principle Component Analysis (PCA) *130*

Appendix 3.3. PICs, Composite index correlation cut-offs *131*

Appendix 3.4. PICs, RISE vs Composite index weights *132*

Appendix 3.5. Instrumental Variables, descriptive statistics *133*

Appendix 3.6. S2 coefficients by PIC and outcome *135*

Appendix 3.7. S2 coefficients for analysis, by region and income group *136*

Appendix 3.8. S2 coefficients for analysis *137*

4 Chapter 4: The evolution of trade in 30 energy technology materials spanning traditional and clean technologies and its implications **139**

4.1 Introduction *139*

4.2 Literature review *143*

4.2.1 Criticality assessments: focus on vulnerability to supply disruptions 143

4.2.2 Resource/reserve assessments and market models 146

4.2.3 Resource governance 147

4.3 Methods *149*

4.3.1 Selecting relevant ETMs 149

4.3.2 Selecting trade products and generating product groups 151

4.3.3 Trade value growth and volatility 157

4.3.4 Export and import quantity concentration 160

4.3.5 Major exporters 161

4.3.6 Summary of metrics 161

4.4 Data *162*

4.5 Results *165*

4.5.1 Growth and volatility 165

4.5.2 Importer and exporter concentration 171

4.5.3 Major exporters over time and over product groups 174

4.6 Discussion *176*

4.7 Conclusion *180*

Appendix 4.1. Data, additional statistics *181*

Appendix 4.2. Growth and volatility results, by product *183*

Appendix 4.3. Growth and volatility, additional visualization *184*

Appendix 4.4. Growth and volatility, additional statistics and tests *185*

Appendix 4.5. Importer and exporter concentration, group comparisons *186*

Appendix 4.6. Exporter analysis, additional visualizations *187*

5 Chapter 5: A novel estimation of structural trade elasticities and an application to energy technology materials **188**

5.1 Introduction *188*

5.2 Literature review *191*

5.2.1 Varieties 191

5.2.2 The love-of-variety monopolistic competition trade framework 192

5.2.3 Feenstra (1994)'s empirical application 192

5.2.4 Improvements on Feenstra (1994)'s empirical specifications 194

5.2.5 Summary 197

5.3 Model and methods *199*

5.3.1 Demand 199

5.3.2 Supply 201

5.3.3 Estimating equation 201

5.4 Data *204*

5.5 Results *206*

5.5.1 Descriptive statistics of the calculated elasticities 206

5.5.2 Product-exporter pairs 208

5.5.3 Exporters 215

5.6 Discussion *218*

5.7 Conclusion *220*

Appendix 1. Amending trade data to fit the model and existing code *222*

Appendix 2. Detailed results and further analysis *223*

Appendix 3. Exporter-ETM combinations for which we have results in the final results sample *225*

Appendix 4. Exporter-ETM elasticities *226*

6 Chapter 6: Conclusion **229**

6.1 Main results *229*

6.2 Cross-chapter considerations and future research *232*

Bibliography **234**

LIST OF ACRONYMS

2SLS	Two Squared Least Squares
AI	Attributes of Financial and Regulatory Incentives
ANOVA	Analysis of Variance
BACI	Database for International Trade Analysis
CEPII	Center for Prospective Studies and International Information
CO2	Carbon Dioxide
COVID-19	Coronavirus Disease 2019
CP	Clean Plus (All Except Fossil Fuels and Nuclear)
CP	Carbon Pricing and Monitoring (only within Chapter 3)
CR	Counterparty Risk
DPET	Decarbonisation Policy Evaluation Tool
EA	Energy Access
EAP	East Asia and the Pacific
ECA	Europe and Central Asia
EE	Energy Efficiency
EFF	Electricity Production from Fossil Fuels
EOS	Electricity Production from Oil Sources
ERD&D	Energy Research, Development, and Demonstration
ESMAP	Energy Sector Management Assistance Program
ETIS	Energy Technology Innovation System
ETMs	Energy Technology Materials
ETS	Emissions Trading Schemes
FC	2008 Financial Crisis
FE	Fixed Effects Regression
FF	Fossil Fuels
FFC	Fossil Fuel Energy Consumption
FIPSs	Feed-in Premiums
FITs	Feed-in Tariffs
GDP	Gross Domestic Product
HS	Harmonized System
IAMs	Integrated Assessment Models
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency
IVs	Instrumental Variables
LAC	Latin America and the Caribbean
LF	Legal Framework
LIML	Limited Information Maximum Likelihood
M6	Germany, France, Japan, Kora, UK, and US
M8	China, Germany, France, India, Japan, Kora, UK, and US
MDs	Major Donors
MENA	Middle East and North Africa
MI	Mission Innovation
NC	Network Connection and Usage
NDCs	Nationally Determined Contributions

OC	Ores and Concentrates
OECD	Organisation for Economic Co-Operation and Development
OH	Oxides and Hydroxides
PE	Planning for Expansion
PF	Powders and Flakes
PICs	Policy Instrument Categories
PSR	Power Sector Reform
RD&D	Research, Development, and Demonstration
RE	Renewable Energy
REC	Renewable Energy Consumption
REE	Rare Earth Elements
REO	Renewable Electricity Output
RISE	Regulatory Indicators for Sustainable Energy
SAS	South Asia
SDG	UN Sustainable Development Goals
SDS	Sustainable Development Scenario
SSA	Sub-Saharan Africa
SSP	Shared Socioeconomic Pathways
UN	United Nations
UNFCCC	United Nations Framework Convention on Climate Change
UNGA	United Nations General Assembly
USD	United States Dollar
UW	Unwrought
WB	World Bank
WDI	World Development Indicators

LIST OF TABLES

Table 2.1.	Summary of the founding systems of innovation perspectives.	47
Table 2.2.	Main technology categories in the 2020 IEA Energy Technologies RD&D Budgets dataset, and our technological classification for the rest of the analysis.	50
Table 2.3.	Institutions of interest for ERD&D in Indian Union Budget budget documents.	52
Table 2.4.	Challenges of using Indian Union Budgets as the main source of data.	52
Table 2.5.	Final list of Government of India institutions included in this analysis.	54
Table 2.6.	Statistics and indices to study public ERD&D expenditure volatility by country and technologies.	54
Table 2.7.	Regression specifications used to test the presence of structural change in growth rates of ERD&D in several country sub-samples.	56
Table 2.8.	Data availability by country.	57
Table 2.9.	India ERD&D budget, 2010-2018, million 2019 USD.	59
Table 2.10.	Comparison of the results of the methods in this chapter and Zhang et al. (2021).	60
Table 2.11.	Regression summary results. Columns indicate country groups (All countries, M8 and MI) and technologies (total and CP). The rows indicate the window of opportunity being studied (the FC, MI, or both).	66
Table 2.12.	Web of Science categories assumed to qualify in IEA technology categories.	71
Table 2.13.	Technology categories excluded from Web of Science analysis.	71
Table 2.14.	Key institutions identified through Web of Science relevant for Web of Science energy categories.	72
Table 2.15.	Citations by main funders in Web of Science categories.	73
Table 2.16.	Limitations to the Web of Science methods described in this section.	73
Table 2.17.	Country samples and data availability.	75
Table 2.18.	China renewables, hydrogen, and cross-cutting RD&D funding (technologies our methods do not differentiate) between 2015-2019 as reported in the 2020 Mission Innovation Country Highlights Report, million 2019 USD.	76
Table 2.19.	Technology, country groups, and coefficients for regressions with significant results.	80
Table 3.1.	Outcomes of energy decarbonization policies studied in social sciences according to an SR by Peñasco, Anadón, and Verdolini (2021).	86

Table 3.2.	Energy decarbonization policies studied in social sciences according to Peñasco, Anadón, and Verdolini (2021) (first three columns), and whether we include them in this study (last column).	87
Table 3.3.	Energy decarbonization categories and policies in Peñasco, Anadón, and Verdolini (2021) (first two columns), whether they are covered in this study (third column), and their effect on our outcome of interest, technological effectiveness (last column).	89
Table 3.4.	Selected power sector reform studies that use instrumental variables (IVs) to address endogeneity (Challenge 2), as well as how they address other challenges.	92
Table 3.5.	Regions and acronyms.	96
Table 3.6.	Outcome variables, their units, and their expected relationships with the poilcy instrument categories (PICs).	99
Table 3.7.	Headings/PICs in RISE.	101
Table 3.8.	Discrepancies in RISE primary data.	102
Table 3.9.	Attributes of the primary and final datasets.	103
Table 3.10.	PICs and policies covered in the RISE dataset, as well as their structure.	103
Table 3.11.	Variables in the Jaccard coefficient.	105
Table 3.12.	Summary of IVs that capture relations with major donors.	112
Table 3.13.	Countries in the RISE dataset, organized by the regions previously introduced, and whether they are included in the regression analysis of this chapter.	114
Table 3.14.	Regression specifications resulting from the Methods and Data sections of this chapter.	116
Table 3.15.	Eligible S1 coefficients for base specifications; green is higher, red is lower.	117
Table 3.16.	IV exogeneity robustness regression test.	118
Table 3.17.	Kruskal-Wallis H tests for the three options in the regression base specifications: Indices, IVs, and IV moving averages.	119
Table 3.18.	Average effect of PIC, by S2 lag.	121
Table 3.19.	RISE and Composite index weights used to create the PIC (independent) variables in the PIC column.	132
Table 3.20.	Trade agreements in place with the EU Commission.	134
Table 3.21.	Number of S2 eligible coefficients, by PICs and outcomes, lag 3. Higher numbers are green, lower are red.	135
Table 3.22.	Coefficients for analysis, by region.	136
Table 3.23.	Coefficients for analysis, by World Bank income group.	136

Table 3.24. S2 coefficients with a p-value <0.1 with a positive S1 coefficient with a p-valu<0.05 and an f-statistic>10. 137
Table 4.1. Summary and comparison of concentration metrics used in criticality studies and evaluated in Brown (2018). 145
Table 4.2. Materials analyzed in World Bank (2020), including their projected annual demand from energy technologies as a percent of 2018 annual production, the technologies in which materials are used, and whether they were selected (green) or not selected (grey). 150
Table 4.3. Final materials selection. Check=Sourced from World Bank (2020). X=Explained in the text. 151
Table 4.4. HS Sections and chapters containing the materials we identified in the literature. 153
Table 4.5. Selected UN Comtrade 4 and 6-digits products that correspond to materials identified in the literature. 154
Table 4.6. Product, HS codes, and groups. Following the colors in Figure 4.1, Clean Energy Materials (CEMs) are blue, Traditional Energy Materials (TEMs) are light blue; Ores and concentrates (OCs) are red, Metals and chemicals (MCs) are light red. 156
Table 4.7. Summary of assumptions and metrics used in the analysis of this chapter. 162
Table 4.8. Country groups in the trade dataset. 162
Table 4.9. UN Comtrade description and simplified labels. 163
Table 4.10. Descriptive statistics, value (in constant USD million) and volume, by decade and groups. 165
Table 4.11. P-values of nonparametric equality-of-medians test and Wilcoxon rank-sum test/Mann –Whitney two-sample statistic for the difference in growth rates and volatility of growth rates. 166
Table 4.12. Paired t-Tests comparing Decades 1 and 2. 167
Table 4.13. Top growth (green check) and top volatility (red X) products, in Decades 1 and 2. Ordered by growth in each decade. CEMs are blue, TEMs are dark blue; OCs are red, MCs are light red. 170
Table 4.14. Notable products that stand out in the static and dynamic analyses. 178
Table 4.15. Major exporter market share rank, by notable product. Count of notable products for which each main exporter is a main exporter, and average rank across notable products. Green = first, light green= second, gray= third, light red= fourth, and red= fifth major exporter. 179
Table 4.16. Detailed statistics, value (constant 2018 USD mil) and quantity, 1995-2018, all selected products. 181

Table 4.17. Summary trade statistics v (value, in constant 2018 USD million) and q (quantity), 1995-2018, by product. 181
Table 4.18. Average yearly growth and average yearly growth standard deviation, 1999-2018, Decade 1, and Decade 2. 183
Table 4.19. Average growth rates and volatility by groups, 1999-2018. 185
Table 4.20. Average growth rates and volatility by groups and decade. 185
Table 4.21. Differences in growth rates and volatility of growth rates, P-values of nonparametric equality-of-medians test and Wilcoxon rank-sum test/ Mann –Whitney two-sample statistic. 185
Table 5.1. Key publications that advanced trade theory and methods relevant to this paper, and their main takeaways. 197
Table 5.2. Varieties, by ETM and decade. Ordered by highest to lowest, overall. 205
Table 5.3. Varieties, by major exporter and decade. 206
Table 5.4. Trade demand elasticities summary statistics, by sample. 207
Table 5.5. Summary statistics, by exporter. 215
Table 5.6. P-values of statistical tests comparing the ETM trade demand elasticities, developing versus developed country exporters. 217
Table 5.7. P-values statistical tests comparing the ETM trade demand elasticities, developing versus developed country exporters, by decade. 218
Table 5.8. Original layout of the input data layout. 222
Table 5.9. Layout for the input data necessary to obtain the modified elasticities. 222
Table 5.10. Trade demand elasticities, detailed statistics. 223
Table 5.11. Trade demand elasticity summary statistics for ETMs for which there are two decades, by ETM. 223
Table 5.12. Summary statistics, by decade and product groups. 224
Table 5.13. P-values of nonparametric test that the median of differences between matched pairs is zero and the Wilcoxon matched-pairs signed-rank test. 224
Table 5.14. ETM (columns) and exporter (rows) combinations, and whether trade demand elasticities are included in the final sample (green), not included or not output by the model (red), not applicable (blank). 225
Table 5.15. Elasticities by exporter-product pair and decade, calculated by the methods described in this chapter. 226

LIST OF FIGURES

Figure 1.1.	Global energy sector CO2 emissions reductions percentages, 2019-2070, by current technology readiness level (TRL) category. The vertical axis represents the percentage of emissions reductions needed under the Sustainable Development Scenario relative to the Stated Policies Scenario from mature versus not mature technologies.	23
Figure 1.2.	Fraction of top 20 country emissions in 2019 from developed (blue) versus developing (red) countries.	23
Figure 1.3.	Annual installed capacity from renewable versus non-renewable sources (left axis) and share of renewable installed capacity over total annual installations (right axis) (2001-2020).	27
Figure 1.4.	Policy types relating to the non-linear stages of the innovation process (top); simplified Energy Technology Innovation System (ETIS) model of the innovation process (middle); and how the dissertation chapters relate (bottom).	31
Figure 1.5.	Chapter titles, research questions, and literatures.	34
Figure 1.6.	Summary of statistical and regression methods in the dissertation.	35
Figure 1.7.	Major datasets created or used in this dissertation.	36
Figure 2.1.	Expenses covered in “Expenditure Budget” documents of the Government of India Union Budgets (top) and an extract of the 2019 “Summary of expenditure (bottom).	51
Figure 2.2.	Design of Web of Science method to determine ERD&D data expenditure by the Government of India.	53
Figure 2.3.	Total public ERD&D expenditure, IEA and our data for China and India in million 2019 USD. China=blue; India=light blue; Asian countries = shades of red; European countries=green; Countries in the Americas= shades of yellow.	58
Figure 2.4.	India's ERD&D funding by technology, million 2019 USD.	59
Figure 2.5.	Shares of technology groups in 2002 and 2018, by country groups. Fossil fuels=red; nuclear=blue; clean plus=green.	61
Figure 2.6.	World ERD&D expenditure by technology, 2010, 2015 and 2018. China=blue; India=light blue; Asian countries = shades of red; European countries=green; countries in the Americas= shades of yellow.	62
Figure 2.7.	Top: Indices 1 and 2, left and right, respectively. Based on growth rates of data 2010-2018, left to right = most to least volatile. Red depicts FF spending, blue depicts nuclear spending, and green depicts CP spending.	

	Bottom: Comparison of Index 1 and 2. High= more volatile; Reds and long-dash-short-dash=Asia; Yellows and solid=Americas; Greens and dashes=Europe; Blue and dotted=China and India.	63
Figure 2.8.	Top: Indices 3 and 4, left to right. Based on the consistency of growth expenditure, 2010-2018. Red depicts FF spending, yellow depicts nuclear spending, and green depicts CP spending. Bottom: Comparison of Index 3 and 4. High= more volatile; Reds and long-dash-short-dash=Asia; Yellows and solid=Americas; Greens and dashes=Europe; Blue and dotted=China and India.	64
Figure 2.9.	Example of Union Budget spending data for ERD&D expenditure by the Ministry of Power for the year 2010.	70
Figure 2.10.	Example of Union Budget source for extra information on spending lines for ERD&D expenditure by the Ministry of Power for the year 2010.	70
Figure 2.11.	Main funders of citations related to Selected Web of Science categories and India.	72
Figure 2.12.	Web of Science categories to which the Ministry of New and Renewable Energy contributed.	74
Figure 2.13.	Percentage changes in funding, by technology and country.	78
Figure 2.14.	Demeaned annual percentage changes of spending, by technology (all technology and CP) and country groups (All countries, MI, and M8), excluding outliers. 2009-2011 FC dummies= red ; 2016-2018 MI dummies= green. The left column corresponds to total funding; the right column corresponds to clean plus. The rows correspond to All countries, M8, and MI countries, top to bottom.	79
Figure 3.1.	Dendrogram cluster visualization of policies in the RISE dataset.	107
Figure 3.2.	Comparison of the RISE, Summation, and Composite Indices, by heading/PIC, over region, for 2015.	110
Figure 3.3.	S2 coefficients of outcomes by country tend to cluster. Scatter of S2 coefficients for SSA region including country labels, by PICs (x-axis) and outcomes (colors). S2 lag 3.	120
Figure 3.4.	Boxplot of all S2 coefficients, by PICs (x-axis), outcomes (colors), and S2 lags.	121
Figure 3.5.	S2 coefficients, lag 3, 5, and 7 (blue, red, and green, respectively) by PIC. Only Sub-Saharan Africa.	123
Figure 3.6.	S2 coefficients, lag 3, 5, and 7 (blue, red, and green, respectively) by PIC. All regions except Sub-Saharan Africa.	123

Figure 3.7.	Dependent variables that should be positively affected by energy decarbonization policies.	128
Figure 3.8.	Dependent variables that should be negatively affected by energy decarbonization policies.	127
Figure 3.9.	Number of components needed (y-axis) to explain the proportion of information (color); Overall (left), by heading/PIC (right)	130
Figure 3.10.	Number of variables/groups/headings remaining (y-axis), by cut-off point (x-axis), Survival method (dashed), Average method (solid) (left); data (right).	131
Figure 3.11.	Closeness to major donors through UNGA voting (top); Closeness with major donors through trade, 1995-2015, % of total (bottom).	133
Figure 4.1.	Classifications and product groups used in this chapter.	155
Figure 4.2.	Traditional energy materials (TEMs), world trade value, 1999-2018, constant USD trillion. Left of vertical red line = Decade 1. Right of vertical red line=Decade 2.	164
Figure 4.3.	Clean energy materials (CEM), world trade value, 1999-2018, constant USD trillion. Left of vertical red line = Decade 1. Right of vertical red line=Decade 2.	164
Figure 4.4.	Average of yearly growth rates (circles) and the volatility of yearly growth rates (diamonds, right axis), by product groups. All products (green); CEMs (blue) versus TEMs (light blue); OCs (red) versus MCs (light red).	166
Figure 4.5.	Average of yearly growth rates (circles) and the volatility of yearly growth rates (diamonds, right axis), by product groups and decades. All products (green); CEMs (blue) versus TEMs (light blue); OCs (red) versus MCs (light red). No outline= Decade 1. Black outline=Decade 2. Solid arrows = change between decades is detrimental to exporters. Dashed arrows = change between decades is beneficial to exporters.	167
Figure 4.6.	Average yearly growth (x axis), volatility of yearly growth rates (y axis), Decade 1 (left); Decade 2 (right) Red = TEMs, Green=CEMS; + markers = OCs; X markers=MCs.	169
Figure 4.7.	Exporter and importer concentration (HHI), by product, 1999-2018; Red = TEMs, Green=CEMS; + markers = OCs; X markers=MCs.	171
Figure 4.8.	Change in market concentration by exporter (x-axis), importer (y-axis), Decade 2 minus Decade 1. CEMs are in green, TEMs are in red. OC markers are crosses, and MC markers are x's. The colors of quadrants represent the preference for exporters. Green indicates an increase in the	

	export concentration and a decrease in the import concentration. The opposite happens on the red quadrant.	173
Figure 4.9.	Major exporters by product 1999-2018. Exporters are ordered in descending order of exporter size in the market, left to right. Green = first, light green= second, gray= third, light red= fourth, and red= fifth major exporter.	174
Figure 4.10.	Number of products for which major exporters gained/lost major exporter status, Decade 2 minus Decade 1 (x-axis) and average number of products across decades for which each country was a major exporter (y-axis). Red labels=country lost products; orange=no change; green labels=country gained products.	176
Figure 4.11.	Average yearly growth (x axis), volatility of average yearly growth rates (y axis), 1999-2018; Red = TEMs, Green=CEMS; + markers = OCs; X markers=MCs.	184
Figure 4.12.	Export and import concentration by CEMs and TEMs and OCs versus MCs, using the same Area colors as Figure 4.7.	186
Figure 4.13.	Percentage of a country's export made up of OCs versus MCs (top) and TEMs versus CEMs (bottom), by developing (orange) or developed countries (green).	187
Figure 5.1	Frequency of trade demand elasticities.	208
Figure 5.2.	Frequency of ETMs according to median ETM trade demand elasticity.	208
Figure 5.3.	Trade demand elasticity (x-axis), market share by value, % (y-axis), market share by volume (bubble size); Decade 1 (blue); Decade 2 (red) for all available countries output by the model; background colors correspond to bins from Figure 8.	210
Figure 5.4.	Boxplots of elasticities, by developed and developing country exporters.	216
Figure 5.5.	Boxplots of elasticities, by developed and developing country exporters, and decades.	217

CHAPTER 1: INTRODUCTION

1.1 MOTIVATION

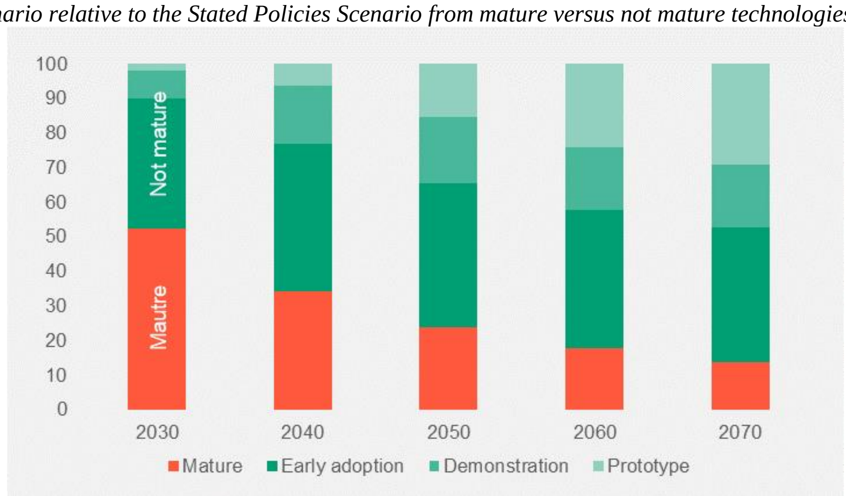
Climate Change 2021: The Physical Science Basis of the Intergovernmental Panel on Climate Change (IPCC) 6th Assessment Report confirmed that "global warming of 1.5°C and 2°C will be exceeded during the 21st century unless deep reductions in carbon dioxide (CO2) and other greenhouse gas emissions occur in the coming decades," (IPCC 2021) with broad implications for the global economy (Nordhaus 2019). Energy production and use in power, heat, and transport are responsible for close to two-thirds of greenhouse gas emissions, which is why decarbonizing the sector is crucial (International Renewable Energy Agency (IRENA) 2019).

Energy decarbonization can be achieved through a range of efforts. These include, but are not limited to, pricing emissions to align market incentives to make existing low-carbon technologies competitive with those that dominate the sector, and allocating public investment to accelerate the innovation of technologies that are not yet ready for deployment (Peñasco, Anadón, and Verdolini 2021), where innovation is defined as the "process by which technology is conceived, developed, codified, and deployed" and technology is defined as "the subset of knowledge that includes the full range of devices, methods, processes, and practices that can be used 'to fulfill certain human purposes in a specifiable and reproducible way'" (Brooks 1980; Anadón, Chan, et al. 2016). In addition to serving climate goals, innovation is "a key driver of long-term productivity growth" (International Monetary Fund (IMF) 2016).

Several estimates exist for the innovation gap to meet decarbonization goals. According to the International Energy Agency (IEA), almost 75% of the cumulative CO2 emissions by 2070 compared to business as usual come from technologies that will not become available at scale without further research, development, and demonstration (RD&D), or that "have not yet been commercially deployed in mass-market applications" (IEA 2020a) (Figure 1.1).

Recognizing the need to incentivize the development and deployment of nascent technologies, the Paris Agreement of the United Nations (UN) Framework Convention on Climate Change, which aimed at "holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels" was accompanied by the creation of Mission Innovation (MI). MI is an international cooperation agreement between more than 20 countries to double their clean energy research, development and demonstration (ERD&D) investment by 2020-2021 (amongst other goals), with varying levels of success to date (Hannon and Bolton 2021; Myslikova and Gallagher 2020).

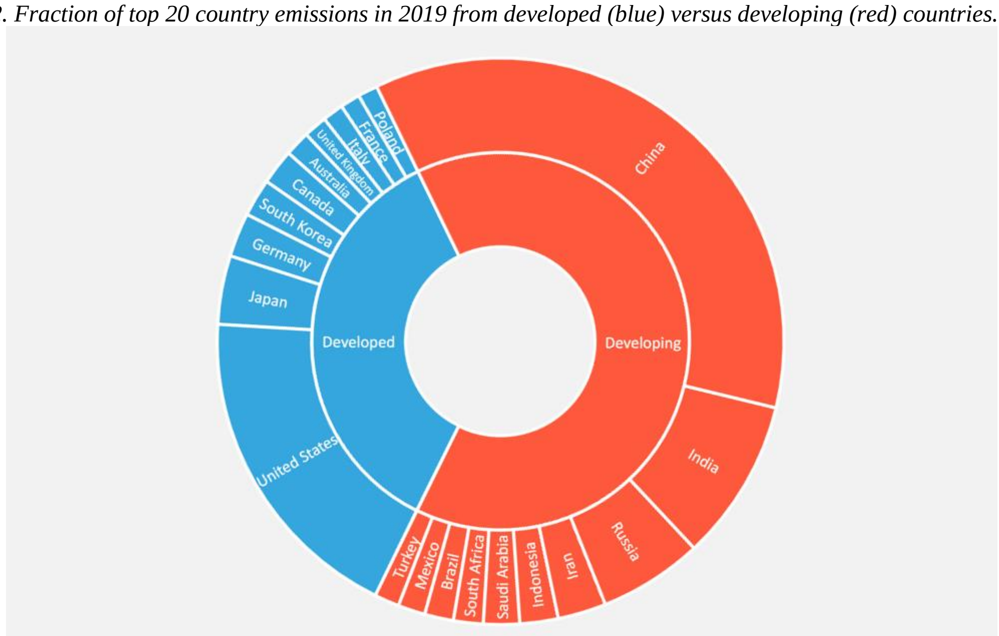
Figure 1.1. Global energy sector CO2 emissions reductions percentages, 2019-2070, by current technology readiness level (TRL) category. The vertical axis represents the percentage of emissions reductions needed under the Sustainable Development Scenario relative to the Stated Policies Scenario from mature versus not mature technologies.



Source: Adapted from International Energy Agency (2020a).

Decarbonization efforts must involve both developed and developing countries (Nordhaus 2019). Unless otherwise specified, we define developed countries as those that are both members of the Organization for Economic Development (OECD) and classified as World Bank high-income with a gross national income per capita above 12,535 USD in 2020 (World Bank 2020a). As a group, OECD high income countries hold exceptionally high scores in quality of life indicators such as the UN Human Development Indicator and regulatory metrics such as the World Bank Doing Business (UN Development Programme 2020; World Bank 2020b). Although developed countries have higher historical emissions, China and India are amongst the top three emitters today, along with the United States. Furthermore, about 50% of the top 20 emitters are developing countries; and, within the top 20 countries, developing countries make up 64% of emissions (Figure 1.2) (Global Carbon Atlas 2021).

Figure 1.2. Fraction of top 20 country emissions in 2019 from developed (blue) versus developing (red) countries.



Source: Authors' elaboration based on data from Global Carbon Atlas (2021).

However, Nationally Determined Contributions (NDCs), the emissions reductions pledges by countries under the Paris Agreement, are inadequate (Robiou du Pont et al. 2016). A recent study finds that the probability of staying below 2°C of warming if all countries meet their NDCs and continue to reduce emissions at the same rate after 2030 is 26% (and 2% if countries continue current trends) (Liu and Raftery 2021).

Amongst other forces at play, real or perceived trade-offs related to decreasing emissions contribute to the gap between emissions reduction pledges and what is required, as well as between pledges and progress towards achieving them (Deng et al. 2018). As an unexpected global shock, the COVID-19 pandemic illustrated the compromise between short-term economic performance and emissions, barring policies that support structural economic change and the development and deployment of new technologies (UN Conference on Trade and Development (UNDP) 2021). Early estimates show that in 2020, the Covid-19 pandemic decreased emissions by 4-7% (Le Quéré et al. 2020). What is worrisome is that this large shock reduced annual emissions less than the 7.6% yearly estimated decrease needed from 2020-2030 to keep global temperatures below 1.5 degrees (UN Environment Programme (UNEP) 2019). These decreases were also accompanied by an economic recession of about 3.59% of GDP (World Bank 2021a).

Ultimately, we must improve our understanding of how to use government policy as a tool to transition to a globally decarbonized energy system in the coming decades while also pursuing other objectives, including inclusive and sustainable and the other interrelated UN Sustainable Development Goals (Anadón, Chan, et al. 2016; Mazzucato 2018). Failure to address climate change with other objectives may compromise several societal goals at once (Anadón, Chan, et al. 2016).

Through four stand-alone chapters (or papers), this dissertation in energy economics uses empirical methods to contribute to our understanding of policies and other areas of policy consideration (i.e., trade), for energy decarbonization at a global level. This introductory chapter begins with a general literature background in three parts. First, it presents the market failure rationale and policy prescriptions for climate change and decarbonization. Second, it considers the importance of competing policy priorities between climate change and other challenges that policymakers face. Third, it introduces the Energy Technology Innovation Systems (ETIS) conceptual framework that helps bridge the first two literatures together. The introduction then situates the research questions of the dissertation within ETIS and describes the methods and data of each chapter, concluding with a summary of the contributions.

1.2 BACKGROUND

1.2.1 Climate change as a market failure

Economics perspectives applied to energy and environmental challenges build upon and adapt the neoclassical economic concepts of upward-facing supply and downward-facing demand curves that meet at one point, the market equilibrium, due to profit-maximizing (and wellbeing-optimizing) decisions of (at least bounded) rational agents (Samuelson and Nordhaus 2009; Steinmueller 2010).

In this framework, the market fails when it does not allocate scarce resources in a Pareto-efficient way (simply, in which no individual can be better off without making another worse off), causing a decrease in aggregate social welfare, or a "deadweight loss" (Samuelson and Nordhaus 2009). Government intervention is justified if it can increase aggregate welfare in such a way that lowers the deadweight loss (Steinmueller 2010). In other words, the marginal cost of the intervention should be smaller than the marginal benefit of its outcome.

Externalities are a specific type of market failure that occur when the market fails to price the effects (both positive or negative) of a certain economic activity (Samuelson and Nordhaus 2009). Climate change is caused by negative environmental externalities where the market fails to "internalize" the environmental and human health costs of fossil fuel production. This is a result of "free-riding" global environmental resources that are "nonrivalrous" and "nonexcludable" (Jaffe, Newell, and Stavins 2005; Popp 2019; Samuelson 1954). In that sense, climate change is also a case of the Tragedy of the Commons (Hardin 1968), where uncoordinated self-interest results in negative externalities that deplete a collective resource in a way that harms all agents.

The general prescription to address environmental externalities is to intervene in the market so that the negative aggregate environmental and health costs are either internalized by the firms causing the externalities (market-based approach) or are minimized (through regulation) (Samuelson and Nordhaus 2009). The possible policies (also referred to as policy instruments) to directly address the environmental externalities include (Pigouvian) taxation (or pricing emissions) and cap and trade (or limiting the quantity) of emissions (Jaffe, Newell, and Stavins 2005).

However, other externalities contribute to or reinforce climate change. RD&D in technologies that might mitigate environmental problems is underprovided by the market largely due to the "appropriability problem," consisting of two interrelated sub-issues (Teece 1986). The first is that scientific knowledge frequently has positive externalities so that the investor cannot internalize the entire stream of returns on their investment (Nelson 1959; Arrow 1962). The second portion of the appropriability problem is that scientific knowledge can have knowledge spillovers and may be used by rival firms. In this case, competitors may free-ride on the investment, making scientific research a public good (Popp 2019). Based on the arguments above, three science and technology policy interventions can increase the rate of technological change: subsidies to RD&D producers, intellectual property rights, and government procurement where the RD&D is in a public good for which the government is the main customer (Steinmueller 2010). The first increases the supply of research, the second increases private returns to investment in research, and the third sees the government translating social preferences into market demand (Dalpé, DeBresson, and Xiaoping 1992).

Several additional market failures contribute to the overproduction of fossil fuels and the underproduction of knowledge. These include adoption externalities (related to dynamic increasing returns through learning-by-using, learning-by-doing, or network externalities of technologies), incomplete information, a divergence of social and private discount rates, and the failure of markets to translate social preferences (especially those of future generations) into market demand (Steinmueller 2010; Jaffe, Newell, and Stavins 2005). The severity of these market failures is exacerbated by the "fat tail" shape predicted by climate models of the probability of exceeding "dangerous" warming, and the costs associated with such warming (Weitzman 2011). Policies ranging from renewable performance standards, feed-in tariffs, auctions, and other regulations have been put in place to address externalities related to learning by doing and using the infant industry argument (Peñasco, Anadón, and Verdolini 2021; Grubb et al. 2021).

Overall, it is widely acknowledged that a portfolio of policies that address several externalities are needed, a perspective espoused in this dissertation. Said policies, however, may interact with one another, as well as with the externalities they are trying to address, making the estimation of the cost and benefits of each intervention complex (Jaffe, Newell, and Stavins 2005). For instance, taxing emissions alters the cost-benefit of production and may lead to innovation in a polluting firm (Popp, Newell, and Jaffe 2010), which may also be influenced by other coexisting policies focusing on innovation.

Note that while this brief discussion on externalities is not meant to be exhaustive, the existing theory is incomplete. For instance, the current theory fails to recognize that policy today shapes future markets that do not yet exist (Stern and Stiglitz 2021). In fact, while the "market failure" perspective provides a versatile theoretical framework, it can generally lack a conceptual background of how the market is shaped and changes over time, where policies come from, and how they evolve (Coase 1991). This finding is shared by the cross-disciplinary literature that focuses on innovation systems, as discussed in the following sections.

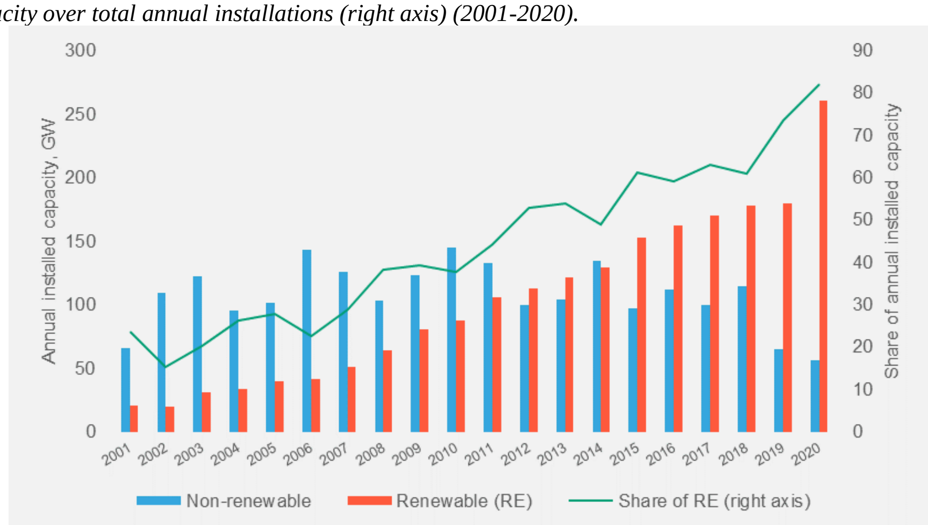
1.2.2 Competing policy priorities

As the targeted discussion above suggested, there are compounding relationships between externalities and the effects of policies that can be applied to rectify them. Policymakers also have several competing rationales for implementing decarbonization policies (IPCC 2001). For instance, because it affects a myriad of sectors in both developing and developed countries, efforts to address climate change are often pursued along with other objectives like inclusive and sustainable growth, or UN Sustainable Development Goal 8. This has contributed to research and policymaking on climate change as a "complex," "systemic," and "urgent," or "wicked," problem (or "grand challenge") (Mazzucato 2018).

A crucial component for continued growth in both developing and developed countries is international trade (Lopez 2005; Krugman, Obstfeld, and Melitz 2014). To this end, several studies have considered how decarbonization policies affect export competitiveness. For instance, Costantini and Mazzanti (2012) test strong and weak versions of the Porter hypothesis, which posits that environmental policies can foster competitiveness by inducing technological innovation, in five manufacturing sectors within the European Union (EU). They find that environmental policies generally have positive effects on competitiveness. However, reviews by Dechezleprêtre and Sato (2017) and Peñasco, Anadón, and Verdolini (2021) found mixed results. Dechezleprêtre and Sato (2017) suggest that complex relationships may explain these mixed results, such as the possibility that policy is endogenously determined, "governments [may] strategically set stringency levels to be low (high) where there is a high (low) risk of competitiveness distortions."

The effects of decarbonization on trade are not limited to the industrial and manufacturing sectors. Over the last ten years, annual growth in renewable capacity installations has increased steadily, while annual installations for electricity from fossil fuels have decreased (Figure 1.3), a trend that must continue and accelerate if we are to reach climate goals (IRENA 2021a). This increased rate of growth in energy derived from renewable sources versus fossil fuels will affect trade patterns in several raw and refined materials at varying levels of the manufacturing spectrum across energy technologies, or what we refer to in this dissertation as energy technology materials (ETMs) (Bazilian 2018; Lee et al. 2020).

Figure 1.3. Annual installed capacity from renewable versus non-renewable sources (left axis) and share of renewable installed capacity over total annual installations (right axis) (2001-2020).



Source: Renewable energy statistics data from IRENA (2021). "Renewable" includes bio, geothermal, hydropower, marine, solar, wind, and other. Non-renewable includes fossil fuel, nuclear, pumped storage, and other.

Galeazzi, Steinbuks, and Cust (2020) consider the possible implications of decarbonization on ETM trade in Sub-Saharan Africa (SSA), a region where the export of natural resources (natural gas, crude oil, and metals) generates approximately 25% of government revenue on average. We forecast the value of SSA trade for ETMs like cobalt, a material used in lithium-ion batteries. Amongst other things, we find that countries with reserves of materials used in clean energy have an opportunity to expand their exports and that hydrocarbon producing countries will need to adapt. Reviews on co-benefits and trade-offs of decarbonization policies, such as Peñasco, Anadón, and Verdolini (2021), ascertain that transforming trade, competitiveness, and other economic development trade-offs into co-benefits is possible, with targeted consideration. However, the extent to which countries may be well-positioned to benefit from this opportunity (in other words, to achieve both climate and development goals) based on trade trajectories over the past two decades has not been systematically investigated.

1.2.3 Energy technology innovation systems (ETIS)

Due to the grand challenge of climate change, it behooves researchers and policymakers to assess courses of action from multiple theoretical frameworks (Grubb, Hourcade, and Neuhoff 2014). A growing appreciation for endogeneity between different actors, their actions, the development of knowledge, and the diffusion of technologies, promoted a theoretical examination of decarbonization from a comprehensive perspective in what was initially called the "national innovation systems" framework. In that framework, institutions, "habits and practices, or routines," shape the interplay of complementary inputs, and coordinating, performing, and cooperating actors (Winter and Nelson 1982).

The innovation systems conceptualization of innovation is different from Bush's (1945) "linear" model where discoveries are successively made through basic research, demonstrated through applied research, refined through prototypes, and commercialized. It includes a range of models, like national/sectoral/regional/global "systems of innovation" (Edquist 1997; Lundvall 1992; Freeman 1987; Nelson 1993; Malerba 2004; Binz and Truffer 2017), "techno-economic networks" (Callon et al. 1992) and "technological infrastructure policy" (Justman and Teubal 1986) that treat innovation as a non-linear and systemic complex process involving dynamic feedbacks and heterogeneous actors.

Innovation systems analysis characterizes innovation as occurring in complex feedback loops between actors (a heterogeneous group, from university systems to lone entrepreneurs, of those responsible for developing, diffusing, and implementing new technologies), networks (that connect actors), and institutions (informal and formal "rules of the game" that characterize actors' behavior, expectations, and values [North 1990; Anadón, Chan, et al. 2016; Hannon and Bolton 2021]). Innovation occurs through stages that "can be tightly linked, often overlap, and do not necessarily occur in a specific sequence;" as a result, "innovation systems are complex adaptive systems characterized by codependent innovation stages with multiple feedbacks, positive and negative ripple effects, and the potential for nonlinear impacts" (Anadón, Chan, et al. 2016).

Coupled with the chain-linked model of the innovation process, espousing the stages of research, development, demonstration, market formation, and diffusion, the innovation systems model is "an interactive process involving a network of firms and other economic agents that, together with the institutions and policies that influence their innovative behavior and performance, bring new products, processes, and forms of organization into economic use" (Grübler et al. 2012).

Note the conceptual difference between the perspective we discussed in Section 1.2.1, where profit-maximizing agents act in response to market forces and government-mandated incentives, and the innovation systems perspective where "markets do not play the overarching role of generating an optimal state. Instead, nonmarket-based institutions are an important ingredient in the 'macro' innovation outcome" (Soete, Verspagen, and Weel 2010).

The ETIS framework applies innovation systems specifically to energy technologies (Gallagher, Holdren, and Sagar 2006; Grübler et al. 2012; Grübler and Wilson 2014). It is a "systemic perspective on innovation comprising all aspects of energy transformations (supply and demand); all stages of the technology development cycle; and all the major innovation processes, feedbacks, actors, institutions, and networks" (Gallagher et al. 2012). Some recurring characteristics of ETIS are (1) interdependence between components; (2) uncertainty of the outcomes; (3) complexity (due to the interdependency and uncertainty); and, (4) inertia, at least partially due to existing capital stock (Gallagher et al. 2012).

Three main types of metrics can help characterize ETIS: (1) *inputs* ("financial and labor inputs to the innovation process") like RD&D expenditure; (2) *outputs* ("products of the innovation process") like patents and publications; and, (3) *outcomes* ("sector or economy-wide impacts of the successful diffusion of innovations into the marketplace") like the market penetration of a technology (Gallagher et al. 2011). We discuss these metrics below in the context of the dissertation.

1.3 DISSERTATION RESEARCH QUESTIONS, METHODS, AND DATA

1.3.1 Dissertation structure

This introductory dissertation chapter proposes that the four analytical dissertation chapters, which apply questions, methods, and assumptions from economics, can be understood together within the cross-disciplinary ETIS conceptual framework.

Before proceeding, observe the differences in the lexicon and focus between the market failure and the ETIS perspectives, as they may label and interpret the same policy interventions differently. For example, in the market failure framework "policies aimed at stimulating cooperation […] between university and industry, would be motivated in the market failure-based approach by internalizing externalities" (in this case related to knowledge spillovers and/or networks); instead, "in a systems approach, such policies could be aimed at influencing the distribution of knowledge, to achieve coordination (not provided by markets), or to increase the cognitive capacity of firms" (Soete, Verspagen, and Weel 2010).

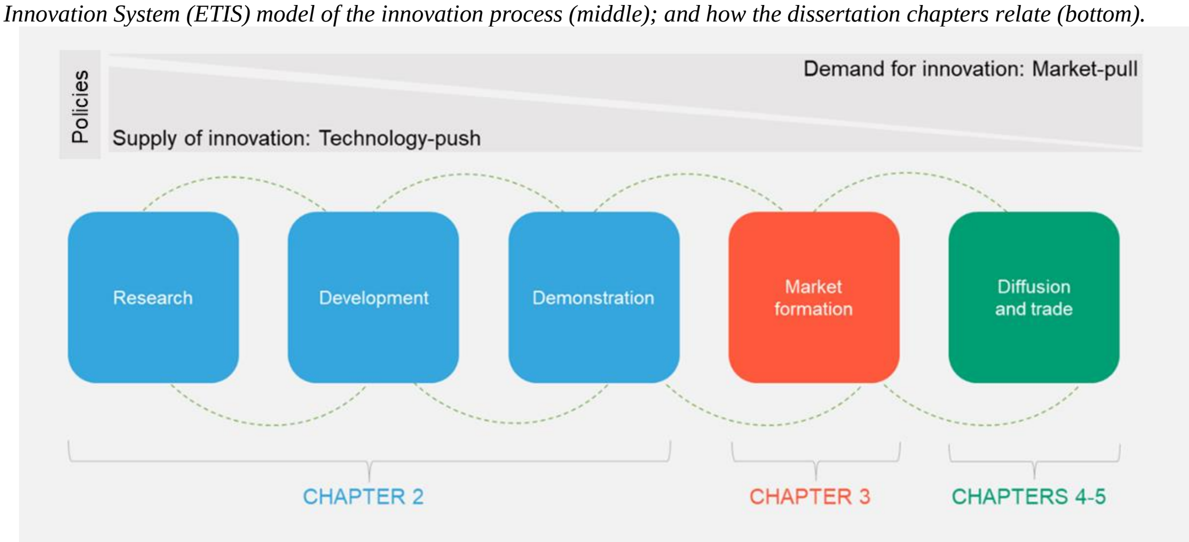
The market failure of positive knowledge externalities discussed previously is closely associated with the earlier stages of the TIS innovation process. Aside from securing intellectual property rights, the market failure approach prescribes public RD&D support as a fiscal expenditure aimed at providing "critical innovation that firms are unlikely to undertake" to increase total factor productivity (IMF 2016). Viewed from the ETIS perspective, the same ERD&D policies would be classified as "pushing" technology through the chain-linked model of innovation, or as "technology-push" policy.

On the other hand, negative environmental externalities are more closely associated with the actions of firms and technologies in the later innovation stages. As discussed, these externalities can be corrected by policies that increase the price of polluting (making non-polluting actions cost-competitive) or by regulations that "pull" low-carbon technologies through the innovation process, otherwise called "market-pull" policy.

Visual representations of ETIS vary. Figure 1.4 is adapted from Grübler et al. (2012) for this dissertation. It is composed of the following stages: (1) RD&D; (2) market formation (the "application of a technology in a specific limited market setting […] by harnessing either a specific comparative advantage […] or via public early deployment incentives […]"); and, (3) diffusion and trade (or the "widespread uptake of a technological innovation throughout the market of potential adopters") (Grübler et al. 2012).

The four stand-alone analytical chapters (or papers) of this dissertation reflect the challenges of supporting technologies across the innovation process stages (Figure 1.4, bottom). The first analytical chapter of this dissertation (Chapter 2) focuses on supply-push policies, and information related to it will be easy to distinguish in the rest of the figures and tables in this introduction by the color blue. Chapter 3 poses research questions mostly related to the market formation stage of the innovation process and will be distinguishable in the rest of the figures and tables in this introduction by the color red. Chapters 4-5 engage with the diffusion stage of mature decarbonization technologies. Those chapters consider the cross-country implications of decarbonization on international trade, and can be distinguished in figures and tables of this introduction by the color green.

Figure 1.4. Policy types relating to the non-linear stages of the innovation process (top); simplified Energy Technology Innovation System (ETIS) model of the innovation process (middle); and how the dissertation chapters relate (bottom).



Source: Simplified model of the ETIS innovation process, adapted from Grübler et al. 2012.

1.3.2 Research questions organized by ETIS stages

Chapter 2 – RD&D

Public investment in ERD&D is a crucial component of climate policy (Cunliff 2019). More broadly, public RD&D investment is a type of fiscal expenditure that helps expand total factor productivity through innovation in areas where firms are unwilling to invest (IMF 2016).

ERD&D supply-push expenditure data is available for OECD countries since the 1970s (IEA 2020b) and it is the most commonly used ETIS *input* metric used in "international comparative assessments" (Gallagher et al. 2011). Over the past two decades, India and China have grown into both large emitters and a growing part of the global economy (Global Carbon Atlas 2021), but comparable ERD&D data is not readily available for them (Gallagher et al. 2011). Chapter 2 contributes to our understanding of the ERD&D efforts by including data on India and China in a format that corresponds to the technologies covered in existing data from the IEA.

The additional data on India and China allows researchers to answer some new questions, outlined in blue in Figure 1.4. For instance, how have expenditures evolved by country and technologies over time, and are current efforts large enough compared to existing forecasted needs? Are there any patterns over regions? The Multiple Streams Framework suggests that "windows of opportunity" can help policymakers deal with crises (Kingdon 1984). Since the Paris Agreement, have the years after MI been associated with a statistically significant change in expenditure efforts, or to a reallocation of spending towards certain technologies? How does expenditure after MI compare to expenditure after other opportunities for policy change, like the Financial Crisis?

To answer these questions, we draw on and engage with various disciplines and a diverse set of literatures, including how large ERD&D expenditures should be according to Integrated Assessment

Models (IAMs), innovation systems and ERD&D funding trends, and Multiple Streams Framework of policymaking.

Chapter 3 – Market formation

Improving our understanding of the effects of different decarbonization policies on decarbonization itself (as measured through the deployment, or market share, of non-fossil fuels) is crucial to meeting climate goals. Just like in ERD&D, we know much more about the effects of such market-pull decarbonization policies in developed countries than in developing countries (Peñasco, Anadón, and Verdolini 2021).

To answer this question, we compare the causal effects of seven energy policy instrument categories (PICs), such as legal frameworks for renewable energy, on more than 100 developing countries over time. We also ask: How do such effects change from the short to medium term after implementation, by policy category?

The questions lead us to interact and contribute to two broad literatures. The first is the policy evaluation literature that evaluates different decarbonization policies (mostly centered on developed countries); the second is the literature focusing on specific power sector reforms that took place in the 1980s and 1990s (and includes both developing and developed countries).

Chapter 4 – Diffusion and trade

Deep energy decarbonization will change the materials (a general term that refers to the matter from which a thing is or can be made) demanded for energy technologies. Real or forecasted potential supply chain vulnerabilities and reserve shortages motivate many existing studies on the materials used in energy technologies from the point of view of importers. Changing demand patterns of materials from the point of view of exporters, however, is relatively unexplored and relevant to macroeconomic goals such as competitiveness, growth, and fiscal sustainability, which interact with climate change goals.

In Chapter 4, therefore, we ask: How have the characteristics of growth, volatility, and importer and exporter concentration in trade value and volume evolved for the products in the two decades between 1999-2018? What are the products (and product groups) that have exhibited characteristics that are more beneficial to exporters?

We divide ETMs into those that support decarbonization, and those that represent the existing traditional energy paradigm. We also divide the same products into those that are unrefined versus are refined. We show that this characterization is important because it can aid countries in setting policies to best direct their position in trade according to their existing export profile.

Our questions lead us to interact with and further the ETM literature, which we broadly divide into three streams: criticality assessments as they relate to national security, general reserve and resource assessments, and resource governance.

Chapter 5 - Diffusion and trade

A key concept in economics is the elasticity, or the change in one variable due to the change in another. A common elasticity is the "price elasticity of demand," which refers to how much demand changes for a given change in price. It can be understood as the slope of the demand curve on a quantity (horizontal) and price (vertical) graphical representation of the market. The lower the elasticity of demand, the less change in demand with a given change in price.

Knowing the price elasticity of demand is useful in many ways. For instance, an exporting country that knows the price elasticity of demand for their exports is in a better position to tax their exports appropriately for optimal fiscal revenue. Conversely, an exporting firm that knows the price elasticity of demand for their product is in a better position to price their product appropriately.

In Chapter 5, we ask: What is the price elasticity of import demand (simplified as "trade demand elasticity") for each product-and-main-exporter pair of ETMs (e.g., gas from Russia or lithium from Argentina)? And, is there a difference between developed and developing exporters in ETM trade demand elasticities?

Despite their importance in economics, calculating price elasticities of demand and supply from existing data is a complex and frequently elusive task. This is because existing data only tells you where the curves meet (the market equilibrium), and nothing about the slopes of the curves. In other words, it is difficult to "identify" the demand and supply curves.

Our questions regarding the elasticities lead us to consider and advance the literature that explores how to calculate trade elasticities in a low-data environment for many countries and products at once, including how to "structurally" (i.e., from first-principles) identify supply and demand functions from trade data. For this, we modify and calculate existing elasticity methods based on a series of seminal methodological and theoretical improvements including Armington (1969), Leamer (1981), Feenstra (1994); Krugman (1979), Broda and Weinstein (2006), Soderbery (2015), and more. To our knowledge, we are the first to modify them in this way, and also to ask the question in the context of ETMs.

In the literature review, we explore how that the aim of structural elasticity methods is (usually) to calculate the benefits of trade in the whole economy. And, while we focus on the methodological portions of the literature to measure the elasticities relevant to ETMs in the context of energy decarbonization, the conclusions of that literature largely support economic theory on the benefits of trade. Therefore, the literature both provides a springboard for the calculations and upholds our exploration of ETM trade in the context of the transition to decarbonized energy and competing policy priorities.

Chapters 4 and 5 have distinct perspectives. Chapter 4 focuses on identifying trends over products and product groups at the market equilibrium. Chapter 5 attempts to identify supply and demand curves from the trade data and looks at product-exporter pairs instead of products and product groups. Just like Chapters 2 and 3, Chapters 4-5 attempt to elucidate economic and climate policy implications from the results for developing and developed countries. Figure 1.5 summarizes the chapters, research questions, and literatures used to answer the research questions.

Figure 1.5. Chapter titles, research questions, and literatures.

Ch.	Title	Question 1	Question 2	Question 3	Literatures
2	Characterizing and assessing the evolution of public ERD&D investments in eight major economies, including China and India	How have expenditures evolved by country and technologies over time, and are current efforts large enough compared to existing forecasts of needs?	How does the volatility in China, India, and other major countries compare overall and over major technology groups? Are there patterns over regions?	Have the years after MI been ass. with changes in expenditure, or to a reallocation of spending towards certain tech.? How does it compare to other opportunities, like the Financial Crisis?	Integrated Assessment Modelling; Innovation systems & funding trends; Multiple Streams Framework
3	Comparing the causal effects of seven energy policy instrument categories on energy decarbonization in 100+ developing countries 3-7 years after implementation	How do the effects of seven major policy instrument categories on the deployment of clean energy technologies compare in developing countries?	How do such effects change from the short to medium term after implementation, by policy category?		Decarbonization policy and evaluation; Power sector reform and evaluation
4	The evolution of trade in 30 energy technology materials spanning traditional and clean technologies and its implications	How have metrics in trade value and volume evolved for the products in the two decades between 1999-2018?	What are the products that exhibit characteristics that are more beneficial to exporters?	What are the product groups that exhibit characteristics that are more beneficial to exporters?	Criticality assessments; Reserve and resources assessments; Resource governance
5	A novel estimation of structural trade elasticities and an application to ETMs	What are the trade demand elasticities for each product-and-main-exporter pair of ETMs (e.g. gas from Russia or lithium from Argentina)?	Is there a difference between developed and developing exporters in ETM trade demand elasticities?		New trade theory; Trade elasticity methods

Source: Authors' elaboration.
Note: Energy Research, Development & Demonstration (ERD&D); Energy technology materials (ETMs).

1.3.3 Methods and data

We answer the questions introduced in Figure 1.5 with empirical (statistical and econometric methods), summarized in Figure 1.6. These include descriptive statistics (all chapters), parametric and non-parametric tests to determine differences between groups (Chapter 4), and linear regression analysis with a range of robustness checks and specifications, including intercept-only fixed effects regressions to instrumental variables (IVs) (Chapters 2 and 3) and the estimation of parameters from structural models (Chapter 5).

Figure 1.6. Summary of statistical and regression methods in the dissertation.

Ch.	Title	Methods	Method is used to study:
2	Characterizing and assessing the evolution of public ERD&D investments in eight major economies, including China and India	Design and comparison of four indices to quantify volatility.	Stability of funding by country and technology.
		Intercept-only fixed effects regression analysis. Several robustness checks, including: stratified and non-stratified models, regional samples.	Relationship between windows of policy opportunity (the 2008 Financial Crisis and Mission Innovation) on the growth rate of public ERD&D expenditures.
3	Comparing the causal effects of seven energy policy instrument categories on energy decarbonization in 100+ developing countries 3-7 years after implementation	Instrumental variable (IV) regression with fixed effects and interaction terms. Several robustness checks, including: different methods to measure independent and dependent variables, used of different lags and moving averages, different IVs, regional samples.	Effect of different renewable energy policy instruments on the deployment of clean energy technologies over time.
4	The evolution of trade in 30 energy technology materials spanning traditional and clean technologies and its implications	Average growth, volatility, and market concentration measures of value and volume of trade for 30 ETMs. Parametric and non-parametric statistical inference.	Which product groups and products seem to be accelerating their involvement in trade for the transition to decarbonized energy.
5	A novel estimation of structural trade elasticities and an application to ETMs	IV regression with a limited information maximum likelihood (LIML) estimation strategy, based on Leamer (1981)'s supply and demand identification strategy and Feenstra (1994)'s estimation strategy, which was improved by Broda and Weinstein (2006) and Soderbery (2015).	The trade demand elasticty, by ETM and exporter.

Source: Authors' elaboration.
Note: Energy Research, Development & Demonstration (ERD&D); Energy technology materials (ETMs).

The data selection, creation, and handling for empirical analyses are, along with the methods, a major component of the efforts behind this dissertation. Figure 1.7 displays a non-exhaustive list of data sources.

In Chapter 2, we are among the first to include India and China in public ERD&D estimates by technology since 2000 and 2010 (respectively) to 2018. Amongst other things, this inclusion allows us to more adequately compare aggregate ERD&D expenditures with estimates of what is needed to meet climate goals. This study is also the first to subject this data regression analysis to detect structural changes around two major potential windows of opportunity for policy change.

Chapter 3 compares the causal effect of a wide range of demand-pull policy instruments in developing countries for several decades from 1980-2018. This unique coverage is made possible by the first causal analysis of the comprehensive Regulatory Indicators for Sustainable Energy (RISE) dataset that spans more than one hundred and thirty countries.

In Chapter 4, we take a unique and comprehensive view of ETM traded products. We are the first to distinguish 30 unrefined and refined traded products used as materials in energy technologies using the Harmonized System classification of UN Comtrade, a database with yearly bilateral trade flows between 170+ countries from 1998-2018. To provide the most inclusive analysis possible, we consider both clean energy and traditional energy materials. Our methods yield a product code list that may be useful to other researchers willing to undertake subsequent ETM studies with trade data. Unlike most

ETM studies, we are one of few to consider the viewpoint of developing and developed countries equally.

Last, previous trade elasticity of demand analysis is from the point of view of one importer, usually a developed country, to the products from the rest of the world. To apply the elasticities to our broader ETM perspective, we make an analytical contribution in Chapter 5 that makes it possible to calculate the trade elasticity of demand of a product by the whole world towards one exporter. This is the first application of this change and the first application to ETMs.

Figure 1.7. Key datasets created or used in this dissertation.

Chapter 2: Characterizing and assessing the evolution of public ERD&D investments in eight major economies, including China and India

- **Creation** of own India public ERD&D expenditure from Government of India Union Budgets and Web of Science citations
- Use of new public ERD&D expenditure data based on Chinese Chinese Statistical Yearbook
- ERD&D Budgets from the IEA

Chapter 3: Comparing the causal effects of seven energy policy instrument categories on energy decarbonization in 100+ developing countries 3-7 years after implementation

- **First use** of RISE dataset from Energy Sector Management Program (ESMAP), World Bank
- The Affinity of Nations dataset on the Similarity of State Voting Positions in the UN General Assembly from Bailey et al. (2017)
- Bilateral EU Trade agreements from the EU Commission
- UN International Trade Statistics Database (UN Comtrade) from UN Statistics Division
- World Development Indicators (WDI) from World Bank

Chapter 4: The evolution of trade in 30 energy technology materials spanning traditional and clean technologies and its implications

- **Creation** of sub-dataset on traded products based on UN Comtrade and ETM literature through a systematic process to identify relevant trade product codes across traditional and clean energy technologies
- **Product code list** may be useful to other researchers willing to undertake subsequent ETM studies as broad as ours with trade data

Chapter 5: A novel estimation of structural trade elasticities and an application to ETMs

- Focus on development of elasticities methods. An exemplification of the application of the product code list created in Chapter 4

Source: Authors' elaboration.
Note: Energy Research, Development & Demonstration (ERD&D); Energy technology materials (ETMs); Regulatory Indicators for Sustainable Energy (RISE), World Development Indicators (WDI).

1.4 SUMMARY

1.4.1 Chapter summaries

To aid in the navigation of the dissertation, the sections below provide a summary of each chapter.

Chapter 2: Characterizing and assessing the evolution of public ERD&D investments in eight major economies, including China and India, from 2000-2018

Public efforts in energy research, development, and demonstration (ERD&D) is a crucial component of both economic and climate policy. Yet characterizing and assessing the evolution of ERD&D has been limited by missing data on two major countries and emitters, China and India, except for a recent paper that does not explicitly provide data over time for the two countries.

We ask what the expenditure has been for China and India, and, once including them, how global close spending is to the estimated ERD&D amounts needed to reach climate goals. Focusing on a group of eight major countries, including China and India, we also ask how public ERD&D funding volatility compares by country, overall and by major technology groups. Last, we ask whether past "windows of opportunity" for policy change materialized, and what this can tell us about upcoming ERD&D policy challenges.

Combining the new data on China and India with existing open-access data, we show that public ERD&D is at less than half of what previous estimates say is necessary. We design four indices to study the volatility of funding by country and three technology groups (fossil fuels including carbon capture and sequestration, nuclear, and all the rest, entitled clean plus, CP). The results point towards innovation systems characteristics over three regions: the United States/United Kingdom, continental Europe, and Asia. Last, we evaluate the possible effects of two windows of opportunity for policy change, the 2008 financial crisis (FC) and Mission Innovation (MI). The years after the FC are associated with changes in total funding and minimal increases in CP; the years after MI are associated with minimal increases in CP, but only in a select group of countries. Our results show that public ERD&D requires sustained attention and impetus if we are to reach climate goals.

Chapter 3: Comparing the causal effects of seven energy policy instrument categories on energy decarbonization in 100+ developing countries 3-7 years after implementation

There is a variety of energy policies, all over the world, aiming to advance one or several environmental, economic, security, or equity policy goals. We offer the first consistent attempt to identify how seven energy policy instrument categories (PICs), representing 75+ policies for energy decarbonization, each individually affect the energy mix across 100+ developing countries over time (three, five, and seven years after implementation).

We apply 2SLS with country interactions and country and time fixed effects in regional panels to account for a host of well-documented issues in existing comparable research. These issues include omitted variables that relate to country and regional characteristics and simultaneity and reverse causality between policy enactment and outcomes. Additionally, we design the variables that represent each of the seven PICs using three indices that help account for the degree of reform and collinearity of policies.

We find that generally the effects of PICs improve with time and that policies that address counterparty risks (those that help improve bankability for private participation, including backstops for government auction guarantees) have the most immediate positive effect on energy decarbonization. We suggest that incumbent forces could be behind the immediately lackluster or negative effects in other PICs and consider the effects that long-term country-specific characteristics, like enforcement, are likely to have on the effects of PICs.

Chapter 4: The evolution of trade in 30 energy technology materials spanning traditional and clean technologies and its implications

Deep energy decarbonization will require a shift in the materials used in energy technologies. Many existing ETM studies are motivated by perceived supply chain vulnerabilities or potential reserve shortages from the point of view of importers of ETMs. The effect of changing demand on exporters of materials is relatively less explored, but still relevant to growth, competitiveness, and other policy priorities that coexist with climate change goals in both developing and developed countries.

We ask whether there are ETM products (and product groups) that exhibit characteristics in growth, volatility, and importer and exporter concentration metrics in trade value and volume from 1999-2018 that are beneficial to exporters, and what the policy implications of these metrics may be. The product groups we study are: (1) clean and traditional materials; and, (2) unrefined and refined materials.

To do this, we systematically isolate and categorize 30 relevant traded products in UN Comtrade, an open-access dataset of bilateral trade flows spanning more than two decades, five thousand products, and almost all countries. The product codes and product group definitions can be re-used by other researchers willing to undertake an ETM study with trade data. We establish the direction of each metric that benefits exporters and identify and interpret existing trade trends, employing parametric and non-parametric inferential statistical methods where appropriate.

We find that, of the 30 products, lithium carbonate exhibits the most beneficial metrics for exporters over time. Additionally, among other results, clean energy and refined materials are disproportionately represented in the high-performing products for exporters, compared to traditional and unrefined materials that developing countries tend to export more frequently. Although there are some subtleties, if trends continue, the results make a case for directed policy attention towards enhancing clean and refined ETM trade and capabilities in developing countries.

Chapter 5: A novel estimation of structural trade elasticities and an application to energy technology materials

Elasticities of demand and supply are a core concept in economics with far-reaching applications. For the first time, and in the context of trade and energy decarbonization, we ask: what are the price elasticities of import demand (or the change in trade demand due to a change in price, simplified as "trade demand elasticity"), for each energy technology material (ETM)-and-exporter pair (e.g., gas from Russia or lithium from Argentina)? Additionally, is there a difference between developed and developing exporters in these ETM elasticities?

Despite their importance in economics, calculating trade elasticities is frequently an elusive task because of the difficulty of identifying supply and demand curves from existing data. To answer the research questions, we propose modifications to current structural trade demand and supply price elasticities building on the methods developed by Broda and Weinstein (2006), based on Feenstra

(1994). With a mean trade demand elasticity of 3.94, our trade demand elasticities are broadly in line with the methods on which ours is based.

Our main result is to present the trade elasticities over two decades for 29 products and 22 exporters, which can be used by researchers and policymakers in a variety of settings, including IAMs. Additionally, we find that developed countries have weakly statistically significantly lower ETM trade demand elasticities than developing countries, which we discuss in context of the portfolio of ETM products exported by the two groups.

Nevertheless, there are indications of a convergence of ETM elasticities between developed and developing countries over time. This convergence is at least partially explained by the characteristics of the exporters - i.e., a change how the importer perceives the quality differential between exports from developing and developed countries - rather than a change in the portfolio of exports of the two exporting country groups. The convergence implies that developed country exporters may have lost competitive edge over time. Continued surveillance with more trade data over time is necessary.

1.4.2 Contributions

This dissertation in energy economics is motivated by the urgent, global, and systemic challenge of climate change. Research questions cover technology-push policies, demand-pull policies, and trade considerations in decarbonizing the energy sector, which is the major contributor to climate change.

We pose geographically inclusive questions and make every effort to use inclusive data in all chapters. This leads us to create new datasets or to apply existing ones in novel ways. Because we try to discuss the energy sector of developing economies that are underrepresented in the literature, some portions of the analysis can contribute to the field of applied development economics. We summarize the contribution of each analytical chapter below.

Chapter 2: Characterizing and assessing the evolution of public ERD&D investments in eight major economies, including China and India

- Public ERD&D, even when including China and India, is at least less than half of what IAM estimates say is necessary.
- The volatilities of national ERD&D allocations point to regional innovation systems characteristics over three groups: the United States/United Kingdom, continental Europe, and Asia.
- Despite some technology-specific trends, the years after Mission Innovation do not generally correlate with a statistically significant change in funding allocation towards non-fossil fuel and non-nuclear ERD&D.
- Public ERD&D requires sustained attention and impetus if we are to reach climate goals.

Chapter 3: Comparing the causal effects of seven energy policy instrument categories on energy decarbonization in 100+ developing countries 3-7 years after implementation

- The effects of policies on decarbonization are limited and can be negative, though they tend to improve within the time period studied (3-7 years).
- Policies that address counterparty risks (those that help improve bankability for private participation, including backstops for government auction guarantees) have the most immediate positive effects on energy decarbonization.
- We consider the roles of the Sailing Ship Effect and long-term country-specific characteristics, like the ability to secure financing, on the abovementioned results on the effects of policies.

Chapter 4: Identifying and interpreting the trade trends of 30 energy technology materials

- Clean energy materials and refined products have held relatively larger promise than traditional energy materials and unrefined products for exporters. However, in accordance with existing literature, these are markets in which developing countries are generally underrepresented.
- Of the 30 products analyzed, lithium carbonate exhibits the most beneficial trade patterns, putting its major exporters in a position to benefit the most from trade trends.
- If existing patterns have any bearing on the future, the usual industrial and trade giants are best positioned to continuing reaping the benefits from decarbonization.
- If trends continue, the results make a case for directed policy attention towards enhancing clean and refined ETM trade and capabilities in developing countries. We discuss other options.

Chapter 5: A novel estimation of structural trade elasticities and an application to ETMs

- We make an analytical contribution to empirical trade analysis by proposing modifications to current structural trade demand and supply price elasticities building on the methods developed by Broda and Weinstein (2006), based on Feenstra (1994). The modifications make it possible for us to study the elasticity of demand ETMs, by material and exporter. With a mean trade demand elasticity of 3.94, our trade demand elasticities are broadly in line with analyses with methods on which ours is based.
- Our main result is a visualization with the elasticities over two decades for 29 products and 22 exporters, which can be used by researchers and policymakers.
- A low trade elasticity of demand is beneficial to exporters because it is related to stability that has impacts on a range of economic indicators. Developed countries have weakly statistically significantly lower ETM elasticities overall (which is expected due to the nature of the products they export).
- There are also indications of a convergence of ETM elasticities between developed and developing over the last two decades (not expected). We hypothesize that the changes are at least partly due to product and country characteristics, not the *portfolio* of ETMs exported by each group. This result implies that ETM trade demand elasticity reassessment and surveillance over time are relevant across the board of countries, for competitiveness and other considerations.

CHAPTER 2: CHARACTERIZING AND ASSESSING PUBLIC ERD&D INVESTMENTS IN EIGHT MAJOR ECONOMIES, INCLUDING CHINA AND INDIA

Abstract

Energy research, development, and demonstration (ERD&D) is a crucial component of both economic and climate policy. Yet characterizing and assessing the evolution of ERD&D has been limited by missing data on two major countries and emitters, China and India, except for a recent paper that does not explicitly provide data over time for the two countries.

We ask what the expenditure has been for China and India, and, once including them, how close global spending is to the estimated ERD&D amounts needed to reach climate goals. Focusing on a group of eight major countries, including China and India, we also ask how public ERD&D funding volatility compares by country, overall and by major technology groups. Last, we ask whether past "windows of opportunity" for policy change materialized, and what this can tell us about upcoming ERD&D policy challenges.

Combining the new data on China and India with existing open-access data, we show that public ERD&D is at less than half of what previous estimates say is necessary. We design four indices to study the volatility of funding by country and three technology groups (fossil fuels including carbon capture and sequestration, nuclear, and all the rest, entitled clean plus, CP). The results point towards innovation systems characteristics over three regions: the United States/United Kingdom, continental Europe, and Asia. Last, we evaluate the possible effects of two windows of opportunity for policy change, the 2008 financial crisis (FC) and Mission Innovation (MI). The years after the FC are associated with changes in total funding and minimal increases in CP; the years after MI are associated with minimal increases in CP, but only in a select group of countries. Our results show that public ERD&D requires sustained attention and impetus if we are to reach climate goals.

2.1 INTRODUCTION

Government involvement in research, development and demonstration (RD&D) efforts has long filled a vacuum of investment that is undersupplied by the market but contributes to priorities like economic growth (Jaffe, Newell, and Stavins 2005) through technology-push policies, or policies that direct and finance technological innovation (Nemet 2009). By several accounts, stable increases in public energy RD&D (ERD&D) expenditure are necessary to meet climate goals (IEA 2020a; Narayanamurti, Anadón, and Sagar 2009).

Previous analysis has been hampered by missing or incomplete data for two large emitters: China and India. This chapter aims to characterize and assess the evolution of technology-push policies since the turn of the 21st century, including China and India. We ask the following research questions: (1) How have expenditures evolved by country and technologies over time, including China and India; and are current efforts large enough compared to existing forecasts of needs?; (2) How does the volatility in China, India, and other major countries, compare overall and over major technology groups? Are there any patterns over regions?; and, (3) Since the Paris Agreement, have the years after MI been associated with a statistically significant change in expenditure efforts, or to a reallocation of spending towards certain technologies? How does expenditure after MI compare to expenditure after other opportunities for policy change, like the Financial Crisis?

In addition to China and India, we focus on six major economies (M6), composed of France, Germany, Japan, Korea, the United Kingdom, and the United States. The M6 accounted for almost 80% of global public clean ERD&D investment in 2016 according to 2020 IEA estimates (IEAb 2020). To make the analysis possible over technologies and countries given data coverage, we use three technology categories: fossil fuels (FF), which includes CCS (the process of capturing and geologically storing carbon dioxide from power generation and industrial processes), nuclear, and all the rest, or "clean plus" (CP).

We build upon and adapt concepts and metrics from three literature streams. First, we discuss estimates by integrated assessment models (IAM) on the amount of public spending in RD&D necessary to meet our climate goals. We argue that despite the consensus that public ERD&D expenditure should see an increase several times over, it is impossible to assess our progress without including data on major emerging economies (and emitters), including China and India.

To address this gap, we design methods to acquire public ERD&D expenditure data on China (external source is provided) and India (methodology described here). This chapter was written before Zhang et al. (2021) published estimates for China and India, but we find it impossible to recreate their data because it lacks methodological details and the bulk of their data is provided only in graphs. As a result, we present the longest and most complete public ERD&D investment data for China and India overall and by technology since 2001 and 2010, respectively, in a format that allows us to combine with the existing data on OECD countries to compare the size of investments today and what is needed to reach climate goals.

Second, we consider and engage with two contributions from the innovation studies literature: the need for stable ERD&D funding and systems of innovation. We design four indices to characterize and assess the evolution volatility overall and by technology groups in the M8. The indices allow us to characterize volatility of funding across countries and technologies, as well as to examine whether the evolution of funding displays geographical patterns.

Last, we consider the literature on windows of opportunity for policy change following Kingdon (1984)'s Multiple Streams Framework of the policy process. We focus on two windows of opportunity, a crisis and an international agreement, for increased public ERD&D finding since the turn of the 21st century. The first window of opportunity is the fiscal stimuli related to the 2008-2009 financial crisis (FC). The second is the signing of Mission Innovation (MI) alongside the Paris Agreement in 2015. Amongst other things, MI involved 24 member countries committing to doubling their public ERD&D from 2015-2020. We subject the data to regression analysis to detect potential structural changes in total funding amounts and allocation across technologies.

Our findings are threefold. First, we find that ERD&D investments are less than half of the amounts that IAMs consider is optimal. Expectedly, China has played an increasing role in global ERD&D expenditure. However, the role of India has declined. Importantly, China seems to singlehandedly maintain the global share of FF despite decreases in expenditure from the M6.

Second, we find that China's ERD&D is relatively stable even in its large growth. While India is relatively unstable compared to the rest of the M8, its consistent growth in FF funding is second only to China's. Confirming previous literature, we also find that the United States and the United Kingdom are relatively unstable. They also showed more consistent growth in FF and nuclear over CP, compared to their Western counterparts of our country sample (Germany and France). These results hint at regional innovation systems patterns (US/UK, continental Europe, and Asia).

Third, our regression analysis suggests that voluntary cooperation through MI has not resulted in significant changes in terms of funding amounts and reallocation towards clean energy. The FC has had an impact, although the changes have been small compared to recommended amounts and efforts. MI had an impact only for a select group of countries.

The extent to which voluntary cooperation efforts, as well as crises, could yield changes commensurate with the challenge remains to be seen and should be the subject of additional research. However, the analysis above rings an alarm, as even the FC has not produced ERD&D increases commensurate with the climate challenge and policy goals. It is imperative to continue to surveil RD&D efforts as Covid-related stimulus packages continue to shape the direction of economic recovery and the clean energy transition (Jaeger, Westphal, and Park 2020; Barbier 2019; Larsen et al. 2020).

2.2 LITERATURE REVIEW

In this Literature Review, we first briefly discuss the challenges of estimating the optimal amounts and technological allocation for ERD&D and we show that despite the challenges, the subset of analyses that attempt to make these estimates suggest a real need for major increases in public ERD&D investment. We also point that, until now, it has been difficult to compare these estimates with reality due to the lack of data on non-OECD countries. In the Methods section, we will show that we contribute to this literature by providing data on two major developing countries, China and India. These estimates allow us to better assess current amounts with what is considered optimal in the literature.

In addition to the need for increased ERD&D public investment, we substantiate the need for it to be stable overall, and by technology. We show there have been recent contributions on patterns in developing countries (such as China) in the literature, but that the bulk of existing work focuses on OECD countries. In the Methods section, we propose four volatility indices across countries and technologies to help assess and compare the efforts that have been made in ERD&D.

Last, we ascertain that in accordance with existing research, the FC and MI can be considered potential windows of opportunity for structural change in ERD&D funding. In the Methods section, we will propose subjecting the data regression analysis to compare their potential effects.

2.2.1 Optimal ERD&D investment and technological allocation

Optimal ERD&D investment

Despite the essential role of public ERD&D expenditure in energy innovation (Gallagher, Holdren, and Sagar 2006; Murray 2017), there is no unifying structural theory behind how RD&D, prices, and learning influence the stock of knowledge and growth or other policy priorities (Popp 2019). As a result, designing and evaluating the relationship between these components is complex.

Energy-economy models and climate-economy models are types of integrated assessment models (IAMs) that simulate the relationship between technological change, growth, and the environment. They can help clarify how policies can be applied to incentivize technology diffusion, decrease environmental damage, and sustain long-term growth (Anadón, Baker, and Bosetti 2017). Among the array of model inputs and goals, the way that technological change is treated (broadly, endogenously versus exogenously, but also with variations of these) plays an especially important role in model outputs (Gillingham, Newell, and Pizer 2008). In fact, it is “one of the most important determinants of the results of climate policy analyses” (Popp, Newell, and Jaffe 2010).

Notably, models also differ on the relative strengths given and effects attributed to knowledge spillovers (both over time and firms) in different sectors, and the crowding out of RD&D from sectors unrelated to climate change policy. Growth can occur if spillovers in sectors related to climate change policy are large enough to compensate for the crowding out of RD&D from the remaining sectors (Nemet and Johnson 2012). Amongst a wide array of additional design alternatives, models also differ in their treatment of uncertainty, substitutability, and complementarity between production and innovation. As a result, the appropriate way of incorporating endogenous technological change through R&D, and how this interacts with climate policy and growth, is far from settled (Popp, Newell, and Jaffe 2010).

Despite these difficulties, calls for increases in ERD&D efforts are not new, especially in developed countries (see Schock et al. 1999; Margolis and Kammen 1999a; 1999b). More recently (but still several years before net-zero goals were in place), Nemet and Kammen (2007) asserted that 6 to 9-fold increases in ERD&D investment were necessary and achievable in the United States. They estimate an annual need for 17–27 billion 2002 USD, in the United States (24.16-38.37 billion 2019 USD, which is the unit used in the rest of this chapter).

Today, the subset of models that explicitly include energy and climate RD&D investment have arrived at a consensus regarding the fact that significant increases are needed (Anadón, Bunn, and Narayanamurti 2014). For instance, Marangoni and Tavoni (2014) estimate the RD&D strategy needed for scenarios that are consistent with 2 degrees of warming. They estimate that there is a need for cumulative spending of 1 trillion in 2005 USD (about 1.42 trillion in 2019 USD) between 2010-2030. This is equivalent to 71 billion 2019 USD per year.

Marangoni and Tavoni (2014) estimate a need for about 1.6 trillion in 2005 USD (about 2.27 trillion in 2019 USD) between 2030-2050, and that spending should be evenly split between industrialized and non-industrialized countries after 2030. Notably, progress towards this recommendation would be impossible to verify without the data on non-OECD economies. The need is bound to be larger if analyses (like ours) show that we are already behind.

Marangoni et al. (2017) address the problem of uncertainty in ERD&D by combining input parameters derived from expert elicitations into WITCH, an IAM widely used for policy assessment. They find a need for a 10-fold increase in total budget, and that overlooking uncertainty severely decreases investment estimates. They also find that the optimal RD&D portfolio is dominated by batteries for transportation. Among several limitations, they note that the scope of their inputs is restricted to public expenditure in Europe, and that ignoring public-private and regional spillovers may lead them to overestimate the funding amounts needed.

Technological allocation

Probabilistic assessments of expert elicitations on the optimal technological portfolio of RD&D investments have shown a relative disagreement and should be viewed in the context of macroeconomic policy priorities (Anadón, Baker, et al. 2016). In a review of IAMs that incorporated expert elicitations and decision frameworks, Anadón, Baker, and Bosetti (2017) indicate some salient points on technological allocation.

For instance, as climate stringency increases, technologies that provide flexibility, like storage (facilitating the deployment of intermittent technologies), vehicles (facilitating the abatement of transportation), and CCS (facilitating ex-post emissions abatement) receive higher RD&D investments. As an example of the range of attributes of these technologies, CCS can provide short and long-term flexibility to the power system, enable low-carbon hydrogen, support a just transition, deliver net-negative emissions when combined with bioenergy, and use captured carbon dioxide to manufacture goods or aid in industrial processes, helping offset emissions from hard-to-abate sectors (International Energy Agency 2020b). Under fiscal (compared to emissions) constraints, the portfolios become less diverse. A salient disagreement in IAMs that consider budgetary constraints is in the relative proportion devoted to nuclear versus CCS, because these technologies tend to be substitutes and are both sensitive to factors like public acceptance. Factors such as these "are likely to play a role on whether one or the other technology receives the largest share of R&D portfolios" (Anadón, Baker, and Bosetti 2017).

Importantly, these models lack information about public efforts occurring outside the OECD. We contribute to this conversation with data on the evolution of ERD&D funding in China and India. Adding these two large emerging economies allows us to more accurately assess progress and the magnitude of the efforts needed in public ERD&D.

2.2.2 Funding volatility and systems of innovation

Volatility

The need for more expenditure coexists with the need for it to be stable (Cohen and Noll 1991). New technologies can take decades to develop (Grübler, Nakicenovic, and Victor 1999). Volatility in public ERD&D funding also has a detrimental effect on private investors, as they are uncertain of the direction of public support (Norberg-Bohm 2000; Fuss et al. 2008; Anadón, Chan, et al. 2016; Guellec and Van Pottelsberghe De La Potterie 2003; Nemet 2009).

In a study that includes both developed and developing countries, Anadón (2012) discusses the need for stability in funding in her comparative analysis of the structure and relationships of institutions for ERD&D in China, the United Kingdom, and the United States. Relatedly, Narayanamurti, Anadón, and Sagar (2009), Chan et al. (2017), and Weiss and Bonvillian (2009) include stable funding within elements that are essential to successful innovation institutions.

There are already several studies that specifically quantify and assess ERD&D volatility in specific OECD countries (see Godin (2000)'s paper series and Kassouri et al. (2021)). For instance, Schuelke-Leech (2014) finds high volatility of overall and technology US ERD&D expenditure between 2000-2012 and maintains that volatility may be as much a concern as funding levels. Winskel et al. (2014) find that energy public funding levels have been erratic in the United Kingdom.

More broadly, Baccini and Urpelainen (2012) analyze the causes of "boom and busts" in public ERD&D funding in IEA member states between 1981-2007. They find that volatility is exacerbated by "legislative fractionalization", or competition by several parties, and executive power changes toward the left. We contribute to the discussion by proposing four measures of volatility and comparing the results of these indices across the M6 plus China and India.

Energy RD&D funding volatility has also been researched by technology. Apart from national idiosyncrasies, technological characteristics can play a role in volatility. The capital-intensive nature of some technologies, like CCS demonstration projects, means that capital disbursements can be peak and fall more than others (Wilson et al. 2020; Nemet, Zipperer, and Kraus 2018). Our four indices also allow us to compare volatility across technologies.

Systems of innovation

As suggested in Baccini and Urpelainen (2012)'s analysis mentioned above, support for specific technologies depends on a confluence of factors, including the intermittent alignment of incumbent interest and national needs (Weiss and Bonvillian 2009; Cohen and Noll 1991).

In systems of innovation perspectives, investments in RD&D depend on national (and other) characteristics and complex feedback loops between various types of actors (Anadón, Chan, et al. 2016; Hannon and Bolton 2021). These perspectives are frequently attributed to the work of Freeman (1987); Lundvall (1992); and Nelson (1993) summarized in Table 2.1, and have been further characterized along national (Nelson 1993), sectoral (Malerba 2004), regional (Cooke 2001) and global (Binz and Truffer 2017) horizons.

Table 2.1. Summary of the founding systems of innovation perspectives.

Paper	Focus	Output
Freeman (1987)	Broad interaction between "technology, social embedment and economic growth" as well as their feedback loops.	Coined "national innovation systems". Categorizes and explores the role of four main elements in Japanese NIS: 1. Policy; 2. Corporate R&D; 3. Human capital and organization; and, 4. Conglomerates.
Lundvall (1992)	"The elements and relationships which interact in the production, diffusion, and of new, and economically useful knowledge…and are either located within or rooted inside the borders of a nation state" (Lundvall 1992).	Three major themes: 1. Sources of innovation through types of activities by actors (learning-by-doing routine activities versus R&D efforts); 2. The nature of innovation as either incremental or radical; and 3. The role of nonmarket institutions, including non-monetary user-producer interactions and institutions that provide stability to the system.
Nelson (1993)	"Intertwining of science and technology" and formal R&D institutions	The architecture of the formal R&D system helps to determine how well the system works.

Source: Within table and Steinmueller (2010).

There is a relatively rich discussion of these systems (or parts of these systems) for OECD countries. For instance, from most specific to broader, Winskel et al. (2014) find that the business sector has had a growing influence in moving the focus toward the nearer term and from niche to mainstream technologies in the United Kingdom. Comparing European Union members, Grafström et al. (2020) identify a divergence in RD&D growth rates and find that countries with low dependence on imports in the energy sector and deregulated power markets display lower growth rates in public renewable RD&D. Archibugi and Filippetti (2018) find that overall RD&D is decreasing with respect to private expenditure in OECD countries, and that levels are decreasing overall.

However, as the literature review thus far has shown, there is a growing focus on gathering information and understanding innovation governance in large developing economies (Kempener, Anadón, and Tarco 2010; Yu, Lazonick, and Sun 2016). Two relevant expositions on the complexity of Chinese technological innovation specifically in clean energy include Binz and Anadón (2018) and Lewis

(2013). These two deep dives demonstrate the confluence of national and extra-national factors that affect the development of solar and wind technologies, respectively. In characterizing volatility of technology funding by countries, our analysis engages with systems of innovation literature and finds some support for regional patterns of national innovation systems.

2.2.3 Windows of opportunity

Several researchers indicate that contingent historical shocks affect ERD&D investment in unpredictable ways (Runci and Dooley 2004). Energy RD&D spending peaks of the late 1970s, based on oil crises, energy security, and Cold War concerns, is one of several historical examples (Sagar 2004; Nemet and Kammen 2007; Center and Bates 2019).

These shocks can be opportunities for priority setting and coordination (Gross and Sampat 2020) that can be viewed through Kingdon (1984)'s Multiple Streams Framework of the policy process. In the framework, three proposed streams (of problems, policies, and politics), usually operate independently of one another. However, factors align during "windows of opportunity," and "policy entrepreneurs" may successfully combine the streams and create major policy change (Zahariadis 2007).

One such window for opportunity for ERD&D was the FC of 2008 (Anadón 2012; Narayanamurti, Anadón, and Sagar 2009). Narayanamurti, Anadón, and Sagar (2009) posit that the FC marked "a historical point where the energy innovation system is being examined" in the United States; on the other hand, Anadón (2012) questions the feasibility of continuing the increases in RD&D seen after the FC. Today, the unprecedented shock of COVID-19 has galvanized new and renewed fiscal stimuli, including for ERD&D (Huenteler et al. 2017; Nuclear Energy Agency 2021; IEA 2020c). This makes our question of potential long-term structural effects of the fiscal stimuli related to the FC a topical concern in current policy work.

MI, where 24 member countries (several OECD and others, including China and India) committed to doubling their ERD&D from 2015-2020, alongside the Paris Agreement in 2015, is another potential window of opportunity. Note that while MI includes some collaboration between countries, the initiative falls short of the "deep coordination" strategy of "coordinated research" advocated by Keohane and Victor (2016) and others. Additionally, IAMs have also shown that alone, a deal like MI is unlikely to solve the climate problem (Marangoni and Tavoni 2014). However, this does not mean MI has had no tangible effect in ERD&D investment, immediately or over the longer term. In fact, Keohane and Victor (2016) argue that "serious international cooperation [like coordinated research] will have to emerge incrementally" and that "shallow coordination [as MI could be] can create vital conditions for deeper cooperation."

Evaluating the early success (or failure) of MI as a window of opportunity to galvanize structural change in its member countries to increase the pace of ERD&D would provide information on the intensity of the policy push still needed to achieve our climate goals. In light of the literature, we compare and contrast the potential effects of these two distinct (crisis and cooperation) windows of opportunity. We subject the data to regression analysis and ask whether the FC and/or MI, are correlated to statistically significant structural changes on ERD&D spending. A recent paper by Myslikova and Gallagher (2020) finds that MI is "succeeding in its quest," in part because it finds that expenditure increased 38% since MI begun. Our aim is instead to assess structural change, defined as statistically significantly differences in growth rates after MI.

In sum, IAMs and related literature indicate that increased ERD&D spending several times over is needed globally but assessing our progress has been difficult without data on emerging economies, especially large ones like China and India. We help close that gap by assessing the progress of global ERD&D expenditure by contributing data on China and India. The innovation literature also maintains that such spending should be stable. To this effect, we design four volatility indices that allow us to compare and assess the overall volatility and direction of spending across countries, and technologies. Last, the policy literature supports the idea that windows of opportunity may help drastically change the course of government ERD&D. We subject the data to regression analysis to discern whether two windows of opportunity, a crisis (the FC) and cooperation (MI), are related to changes ERD&D spending.

2.3 METHODS

Most OECD countries provide estimates of RD&D expenditures on an annual basis by technologies to the IEA. In this chapter, we focus on the six major spenders in the IEA dataset (France, Germany, Korea, Japan, UK, and US) separately and aggregate all other countries into three regions: Americas, Europe, and Asia (including Oceania). As new countries join the OECD and provide data, the aggregates may include more countries over time. For instance, the Rest of Americas group consists only of Canada until 2015 and includes Mexico after 2015.

Table 2.2 presents the main IEA technology groups behind the data that underlies our analysis. As will be explained in the Data section, some technology-country combinations are missing. To make the analysis possible over technologies and countries, we use three technology categories: (1) FF, which includes CCS; (2) nuclear; and (3) all the rest, or "clean plus" (CP).

Table 2.2. Main technology categories in the 2020 IEA Energy Technologies RD&D Budgets dataset, and our technological classification for the rest of the analysis.

Our classification	IEA technology	IEA definition
Clean plus (CP)	Energy efficiency	Industry, Residential and commercial buildings, appliances and equipment, Transport, Other energy efficiency, Unallocated energy efficiency
Fossil fuels (FF)	Fossil fuels	Oil and gas, Coal, CO2 capture and storage, Unallocated fossil fuels
CP	Hydrogen and fuel cells	Hydrogen, Fuel cells, Unallocated hydrogen and fuel cells
Nuclear	Nuclear	Nuclear fission, Nuclear fusion, Unallocated nuclear
CP	Other cross-cutting technologies and research	Energy system analysis, Basic energy research that cannot be allocated to a specific category, Other
CP	Other power and storage	Electric power conversion, Electricity transmission and distribution, Energy storage (non-transport applications), Unallocated other power and storage technologies
CP	Renewables	Solar energy, Wind energy, Ocean energy, Biofuels (including liquid biofuels, solid biofuels and biogases), Geothermal energy, Hydroelectricity, Other renewable energy sources, Unallocated renewable energy sources
CP	Unallocated	

Source: Authors' elaboration based on IEA (2020b).

As explained in the Literature Review, the lack of data representing major non-OECD emerging economies has been a blind spot in understanding the evolution of global RD&D governance (Kempener, Anadón, and Tarco 2010), and this is a gap we attempt to address in this chapter by acquiring and including data on China and India. Although the IEA recently published data across five technology categories for China between 2015 and 2019, the level of disaggregation and the timeframe are insufficient for our analysis. MI and IEA data aggregate all energy technologies for India between 2015 and 2019, which again is insufficient for analysis.

Dr. Tong Xu and Professor Laura Díaz Anadón conducted their own data collection effort relying on China's official statistics to provide a consistent picture of the evolution of the relevant ERD&D programs between 2001 and 2018. Since the collection of China ERD&D data is not my work, the reader can refer to the methodology created and executed by my coauthors in the Supplementary Information of "The Evolution of Energy Innovation Governance for Decarbonization," a paper that has been submitted to *Nature Energy*.

Below, we first describe the methods employed to construct the dataset for India. We then explain how we constructed indices to study the volatility of funding, by country and technology. Third, we detail the methods we employed to detect structural change after two windows of opportunity, the FC and MI.

2.3.1 Compiling public ERD&D data for the Government of India

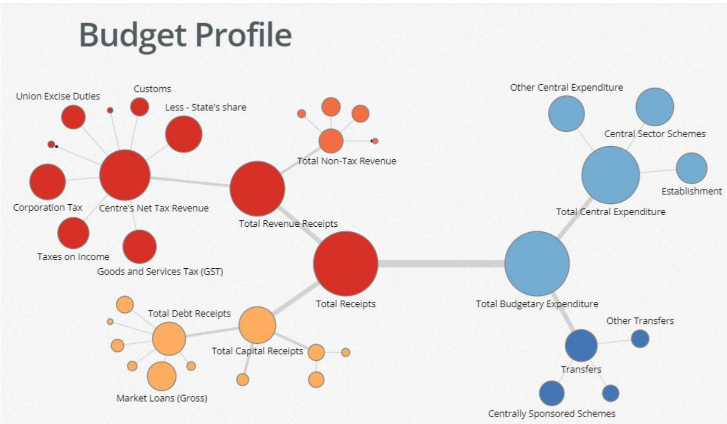
India does not regularly publish what it spends on ERD&D by technology. The National Science and Technology Management Information System (NSTMIS), a part of the Department of Science and Technology (DST), tracks RD&D performance. However, a major shortcoming is that it does not break down funding by type of energy technology. Past literature that has attempted to compile RD&D estimates for energy with similar limitations includes Sagar (2002) and Kempener, Anadón, and Tarco (2010). We discuss Zhang et al. (2021)'s recent estimates below.

Union Budgets (UBs) as the main source of data

Our main sources of data are Union Budgets (UBs) "Notes on Demand for Grants", or government expenditure documents, by Ministries and Departments (Ministry of Finance, Government of India 2020a). This is similar to Zhang et al. (2021). Figure 2.1 demonstrates that a major strength of UB documentation is that it covers all Indian government expenditures. Specifically, Figure 2.1 (top) sourced from Open Budgets India (an initiative led by the Centre for Budget and Governance Accountability) show the total annual expenditure classifications of the government of India. Comparing it with Figure 2.1 (bottom), we can see that UB expenditure budget documents cover the entirety of "Total Budgetary Expenditure" in the top of the figure.

Another key strength of using yearly UBs is that they compile funding data using similar methods over the same timeframe across all Ministries and Departments. Therefore, they allow for a robust and consistent overview of the evolution of how much each Department or Ministry is spending and comparison across types of energy technologies. The exact source of data is the "Total" column of the "Actuals" heading, which shows what was certified to be spent two years before the current UB. For instance, the section shown in Figure 2.1 (bottom) shows the 2017-2018 expenditure and was published in 2019.

Figure 2.1. Expenses covered in "Expenditure Budget" documents of the Government of India Union Budgets (top) and an extract of the 2019 "Summary of expenditure (bottom).



MINISTRY/DEPARTMENT	Actuals 2017-2018 Revenue	Capital	Total
1. Central Expenditure (2+3+4)	1426222.41	257491.75	1683714.16
2. Establishment	466891.28	6139.99	473031.27
3. Central Sector Schemes	342187.87	245597.12	587784.99
4. Other Central Expenditure	617143.26	5754.64	622897.90
5. Transfers (6+7+8)	452611.11	5647.79	458258.90
6. Centrally Sponsored Schemes	284944.42	503.35	285447.77
7. Finance Commission Transfers	92244.47	...	92244.47
8. Other Transfers	75422.22	5144.44	80566.66
9. Total Expenditure through Budget (1+5)	1878833.52	263139.54	2141973.06
10. Resources of Public Enterprises	...	610686.37	610686.37
11. Total Expenditure through Budget and Resources of Public Enterprises (9+10)	1878833.52	873825.91	2752659.43

Source: Top: Centre for Budget and Governance Accountability (2019). Bottom: Extract from Summary of Expenditure Profile 2019-2020 (Ministry of Finance, Government of India 2020b).

We retain the following information for budget lines when they demonstrate relation to both RD&D and energy: expenditure values, description, and line number. To maintain consistency with the bulk of existing data on RD&D expenditures, we attempt to populate expenditure by the main technology categories in the IEA dataset enumerated in Table 2.2. Where possible, budget lines are categorized into IEA headings. Otherwise, they are deemed "unallocated." Appendix 2.1 shows an example of background documentation for the Ministry of Power for 2010. Due to a change in reporting, this "Actuals" heading is available after 2009.

A line-by-line examination of documentation for each Ministry/department by year through 2010-18 yielded the following list of seven institutions that mention energy and RD&D (Table 2.3).

Table 2.3. Institutions of interest for ERD&D in Indian Union Budget documents.

	Institutions of interest
1	Department of Atomic Energy
2	Ministry of Coal
3	Department of Heavy Industry (within Ministry of Heavy Industries and Public Enterprises)
4	Ministry of New and Renewable Energy
5	Ministry of Petroleum and Natural Gas
6	Ministry of Power
7	Department of Water Resources, River Development, and Ganga Rejuvenation (within Ministry of Jal Shakti)

Source: Authors' elaboration based on the methods and data sources described in this chapter.

Despite the strengths of using UBs as our main data sources, we identify at least four challenges associated with them, summarized in Table 2.4. For instance, some obvious contenders for ERD&D research, like the Department of Science and Technology, are missing from Table 2.3. This is due to Challenge 1 and is likely to cause an underestimation of the true ERD&D expenditure for that department. As a result, we expand the list of included ministries/departments by using a complementary methodology, described generally below and in detail in Appendix 2.2.

Table 2.4. Challenges of using Indian Union Budgets as the main source of data.

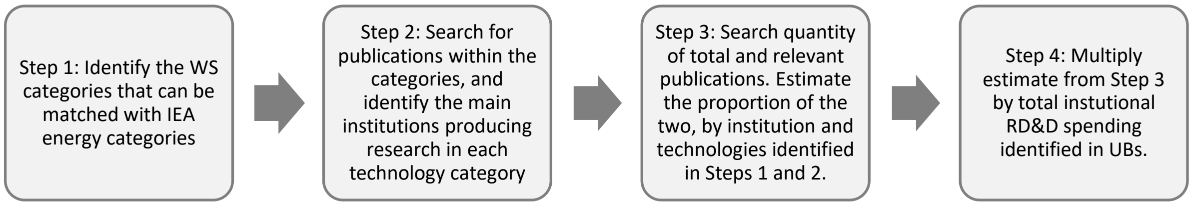
Challenge	Description	Result
1	When a budget line description does not include a mention of both RD&D and some type of energy, we cannot attribute it to ERD&D.	Possible underestimation
2	Budget lines include overhead costs, and in some cases, it is difficult to isolate ERD&D from other RD&D if both are mentioned.	Possible overestimation
3	Lack of data or detail of data on expenditure by State-Owned Enterprises (SOEs). Current SOE data available in Union Budgets is self-reported and non-standardized (F. Zhang et al. 2021).	Possible underestimation
4	Compiled over fiscal years instead of calendar years	Possible mis-categorization over time

Source: Authors' elaboration based on the methods and data sources described in this chapter.

Complementing UBs with Web of Science searches

We attempt to mitigate Challenge 1 of the UB data by complementing the ERD&D expenditure data acquisition process with Web of Science (WS), a multidisciplinary database of bibliographic information. In this portion of the data collection, we assume that the percentage of overall funding by the funding body that is attributed to energy is proportional to the percentage of their publications relevant to energy. We summarize our method in Figure 2.2.

Figure 2.2. Design of Web of Science method to determine ERD&D data expenditure by the Government of India.



Source: Authors' elaboration based on the methods and data sources described in this chapter.

This complementary method is especially useful for institutions that conduct research in various fields because these institutions sometimes do not specify areas of research in UB expenditure budget lines. The method allows us to incorporate estimates for: the Ministry of Science and Technology (specifically the Department of Science and Technology, the Department of Biotechnology, the Department of Scientific and Industrial Research), the Ministry of Human Resource Development (specifically the Department of Higher Education), the Ministry of Defence (specifically the Defence Research and Development Organisation, DRDO).

Appendix 2.2 provides further methodological details. Table 2.16, and the surrounding text, in the Appendix discusses limitations of the method, including possible underestimation and an inability to account for changes in proportion of ERD&D within overall RD&D over time.

Combining UB and WS methods

Table 2.5 shows the final list of ministries that our UB and WS methods indicate are supporting ERD&D in India, and that are included in all analytical sections of this chapter.

Table 2.5. Final list of Government of India institutions included in this analysis.

	Ministries and institutions
1	Department of Atomic Energy
2	Ministry of Coal
3	Ministry of Defence, specifically the Defence Research and Development Organisation (DRDO)
4	Department of Heavy Industry (within Ministry of Heavy Industries and Public Enterprises)
5	Department of Higher Education (within Ministry of Human Resource Development)
6	Department of Water Resources, River Development, and Ganga Rejuvenation (within Ministry of Jal Shakti)
7	Ministry of New and Renewable Energy
8	Ministry of Petroleum and Natural Gas
9	Ministry of Power
10	Department of Science and Technology (within Ministry of Science and Technology)
11	Department of Biotechnology (within Ministry of Science and Technology)
12	Department of Scientific and Industrial Research (within Ministry of Science and Technology)

Source: Authors' elaboration based on the methods and data sources described in this chapter.

Zhang et al. (2021) do not provide a complete list of institutions in their analysis, or how they gathered their information. Overall, they seem to have a more narrow scope because they cover the Ministry of Petroleum and Natural Gas, Ministry of Power, Ministry of Earth Science, Ministry of Coal, and Department of Atomic Energy (Zhang et al. 2021).

UB data is presented current crores (10 million rupees). We use the World Bank's WDI CPI index and the crore to rupee relationship to bring all expenditures to constant 2019 rupees (World Bank 2021a). Last, we used the WDI 2019 USD exchange rate to constant 2019 USD million.

2.3.2 Measuring volatility

In the Literature Review, we discussed the academic consensus that ERD&D expenditure "booms and busts," or volatility, are detrimental to innovation, though some margin of volatility is expected in technologies with large capital costs, like CCS demonstration projects. In addition to curtailment of extreme swings, the academic literature and actors in the ERD&D space (like MI), call for sustained growth in ERD&D. We explore volatility in several different ways, considering both size of the change and the direction, summarized in (Table 2.6) and discussed below.

Table 2.6. Statistics and indices to study public ERD&D expenditure volatility by country and technologies.

Statistics	Description	Focus on
Index 1	The country sum years of change greater than an absolute value of 50%, by technology	Size of change
Index 2	The country sum of standard deviations of the percentage of expenditure growth, by technology	Size of change
Index 3	The country sum of squares of consecutive counts of years of growth, by technology	Consistency of direction of change
Index 4	The country sum of squares of consecutive counts of years of growth in CP, and decrease in FF and nuclear	Consistency of direction of change

Source: Authors' elaboration based on the methods and data sources described in this chapter.

We begin simply. We assume that an annual change above an absolute value of 50% is too much volatility for any technology. To construct Index 1, we sum the number of years for which there is a change of more than 50% in either direction for any technology. We complement it with Index 2, which is more sensitive to the size of changes by technology.

In Index 2, we make use of the standard deviation (SD), a widespread measure of volatility represented by the square root of the sum of the squared difference between each number and the mean divided by the number of observations. Like Index 1, Index 2 uses the percentage change of yearly funding, by technology, which helps to account for country size and allows us to compare across countries. By country, we sum the SDs of the three technologies. Last, we rank countries in ascending order of the sum of the SDs. In the Results, we produce a visualization that shows the make-up of country scores, so that it is possible to tell which technologies each country scored highest and lowest in. A limitation of Index 2 is that despite its increased sensitivity, it can be led by outliers.

We also propose focusing on the annual directions of growth since 2010 by country in Indices 3 and 4. To do this, we sum the squares of consecutive years of positive changes for each technology, by country (Index 3 in Table 2.6). In Index 3, an increase in FF or nuclear RD&D helps boost the country's position as much as CP. To capture the need to pivot from traditional R&D, as put forth in the literature, we also present Index 4, which rewards years that countries decrease funding in fossil fuels (FF) and nuclear energy, and rewards increases in CP.

Last, we compare the rank of countries and technologies by index. The differences between them can help us understand the patterns behind RD&D funding. For instance, a negative difference between rankings in Indices 3 and 4 means that the country relied more on FF and nuclear funding to place higher than others in Index 3.

2.3.3 Identifying structural change through regression analysis

We run intercept-only regressions with country fixed-effects (FE) to investigate the extent to which the years following the FC and MI are associated with significant changes in funding growth rates, for all technologies and for CP.

The dataset is organized in a panel format across countries and time. The dependent variables are the annual percentage funding changes in million 2019 USD of total energy or CP. The independent variables are dummies for the years in which the windows of opportunity occurred: FC (2009-2011 with three variations, 2009, 2009-2010, and 2009-2011, depending on the specification), and MI (2016-2018). We do not have any control variables, other than applying country FE. We study the FC and MI separately Eq. 2.1) and together Eq. 2.2). These methods should give similar results, and we run both to give additional robustness to our conclusions.

Eq. 2.1 shows technology growth g (total or CP, depending on the outcome of interest) as a function of d, which stands for the FC or MI time dummy (depending on the specification) and an error term ε. In addition, c stands for country and t stands for time. Eq. 2.2 does the same but includes both time dummies. Our interest is in the estimation of coefficients β_1, β_2, and β_3.

$$g_{tc} = \beta_1 d_{tc} + \varepsilon_{tc}, fe \quad \textit{Eq. 2.1}$$

$$g_{tc} = \beta_2 fc_{tc} + \beta_3 mi_{tc} + \varepsilon_{tc}, fe \quad \textit{Eq. 2.2}$$

We perform the analysis on three sub-samples of country groups: All IEA plus China and India (in other words, all countries, AC), MI, and M8. See Appendix 2.3 for a list of the countries in the samples. Last, the time sample used depends on the dummy variable of the specification: the FC is studied over 2000-2012; the MI is studied from 2013-2018; and MI+FC is studied over 2000-2018. To improve the data coverage, we interpolate using Stata's "ipolate" function. It linearly interpolates missing observations between non-missing observations by country. The technology, dummy, and country sample variations and robustness checks described in the paragraphs above are summarized in Table 2.7.

Table 2.7. Regression specifications used to test the presence of structural change in growth rates of ERD&D in several country sub-samples.

Regression term	Variable and unit	Specifications
Dependent variable	Expenditure growth rate	1. All technologies
		2. Clean plus (CP)
Independent variable	FC and/or MI, dummy that is equal to one at the year of interest	1. FC1= 2009-2011 (medium-term effect)
		2. FC2=2009-2010 (medium-term effect)
		3. FC3=2009 (shock)
		4. MI = 2016-2018
		5. FC+MI: 2009 and 2016-2018
Countries included	NA	1. All countries (AC)
		2. Mission Innovation (MI)
		3. Major 8 (M8)

Source: Authors' elaboration based on the methods and data sources described in this chapter.

There are, of course, alternative approaches. One would be to apply an econometric technique called "differences-in-differences", in which the mean of a "treatment" group is compared to a "control" group, before and after the treatment. We found this method to be inconsistent with our needs for at least two reasons. First, while the FC affected some countries more than others, it would be difficult to isolate a control group that was not party to crisis. Second, the countries that are in the MI are larger overall economies and EDR&D spenders compared to those outside of the MI. Appendix 2.3 provides a list of countries in each group. Therefore, while differences-in-differences is best practiced using balanced groups with "matching" data, this is not possible in our dataset. Due to these limitations, comparing existing groups to themselves before and after treatment is a better option.

2.4 DATA

Our funding data draws first on the 2020 IEA Energy Technologies RD&D database. We then construct comparable datasets for China and India using public official spending records and combine our data with the IEA dataset.

The volatility analysis focuses on the time period for which we have data for all countries (2010-2018). We study structural change with regression analysis for a variety of periods within 2000-2018, depending on the regression specification. The regression analysis may be affected by some missing data by country between 2000-2010, which is summarized in Table 2.8 (we further discuss the ways in which our results may be affected in the Discussion section).

Table 2.8. Data availability by country.

Country	Missing data on ERD&D spending	Reason for the missing data
China	2000	Data for 2000 was not included because there were changes in how the government published data in that year, which means that the analysis including 2000 numbers would be inconsistent with the rest.
Korea	1999-2001 and 2003	IEA data is incomplete (South Korea did not submit data to the IEA RD&D data collection for those years).
India	2000-2010	Differences in how the government of India published budget data before 2010.

Source: Authors' elaboration based on the methods and data sources described in this chapter, including Ministry of Finance, Government of India (2020a) and International Energy Agency (2020b).

By technology, we also have some missing data. Although we attempted to populate all IEA technology categories with data for China and India, this was not always possible. More specifically, for India, the budget reporting documentation (including the notes at the end of each Demand for Grants) did not make it possible for the data-gathering effort to distinguish or find funding for energy efficiency and hydrogen and fuel cells. We note that it is possible that some funding for these technology areas is captured in the "other cross-cutting" or "unallocated" categories, but it is not possible to confirm this, and it would not change the results of the analysis given the three high-level technology categories (FF, nuclear, and CP) chosen for the analysis.

For China, the documentation used to construct the dataset did not make it possible for us to have separate categories for "renewables" and "hydrogen." According to our estimates, some of the expenditure in these categories is likely categorized under "Other cross-cutting technologies" in our 2001-2018 dataset. For completeness in Appendix 2.4, we show the 2015-2019 RD&D funding that China reported to MI for Renewals, Hydrogen, and Other Cross-Cutting. Like for India, it would not change the results of the analysis given the three high-level technology categories (FF, nuclear, and CP) chosen for the analysis.

2.5 RESULTS

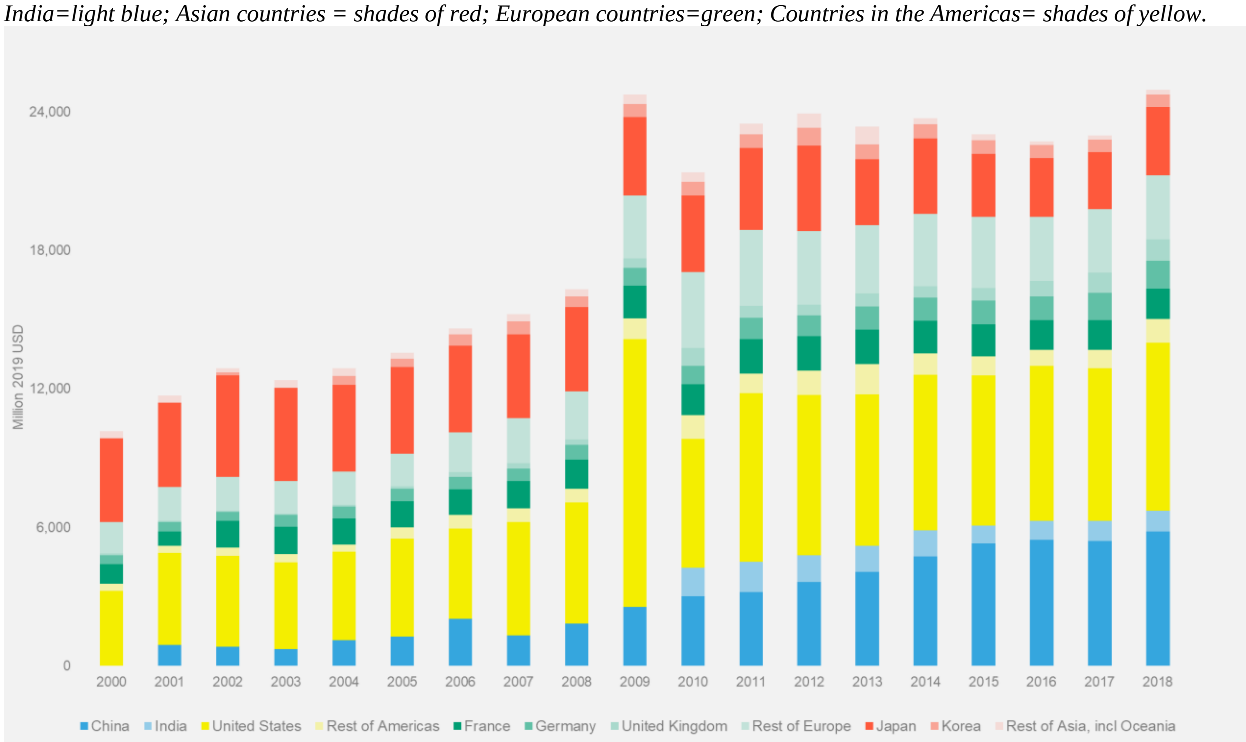
2.5.1 Funding amounts and allocation over time

Overall funding levels

Figure 2.3 displays the entirety of available total public ERD&D expenditures for the M8 and allows us to understand the role of China and India, shaded light and dark shades of blue, respectively, in the global public ERD&D expenditure. Asian countries (except for China and India) are in shades of red;

European countries are in shades of green; and countries in the Americas are in shades of yellow. Integrating India and China to the current OECD data shows that total funding was about 24 billion USD in 2019, less than half of the 71 billion 2019 USD per year estimated by Marangoni and Tavoni (2014) for 2010-2030. The real gap is bound to be much larger, as the amounts indicate that we have not met the optimal amount in any previous year.

Figure 2.3. Total public ERD&D expenditure, IEA and our data for China and India in million 2019 USD. China=blue; India=light blue; Asian countries = shades of red; European countries=green; Countries in the Americas= shades of yellow.



Source: Authors' elaboration based on dataset and methods described in this chapter, including Ministry of Finance, Government of India (2020a) and International Energy Agency (2020b).

The jump in 2009 is a result of the U.S. stimulus packages to address the FC and (to a lesser extent) the fact that data for India is not available before 2010 as indicated in Table 2.8. While there seems to be an increase in RD&D funding levels after 2009, a sustained increase in growth rates between 2010 and 2018 is not visibly obvious. Changes in levels of growth rates for the years 2016-2018 are also not evident. Statistical analysis in the following subsections will help clarify potential structural changes.

China and India compared to existing open-access IEA data

Integrating data from China and India with the existing open-access data available in the IEA dataset is an important contribution of our work. Figure 2.3 shows that at the beginning of available data, India was the sixth largest spender, comparable to that of France and the Rest of Americas (which only includes Canada in 2010 as Mexico started reporting to the IEA in 2015). However, the level of expenditure in India decreased over time. By 2018, it was the eighth largest spender, and its overall public ERD&D funding effort was most comparable to that of the United Kingdom. On the other hand, China was the fourth-largest spender at the beginning of the series. In 2001, it placed fourth after the

United States, Japan, and the Rest of Europe, and the size of expenditure was closest to the Rest of Europe. By the end of the series, in 2018, China was the second-largest spender, and closest to the United States.

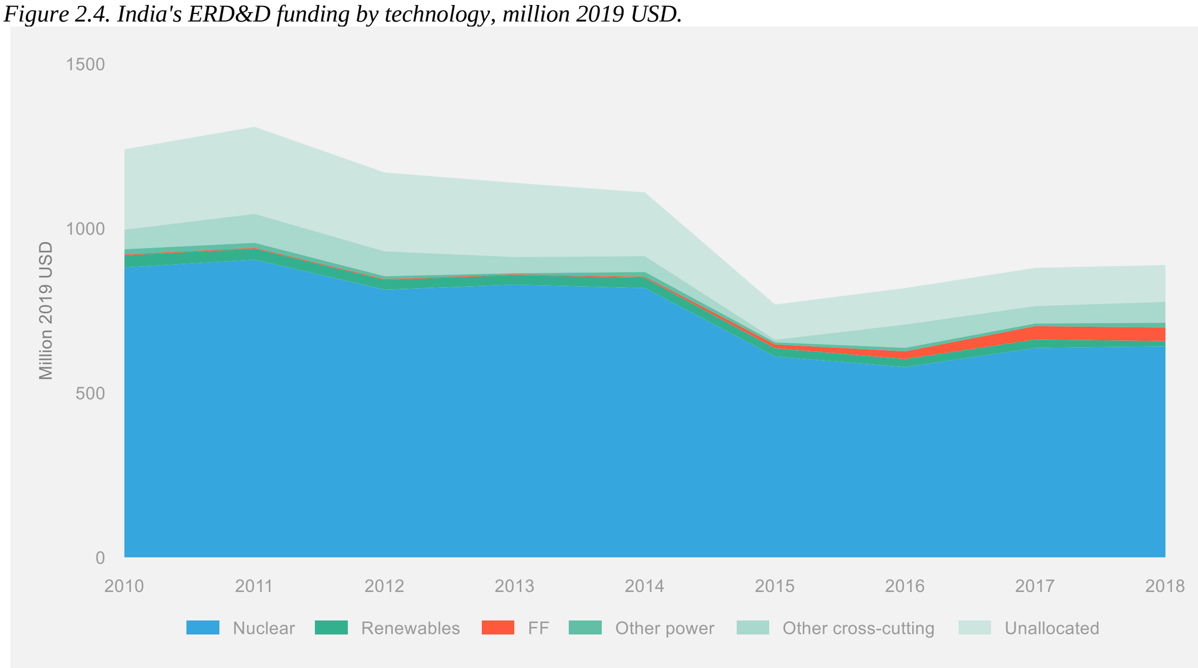
We now focus on India because the methodological work behind it is part of the contributions of this chapter. The data acquisition methods for ERD&D expenditure by the Government of India yielded the following ERD&D expenditure in India between 2010-2018, by technology (Table 2.9 and Figure 2.4) Following historical patterns, nuclear has been the main component of ERD&D expenditure in India. Over time, India has experienced a decrease in overall funding, mostly led by a decrease in the size (and a resulting decrease in the share) of nuclear. In direct contradiction to MI ambitions, all funding levels decreased in 2015, except FF.

Table 2.9. India ERD&D, 2010-2018, million 2019 USD.

Year	EE	FF	RE	Nuclear	HFC	OPS	OCC	UN	Total
2010	-	2.56	36.89	880.73	-	15.76	59.47	244.37	1,239.78
2011	-	2.50	33.77	904.06	-	15.06	87.94	264.66	1,307.99
2012	-	2.45	29.95	813.07	-	8.69	75.39	239.70	1,169.26
2013	-	2.26	29.30	828.19	-	3.45	49.29	225.44	1,137.92
2014	-	3.28	30.95	818.04	-	14.57	48.03	193.82	1,108.68
2015	-	11.38	25.60	609.73	-	6.43	7.75	107.23	768.12
2016	-	23.08	24.63	577.93	-	10.81	70.78	110.82	818.05
2017	-	40.32	26.21	635.74	-	8.07	53.08	116.05	879.47
2018	-	41.01	16.31	640.82	-	14.42	63.42	111.92	887.89

Source: Authors' elaboration based on dataset and methods described in this chapter, including Ministry of Finance, Government of India (2020a).
Note: EE=Energy Efficiency; FF= Fossil fuels; RE=Renewable energy sources; HFC= Hydrogen & fuel cells; OPS= Other power and storage technologies; OCC=Other cross-cutting technologies and research; UN=Unallocated.

Figure 2.4. India's ERD&D funding by technology, million 2019 USD.



Source: Authors' elaboration based on dataset and methods described in this chapter, including Ministry of Finance, Government of India (2020a).

We compare the results for India with Zhang et al. (2021) when they exclude SOEs. They report explicit results only for 2018 in million 2018 USD prices and PPP, the rest of the years are in graphs. To adequately compare data, we convert our estimates into their units using OECD conversion rates. As shown in Table 2.10, our methods are able to distinguish one technology category missing from Zhang et al. (2021) ("other cross-cutting technologies and research").

For the technologies in which we both have data, we find that Zhang et al. (2021) is higher in some instances (fossil fuels, nuclear, and unallocated), similar to ours in "other power and storage technologies," and lower in renewables. Overall, our estimates are substantially lower, just over half of theirs (which would rank India third after the United States and China in our data). The largest difference stems from the "unallocated" column, but we do not have access to detailed information about the source of this discrepancy.

We attempt but cannot verify the source of the overall or particular divergences. Zhang et al. (2021) provide no detailed access to more annual data, or their methods (apart from listing UBs as their main source). As a result, we continue the analysis in chapter with our estimates.

Table 2.10. Comparison of the results of the methods in this chapter and Zhang et al. (2021).

	EE	FF	RE	Nuclear	HFC	OPS	OCC	UN	Total
Zhang et al. (2021)	-	277.1	33.6	2,534	-	44.95	-	1,888.3	4,918.5
Methods in this chapter	-	128.25	51.01	2,004.31	-	45.10	198.36	350.05	2,777.10

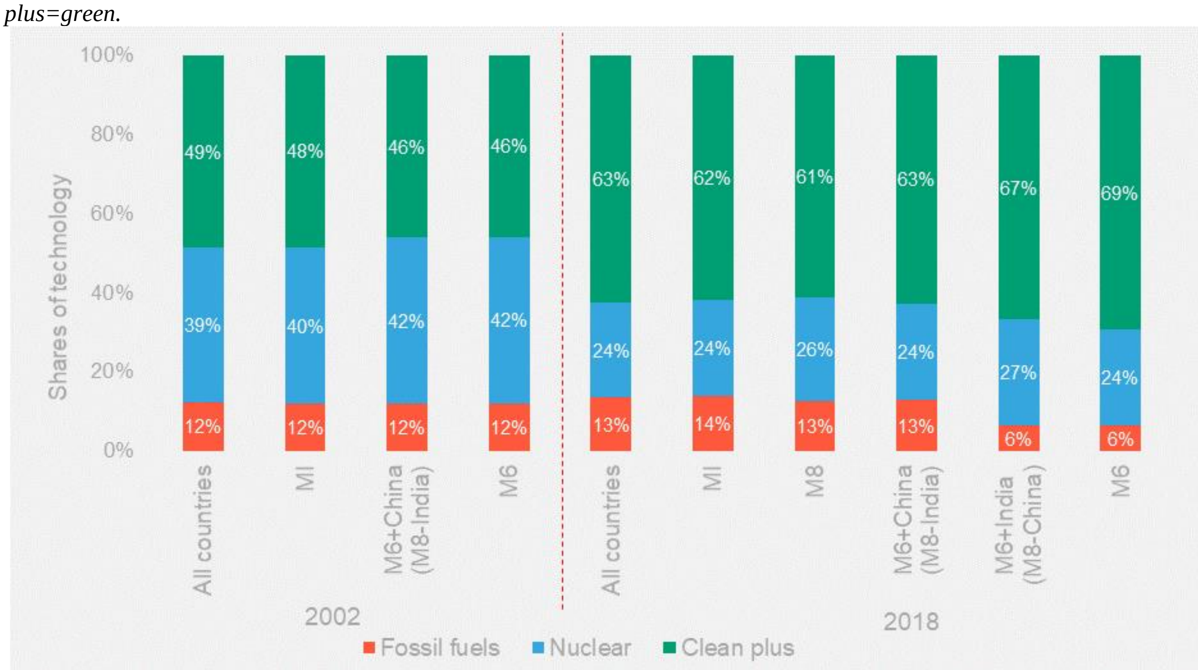
Source: Authors' elaboration based on dataset and methods described in this chapter, including Ministry of Finance, Government of India (2020a) and Zhang et al. (2021).
Note: EE=Energy Efficiency; FF= Fossil fuels; RE=Renewable energy sources; HFC= Hydrogen & fuel cells; OPS= Other power and storage technologies; OCC=Other cross-cutting technologies and research; UN=Unallocated.

Technology groups

The data behind Figure 2.3 can be disaggregated into technology groups and viewed within our country groups of interest. Figure 2.5 offers a simplified breakdown of the shares of three technology areas (nuclear, FF, and CP) for 2002 and 2018. In 2002, we use four country groups ordered in decreasing size: all countries, MI countries, M6+China, and M6 (note that in 2002, there is no data available for India). In 2018, we show the same groups for an accurate comparison. Because we also have data for India in 2018, we include two more: M8 and M6+India.

In 2002, almost all groups had a similar allocation between nuclear, CP, and FF. By 2018 All countries, MI, and M6+China had changed towards giving a larger role to CP and decreasing nuclear. However, when we remove China from the analysis (while both including and excluding India, in M6+India and M6, respectively), the allocation of funding to FF decreases, to the benefit of CP. The figure suggests that while the rest of the sample countries have generally reallocated funding to CP, this is not notable in the aggregate level because of China. In short, China's investment in FF is so large that has made up for the decrease of all other countries, largely maintaining FF shares as they were in 2002.

Figure 2.5. Shares of technology groups in 2002 and 2018, by country groups. Fossil fuels=red; nuclear=blue; clean plus=green.

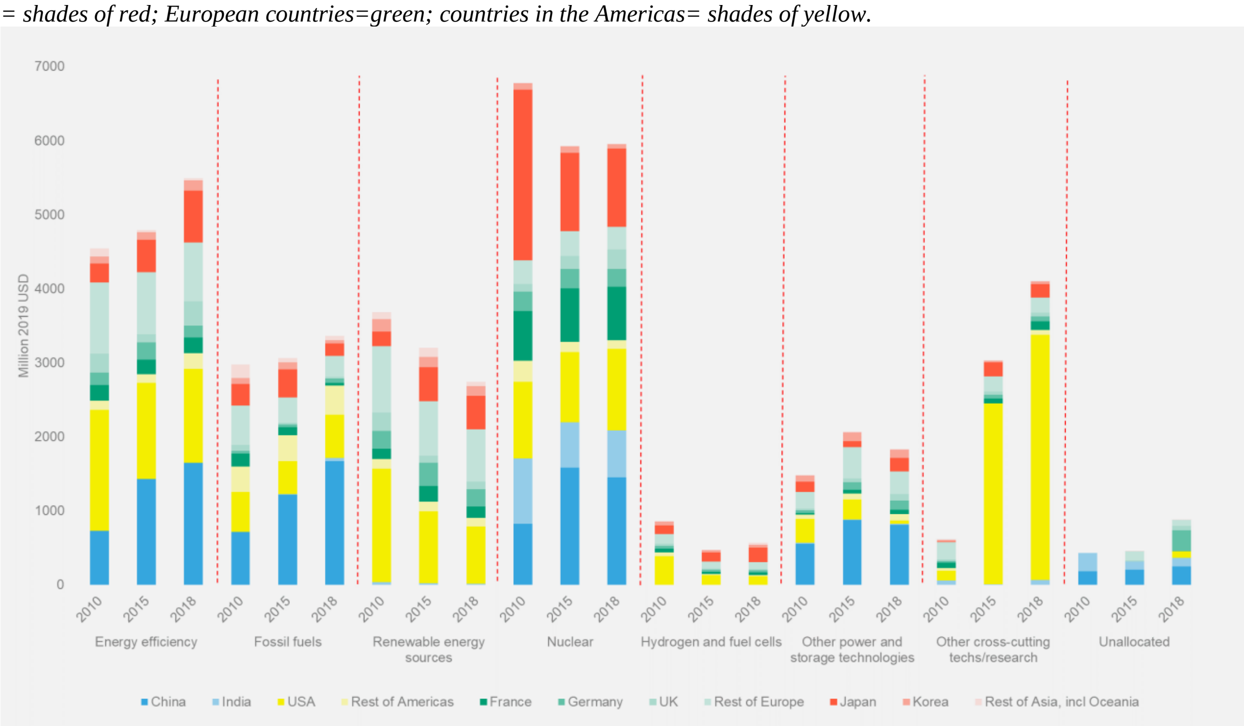


Source: Authors' elaboration based on dataset and methods described in this chapter, including Ministry of Finance, Government of India (2020a) and International Energy Agency (2020b).

Figure 2.6 further helps elucidate the finding of increases in China in FF, and its role in that technology compared to other countries. It shows a crosscut of expenditure in 2010, 2015, and 2018, by country and technology. Over the three years of interest, there is consistent growth in FF, energy efficiency, other power and storage technologies, and unallocated technologies. The colors by country are the same as in Figure 2.3. Despite decreases in other countries (like Japan, the Rest of Europe, and France), the increase in FF is due to China. Notably, China went from 61 to 1,673 million USD in FF between 2001 and 2018.

The growth in energy efficiency seems to be led by China and Japan. The increase in other power and storage technologies is mostly due to the United States and the magnitude of change calls for a detailed exploration, which can be found in Appendix 2.5. Last, looking specifically at clean expenditure (non-nuclear and FF), the momentum shifted to energy efficiency and storage technologies over the last decade. Renewables, nuclear, and hydrogen declined. Expected government initiatives, like the UK "Hydrogen Strategy", may attenuate the downward trend.

Figure 2.6. World ERD&D expenditure by technology, 2010, 2015 and 2018. China=blue; India=light blue; Asian countries = shades of red; European countries=green; countries in the Americas= shades of yellow.



Source: Authors' elaboration based on dataset and methods described in this chapter, including Ministry of Finance, Government of India (2020a) and International Energy Agency (2020b).

2.5.2 Funding volatility by country and technology

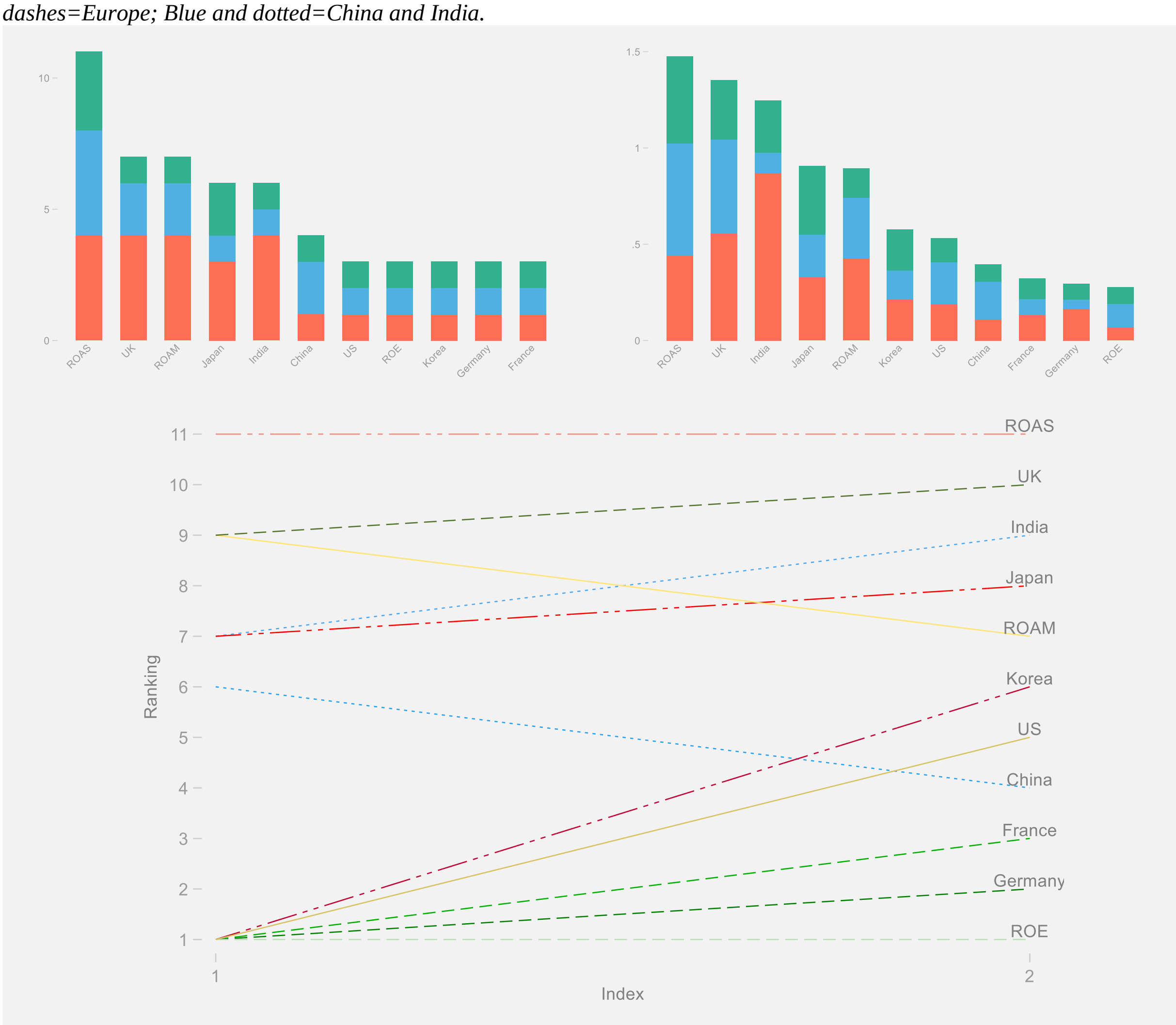
Figure 2.7 depicts the results of Indices 1 and 2 (left and right, respectively), in which we compare the size of changes across countries. Index 1 (Figure 2.7, left) stacks up years of growth above an absolute value of 50% in FF spending (red), nuclear (blue), and green (CP). Index 2, (Figure 2.7, right) stacks the SDs of FF, nuclear, and CP, using the same colors. Index 2 is more sensitive to size to change but can be disproportionately affected by outliers.

Both the rankings themselves Figure 2.7 (top) and the differences between them Figure 2.7 (bottom) aid our understanding of the patterns behind ERD&D funding. Because the regional aggregates contain an increasing number of countries over time, we concentrate on findings across the M8. For further information, Appendix 2.6 provides visualizations of the background data.

First, Indices 1 and 2 support Winskel et al. (2014) in that UK funding has been unstable (Figure 2.7, top). Our findings somewhat support Schuelke-Leech (2014) who claim the same but for the United States. The United States is tied with several countries in Index 1 but is towards the middle of volatility in Index 2. Korea also suffers in Index 2. The results for the United States and Korea suggest that while changes remain below an absolute value of 50%, they are large and frequent compared to France, Germany, and China.

The tie over four of the M8 countries (US, Korea, Germany, France) in Index 1 makes comparisons relatively difficult but Germany and France are consistently among the least volatile countries in both indices (Figure 2.7, bottom). Importantly, China is the only M8 country that is relatively better placed in Index 2 compared to Index 1, suggesting that while it has a relatively high number of changes above an absolute value of 50%, these changes are consistent with a high average growth rate, and not outliers. This is coherent with the findings of the previous section, where we saw that China has grown into the second-largest spender in ERD&D, after the United States.

Figure 2.7. Top: Indices 1 and 2, left and right, respectively. Based on growth rates of data 2010-2018, left to right = most to least volatile. Red depicts FF spending, blue depicts nuclear spending, and green depicts CP spending. Bottom: Comparison of Index 1 and 2. High= more volatile; Reds and long-dash-short-dash=Asia; Yellows and solid=Americas; Greens and dashes=Europe; Blue and dotted=China and India.

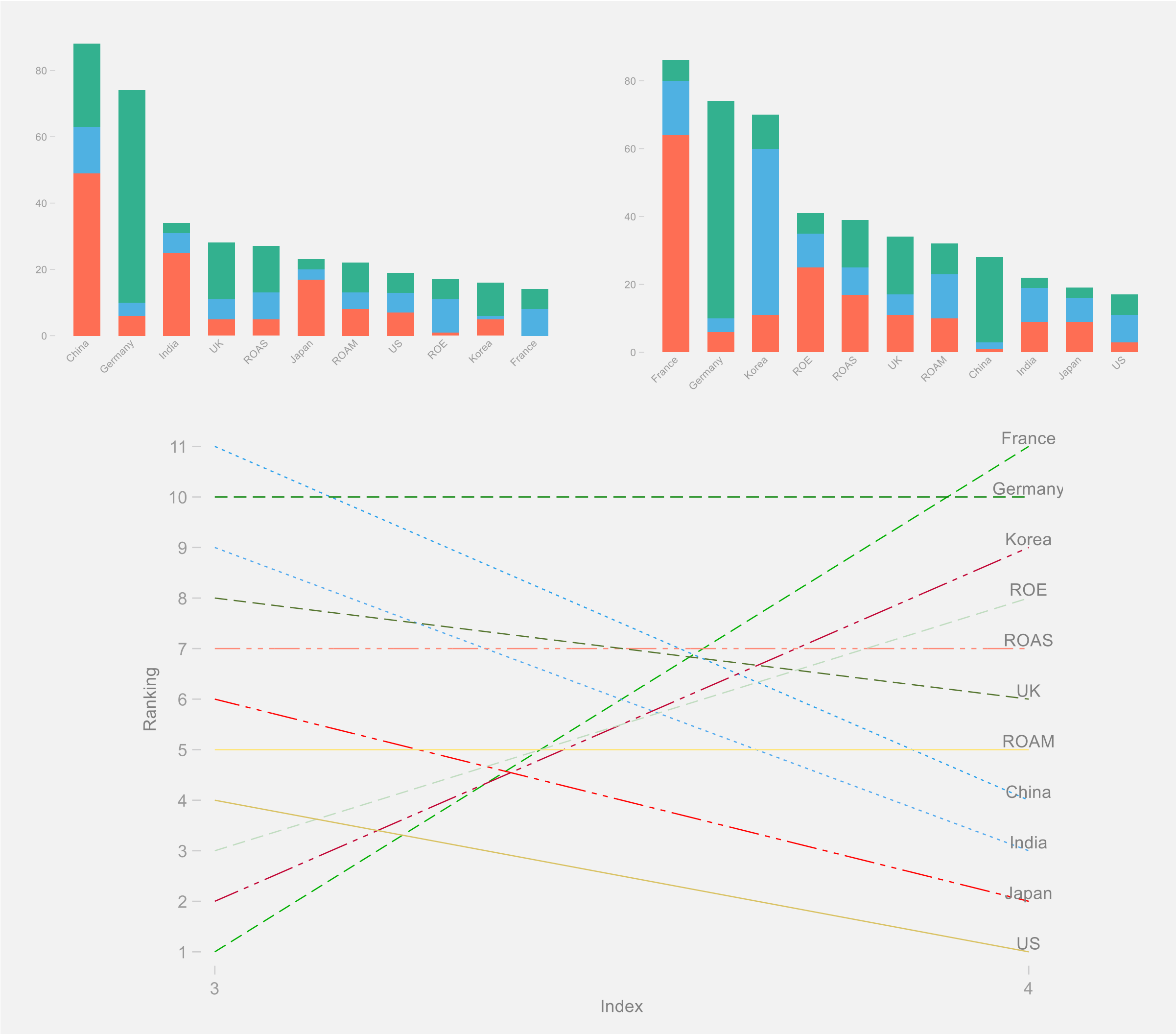


Source: Authors' elaboration based on dataset and methods described in this chapter, including Ministry of Finance, Government of India (2020a) and International Energy Agency (2020b).
Note: Zero expenditure levels are treated as missing. ROAM = Rest of Americas, ROE= Rest of Europe, ROAS = Rest of Asia, including Oceania.

In addition to the size of the change, the literature reviewed showcased the consensus that public ERD&D expenditure growth must be steady to achieve effective climate change mitigation. Index 3 treats all technology growth positively, and we reward more years of consecutive growth by squaring the number of consecutive years. Therefore, in Index 3, an increase in FF or nuclear RD&D helps boost the country's index as much as renewables (and more years of growth in any technology reward the country even further). To capture pivoting from traditional ERD&D, as put forth in the literature, we propose Index 4, which is the same as Index 3 except that it counts countries that refrain from increasing funding in FF and nuclear energy. These are shown in Table 2.8 (top). Red depicts FF spending, blue depicts nuclear spending, and green depicts CP spending.

China India, Japan, the United States, and the United Kingdom, fall when comparing Indices 3 and 4 (Table 2.8, bottom). Of these, China and India changes the most. The color-coding by technology in the figure helps to show the difference between the two indices is mostly due to FF funding. Germany, France, and Korea fare the same or better from Index 3 to 4. In France, this improvement is due to a decrease in FF funding; in Korea, it is due to a decrease in nuclear.

Figure 2.8. Top: Indices 3 and 4, left to right. Based on the consistency of growth expenditure, 2010-2018. Red depicts FF spending, yellow depicts nuclear spending, and green depicts CP spending. Bottom: Comparison of Index 3 and 4. High= more volatile; Reds and long-dash-short-dash=Asia; Yellows and solid=Americas; Greens and dashes=Europe; Blue and dotted=China and India.



Source: Authors' elaboration based on dataset and methods described in this chapter, including Ministry of Finance, Government of India (2020a) and International Energy Agency (2020b).
Note: Zero expenditure levels are treated as missing. ROAM = Rest of Americas, ROE= Rest of Europe, ROAS = Rest of Asia, including Oceania.

Last, the indices can give us an insight into patterns by technologies. Averaging the sum of years above an absolute value of 50% (Index 1) over the M8 yields, 2, 1.25, and 1.125 for FF, nuclear, and CP, respectively. Nuclear and CP trade places when we use the average SD of growth rates (Index 2) (0.32, 0.193, and 0.189 for FF. CP and nuclear, respectively). Despite being the least volatile in Indices 1 and 2, CP scores the highest average of the squared sum years of consecutive funding (Index 3) and nuclear experienced the fewest average years of consistent growth (16.75, 14.25, and 6 for CP, FF, and nuclear, respectively).

Overall, we extract three important points from the indices. First, China's ERD&D expenditure is unlike the other Major 8: it is growing much more than the rest and relies heavily on FF. Without scoring at the top of any of the indices, India is relatively unstable and its reliance on FF in Index 3 is second only to China's. Second, Germany and France are both relatively stable and "clean" compared to the rest of the M8, while the United States and UK are relatively unstable and rely more on FF and nuclear than their "Western" counterparts. Third, CP is the most stable technology group and sustained the highest average sum of squares for consecutive growth in funding; nuclear suffered the fewest years of consecutive funding growth compared to the other technology groups.

2.5.3 Impact of crisis and cooperation on funding

We evaluate whether the FC and the MI are associated (correlated) with significant changes in funding growth rates through regression analysis. Appendix 2.7 provides a visual representation of the data. Table 2.11 synthesizes the regression output; a dash means that there was no significant coefficient. The columns indicate country groups (All countries, M8 and MI) and technologies (all technologies and CP). The rows indicate the window of opportunity (the FC, MI, or both).

One year after the FC (FC3=2009), there seems to have been an increase in total spending that was significantly different from usual spending across several groups studied (AC, M8, and MI). This result across three country groups is robust across two model specifications (FC and FC+MI). In the M8 and MI country groups, there is evidence that there was a significant increase in total funding that lasted two or three years after the FC (FC1 and FC2), albeit the effect is lower the more years after the FC. The evidence for an increase in CP after the FC is less pervasive but present in M8 and MI groups. Note that the effect of the FC on CP is always lower than its effect on all technologies (for the same FC dummy and region).

Table 2.11. Regression summary results. Columns indicate country groups (All countries, M8 and MI) and technologies (total and CP). The rows indicate the window of opportunity being studied (the FC, MI, or both).

	All countries (AC) (except outliers)		M8 countries		MI countries	
	All technologies	Clean plus	All technologies	Clean plus	All technologies	Clean plus
FC only	0.368** (FC3)	-	0.279** (FC3)	-	0.110 * (FC1) 0.249*** (FC2) 0.373*** (FC3)	0.231** (FC2) 0.370*** (FC3)
MI only	-	-	-	0.0904*	-	-
FC + MI	0.356** (FC3)	-	0.158** (FC2) 0.310*** (FC3)	0.248** (FC3)	0.148*** (FC1) 0.280*** (FC2) 0.406*** (FC3)	0.147* (FC1) 0.258*** (FC2) 0.398*** (FC3) -0.126* (MI with FC3)

Source: Authors' elaboration based on dataset and methods described in this chapter.
Note: FC= 2009-2011, FC2=2009-2010, FC3=2009; MI=2016-2018. ***= <1%, **=<5%, *=<10%. A dash means that there was no significant output.

Arguably, the effect of the FC on MI countries is irrelevant, because the FC occurred before they signed on to the MI in the first place. However, we include it because it is possible that significant and positive output in this combination for the FC, as well as a positive and significant potential effect related to MI, could capture that these countries were already more likely to increase spending, and therefore a self-selecting group.

Evidence for changes in funding growth rates after MI is nonexistent for total funding and weak for CP. The only two significant coefficients obtained are not robust across model specifications and they are both only weakly significant. One is negative and the other is closer to zero than any significant coefficient obtained from the analysis.

Last, there would be evidence for reallocation towards CP if there was evidence of a statistically significant change in CP and no statistically significant change for total energy. In the MI case, there is no evidence for changes in either technology category, and therefore no reallocation towards CP. In Appendix 2.8, we provide a detailed discussion of each coefficient.

2.6 Discussion

ERD&D is a crucial component of government policy to decarbonize energy. As discussed in the Literature Review, little has been known about ERD&D spending in two major emitters and developing economies: China and India. We estimate and show the results of India and China alongside existing OECD data from the IEA over time. We ask the following additional research questions: How does the volatility in China, India, and other major countries, compare overall and over major technology groups? Are there patterns over regions? Since the Paris Agreement, have the years after MI been associated with a statistically significant change in expenditure efforts, or to a reallocation of spending towards certain technologies? How does expenditure after MI compare to expenditure after other opportunities for policy change, like the Financial Crisis?

The results show that the recent efforts we see in the literature to include emerging economies, like China and India, are justified. We find that the estimates that exclude China miss the world's second-largest spender in ERD&D, after the United States. Despite having aggregate funding comparable to some M6 countries in 2010, the relative size of spending in India has declined over time. This finding should help buttress the efforts to increase existing efforts to gather more information about ERD&D, and increase ERD&D itself, in the world's third largest emitter. Importantly, the findings support increased ERD&D investment overall too. Even accounting for China and India, total ERD&D funding is at least several times below the level suggested by IAMs discussed in the Literature Review.

China seems to maintain the global share of FF funding at a share of around 13%. As discussed in the Literature Review, the optimal portfolio of RD&D by technology is still unsettled. One salient point from an effort to combine expert elicitations, integrated assessment models, and decision frameworks is that as climate stringency increases, CCS (included in FF spending) has a role in providing flexibility to abate emissions (Anadón, Baker, and Bosetti 2017). Due to China's scale and the dominant role of FF in its energy portfolio, ERD&D investment that leads to advances in clean coal or CCS could have larger tangible effects on emissions than CP investment in countries that play a smaller role in global emissions.

Although it is found to be a complement to CCS (included in FF) (Anadón, Baker, and Bosetti 2017), we find that nuclear has lost relative importance to CP. Within CP, expenditure over the last decade has shifted to energy efficiency and storage technologies. The increase in energy efficiency (mostly attributable to China) may be related to technologies that are in demonstration in hard to decarbonize industry and transport (including shipping and aviation) sectors. As stated, further research is needed to come to a consensus on the optimal allocation of ERD&D; however, investment in transport is likely to be key to deep decarbonization (Anadón, Baker, and Bosetti 2017).

The volatility analysis suggests patterns of innovation systems along the major regions represented in the M8 (America/Asia/Europe) with the United Kingdom as an exception, which is more like the United States. China's ERD&D is consistently growing more than the rest of the M8. India is relatively unstable, but its consistent growth in FF funding is second only to China's. At the same time, Germany and France are both relatively stable and "clean" compared to the rest of the M8. The other "Western" counterparts, the United States and the United Kingdom, are relatively unstable and rely more on FF and nuclear. These patterns along regions underline nuances in the relative focus of efforts needed in the coming years. For instance, the United States and the United Kingdom need to pay relatively more attention to their volatility in ERD&D, if they are to reap the longer-term benefits of stable innovation efforts highlighted in existing literature.

Last, the regression analysis shows that there was an increase in total spending that was significantly different from usual increases across several country groups after the FC, although the effects decreased every subsequent year we studied after the FC. There is also evidence for an increase of spending in CP. However, evidence for changes in funding growth rates after MI is nonexistent for total funding and almost negligible for CP. While the degree to which voluntary efforts and crises can produce changes proportionate with the challenge remains to be seen, the results of our analyses imply that neither window of opportunity has galvanized changes commensurate with the decarbonization challenge. The finding, in conjunction with the magnitude of changes needed, reinforces the calls for increased ERD&D attention underpinning the existing literature.

We consider a range of limitations. First, as shown and discussed in the Methods Table 2.4, India's UBs may under and over-estimate funding in some areas (refer to Appendix 2.1 for a detailed discussion) and we lack estimates from SOEs. We apply the complementary WS method to help deal with some data challenges, though this method also has its own limitations, discussed in Appendix 2.2. In the future, analyzing the institutional provenance of relevant patents could further aid in the quest to estimate India's ERD&D funding. This patents analysis could help both verify and strengthen the current WOS method. We show that our estimates are lower than Zhang et al. (2021), but we are unable to attribute that to any particular methodological error due to insufficient information.

Second, as shown in Table 2.2, the IEA provides detailed information to members on how to categorize their spending by technology, and this helps reduce the risk of misidentified funding data. While we attempted to replicate funding data for China and India, we do not have access to internal government budgets or other program descriptions. Therefore, as detailed in the Data section, some technology groups were impossible to distinguish. In the analysis, we dealt with this limitation by using three simplified groups (FF, nuclear, and CP).

Third, while we made a concerted effort to choose the strongest methods possible for our research questions, our regression specification does not establish causality between the FC/MI and changes in ERD&D funding. This is because our econometric choices are bounded by a short, limited, and aggregate dataset, which lacks definition on drivers behind national ERD&D decisions in a diverse set of countries. The length of the dataset is discussed in the sections related to India and China, and it is also relevant to countries included in the IEA dataset. As a result, we consistently refer to the results as associations and correlations instead of causal relationships.

Last, as introduced in the Data section (summarized in Table 2.8), the chosen regression analysis may be affected by some countries missing data by year. We partially deal with this by interpolating data. This means, for instance, that Korea's missing 2002 data is unlikely to have caused a disturbance. However, interpolation cannot overcome India's shorter time series. Viewed within the entirety of the dataset, it is unlikely that India alone would have changed the course of the results. Additionally, we considered several groups and temporal cuts as robustness checks. Because of the consistency of the results, these limitations are not likely to affect the conclusions, even if resolved.

2.7 CONCLUSION

The results of this analysis confirm that we must increase ERD&D spending several times over, even when including previously unavailable data for China and India. Additionally, the analysis helped clarify some potential areas for direct focus. These include addressing India's decreasing ERD&D budget and volatility in the United States and the United Kingdom. Last, the analysis confirmed that neither the Financial Crisis nor Mission Innovation led to structural changes in RD&D. The results highlight the importance of efforts to increase and stabilize ERD&D, as well as continued attempts to continue to gather information on China and India.

There are numerous ways this analysis can continue to contribute to the academic literature and ultimately advise government policy for deep decarbonization and growth priorities. First, further studies can dig deeper into specific technologies. We are already working on extending the analysis to CCS. The Shared Socioeconomic Pathways (SSP) used as input to the IPCC 6th Assessment Report show that carbon capture and storage (CCS), is crucial in pathways consistent with 1.5°C (Rogelj, Shindell, and Jiang 2018). A part of that research goal is to help identify how ERD&D can best drive innovation in the technology.

Furthermore, the data on China and India in this chapter can be updated with new annual government data, in the spirit of the Database on the U.S. Department of Energy (DOE) Budgets for Energy Research, Development, & Demonstration (1978–2021R) by Gallagher and Anadón (2020). With time, that additional data may, for instance, help us understand the effectiveness of COVID-19 stimuli as a window of opportunity for structural change in ERD&D, compared to the FC and MI.

The data can also help address new research questions. For instance, we are already exploring whether there is a relationship between ERD&D in incumbent countries for a specific technology (say Germany and Spain for wind technology) and competitive threats (for instance, Chinese growth of market share in wind). This may help further our understanding and support theory on competition as a driver of increased ERD&D efforts.

APPENDIX 2.1. EXAMPLE OF GOVERNMENT OF INDIA UNION BUDGET DATA

We extracted line by line information for each relevant Ministry and Department, by year. Figure 2.9 is an example from the Ministry of Power and year 2010. In this case, we extracted the information under the "Actual 2010-2011" column group for line 4, which constitutes funding to RD&D in the power sector through the Central Power Research Institute, Bengalaru.

In addition to line notes, we read the notes at the end of each Demand for Grants. These notes provide more information for specific lines. Figure 2.10 shows the notes that correspond to line 4, used in our database.

Figure 2.9. Example of Union Budget spending data for ERD&D expenditure by the Ministry of Power for the year 2010.

Notes on Demands for Grants, 2012-2013 262

MINISTRY OF POWER

DEMAND NO. 75

Ministry of Power

A. The Budget allocations, net of recoveries and receipts, are given below:

(In crores of Rupees)

	Major Head	Actual 2010-2011			Budget 2011-2012			Revised 2011-2012			Budget 2012-2013		
		Plan	Non-Plan	Total	Plan	Non-Plan	Total	Plan	Non-Plan	Total	Plan	Non-Plan	Total
	Revenue	5221.00	-44.34	5176.66	6779.84	-135.01	6644.83	3816.88	-183.69	3633.19	5929.63	-122.89	5806.74
	Capital	*3074.54*	...	*3074.54*	*2862.16*	...	*2862.16*	*2234.12*	...	*2234.12*	*3712.37*	...	*3712.37*
	Total	**8295.54**	**-44.34**	**8251.20**	**9642.00**	**-135.01**	**9506.99**	**6051.00**	**-183.69**	**5867.31**	**9642.00**	**-122.89**	**9519.11**
1. Secretariat-Economic Services	3451	0.97	21.24	22.21	1.00	24.10	25.10	1.00	24.10	25.10	0.10	25.84	25.94
2. *Waiver of Interest*													
2.01 North Eastern Electric Power Corporation (NEEPCO)	2801	...	...	...	...	...	...	...	16.13	16.13	...	...	...
2.02 Less Receipts Netted	0049	...	...	...	...	...	...	...	-16.13	-16.13	...	...	...
	Net	...	...	...	...	...	...	...	...	...	...	...	...
Power													
General													
3. Central Electricity Authority	2801	4.46	65.11	69.57	13.18	77.03	90.21	6.39	73.80	80.19	18.08	78.80	96.88
	4801	2.12	...	2.12	3.05	...	3.05	2.05	...	2.05	1.00	...	1.00
	Total	*6.58*	*65.11*	*71.69*	*16.23*	*77.03*	*93.26*	*8.44*	*73.80*	*82.24*	*19.08*	*78.80*	*97.88*
4. *Research and Development*													
4.01 Central Power Research Institute, Bengaluru	2801	61.51	...	61.51	163.40	...	163.40	75.00	...	75.00	265.00	...	265.00
5. *Training*													
5.01 National Power Training Institute (NPTI)	2801	17.00	6.40	23.40	16.89	6.40	23.29	2.09	6.40	8.49	5.09	6.40	11.49
6. Setting up of JERC for Manipur & Mizoram	2801	1.20	...	1.20	2.38	...	2.38	2.33	...	2.33	2.46	...	2.46
7. *Central Electricity Regulatory Commission*													
7.01 CERC Fund	2801	...	...	...	...	31.48	31.48	...	33.29	33.29	...	34.79	34.79
7.02 Amount met from CERC Fund	2801	...	...	...	...	-31.48	-31.48	...	-33.29	-33.29	...	-34.79	-34.79
	Net	...	...	...	...	...	...	...	...	...	...	...	...
8. *National Investment Fund (NIF)*													
8.01 Transfer to National Investment Fund	2801	2052.00	...	2052.00	5052.00	...	5052.00	2086.04	...	2086.04	4761.00	...	4761.00
8.02 Amount met from NIF for Subsidy for Rural Electrification - RGGVY	2801	-2000.00	...	-2000.00	-5000.00	...	-5000.00	-2086.04	...	-2086.04	-4761.00	...	-4761.00

No. 75/Ministry of Power

http://indiabudget.nic.in

Source: Ministry of Finance, Government of India (2020a).

Figure 2.10. Example of Union Budget source for extra information on spending lines for ERD&D expenditure by the Ministry of Power for the year 2010.

1. **Secretariat:** Provision is made for expenditure on establishment matters for the Secretariat of the Ministry of Power, under various schemes.

3. **Central Electricity Authority:** The Central Electricity Authority coordinates the activities of various agencies in relation to control and utilization of national power resources. It is also responsible for carrying out the survey and studies, collection and recording of data concerning generation, distribution, utilization and development of power resources.

4. **Research & Development:** Central Power Research Institute, Bangalore serves as a National Laboratory for applied research in the field of electrical power and also functions as an independent authority for testing, evaluation and certification of electrical equipment and components.

5. **Training:** National Power Training Institute is engaged in imparting training in various aspects of power sector including operation and maintenance of power stations.

6. **Joint Electricity Regulatory Commission (JERC) for Manipur and Mizoram:** Pursuant to a Memorandum of Agreement signed by the State Governments of Manipur and Mizoram, authorizing the Central Government to constitute a Joint Electricity Regulatory Commission (JERC), the Central Government has constituted a JERC for these states under section 83 of the Electricity Act 2003. The Central Government has also approved a plan scheme of financial assistance of ₹ 6.60 crore for meeting the recurring and non-recurring expenditure of the Commission during the first five years, ending in January, 2013.

7. **Central Electricity Regulatory Commission:** Under the provision of the ERC Act, 1998, the Central Government had constituted the Central Electricity Regulatory Commission (CERC). The Central Commission continues as a statutory body under the Electricity Act, 2003, which has come into force with effect from 10th June, 2003.

9. **Rajiv Gandhi Grameen Vidyutikaran Yojana (RGGVY):** This scheme of rural Electricity Infrastructure and Household Electrification has been introduced in April, 2005 for providing access to electricity to all rural households. Rural Electrification Corporation (REC) is the nodal agency for the programme. Under the scheme, projects can be financed with 90% capital subsidy for provision of Rural Electricity Distribution Backbone (REDB), creation of Village Electrification Infrastructure (VEI) and Decentralised Distributed Generation and Supply. REDB, VEI and DDG would also cater to the requirement of agriculture and other activities. Under this scheme un-electrified Below Poverty Line (BPL) households will get electricity connection free of charge. The continuation of the scheme in XI Plan was sanctioned on 3rd January, 2008 with the capital subsidy of ₹ 28,000 Crore in Phase-I. To increase the coverage of small habitations, Government sanctioned electrification of habitations upto 100 population instead of 300. RGGVY is a flagship Scheme for creation of Rural Electricity Infrastructure and household electrification. The targets for the year 2012-13 is for electrification of 4800 un-electrified villages and offering electricity connections to the 34 lakh BPL households.

11. **Funds for Evaluation Studies and Consultancy:** This provision is for conducting evaluation studies of various projects/programmes/ schemes.

12. **Appellate Tribunal for Electricity:** Under the provisions of Electricity Act, 2003, the Central Government has set up the Appellate Tribunal for Electricity. It hears appeals against the orders of the adjudicating officer or the Appropriate Commissions under the Electricity Act, 2003. Under the provisions of the Petroleum and Natural Gas Regulatory Board Act, 2006, APTEL is the Appellate Tribunal for the purpose of that Act.

13. **Joint Electricity Regulatory Commission (JERC) for UTs:** The Central Government has set up a Joint Electricity Regulatory Commission (JERC) for Goa and all Union Territories except Delhi. Expenditure of the Joint Commission is borne by the Central Government and the Government of Goa in the ratio of 6:1.

14. **Comprehensive Award Scheme:** Shields and Certificates are given away by the Ministry of Power to the generating stations, transmission and distribution utilities as well as rural distribution franchisees for recognizing meritorious performance in operation, project management and environmental protection.

15. **Energy Conservation:** The funds would be utilized for carrying out the Energy Conservation related activities i.e. National level awareness campaign, National Energy Conservation Awards and National level Painting Competition for children. One of the Missions is National Mission for Enhanced Energy Efficiency. This is being pursued by MoP and Bureau of Energy Efficiency (BEE).

16. **Bureau of Energy Efficiency (BEE):** Fund would be provided to BEE for implementation of its various plan schemes. A number of Demand Side Management (DSM) have been initiated by Government to reduce the overall power consumption and improving efficiency of agriculture irrigation, water pumping, street lighting and sewage pumping to reduce the subsidy burden of the states and energy cost incurred by municipalities. Government has approved Bachat Lamp Yojana (BLY) scheme that seeks to promote energy efficient and high quality compact fluorescent lamps (CFLs) as replacement of incandescent bulbs in household. A Standard & Labeling (S&L) programme has been

No. 75/Ministry of Power

Source: Ministry of Finance, Government of India (2020a).

APPENDIX 2.2. WEB OF SCIENCE METHOD DETAILS

Step 1: Identification of WS categories

Of 255 available options, we identify WS categories that are suitable for our analysis, i.e., that are unlikely to refer to non-ERD&D (Table 2.12). One drawback is that the first two do not fit neatly into IEA categories and will be classified as "unallocated."

Table 2.12. Web of Science categories assumed to qualify in IEA technology categories.

	WS categories
1	Energy and Fuels
2	Green Sustainable Science & Technology
3	Physics, Nuclear
4	Nuclear Science and Technology

Source: Authors' elaboration based on data sources and methods described in this chapter.

We attempted to add more categories that would fit the IEA categories. However, they were either negligible, like "Engineering, Petroleum" (which contributed 29 publications out of a total of 63,000 in the biggest funding institutions), or too broad. Table 2.13 shows some categories that were excluded from our analysis, unless a publication was already cross-categorized in one of the four selected categories in Table 2.12.

Table 2.13. Technology categories excluded from Web of Science analysis.

	WS categories
1	Engineering, Petroleum
2	Transportation Science & Technology
3	Water Resources
4	Engineering (various, incl. civil, mechanical, multidisciplinary)
5	Materials Sciences (various)

Source: Authors' elaboration based on data sources and methods described in this chapter.

Step 2: Identification of funding bodies

WS allows users to enter Boolean searches and identify institutions that fund research in energy technologies in specific countries. Figure 2.11 shows the output of a Boolean search of the funding bodies related to publications between 2010-2018 for the abovementioned WS categories. These may include departments within larger ministries.

Figure 2.11. Main funders of citations related to Selected Web of Science categories and India.

Source: Web of Science searches using the specified search criteria.
Note: Top search criteria: CU=(India) AND WC= (Energy and Fuels OR Green & Sustainable Science & Technology). Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-EXPANDED, IC Timespan=2010-2018. Bottom search criteria: CU=(India) AND WC= (Nuclear Science & Technology OR Physics, Nuclear). Indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-EXPANDED, IC Timespan=2010-2018.

Table 2.14 shows the key institutions that we identified through the WS analysis of public entities funding Indian publications on energy technologies.

Table 2.14. Key institutions identified through Web of Science relevant for Web of Science energy categories.

	Key institution
1	Ministry of Science and Technology Department of Science and Technology Department of Scientific and Industrial Research, including the Council of Scientific Industrial Research (CSIR) and Department of Biotechnology (DBT)
2	Ministry of Human Resource Development, Department of Higher Education, including the University Grants Commission India
3	Ministry of New and Renewable Energy (MNRE)
4	Department of Atomic Energy (DAE), including the Board of Research in Nuclear Sciences (BRNS)
5	Ministry of Defence, including the Defence Research and Development Organisation (DRDO)

Source: Authors' elaboration based on data sources and methods described in this chapter.

Step 3: Estimation of the proportion of publications in energy

Having identified the relevant institutions, we searched their total citations, and those within the WS categories identified in Step 1. Table 2.15 summarizes the contributions of our categories of interest within total publications, by institution.

Table 2.15. Citations by main funders in Web of Science categories.

Relevant WS categories	Indian public organizations within top 10 funding bodies	Publications in categories	Total publications	%
"Energy and Fuels" and "Green or Sustainable Science & Technology"*	Department of Science and Technology	1,935	63,191	3.06
	Council of Scientific Industrial Research CSIR, India	1,669	62,262	2.68
	University Grants Commission, India	1,059	51,424	2.06
	Department of Biotechnology, DBT, India	367	17,791	2.06
	Ministry of New and Renewable Energy	143	341	41.94
	Board of Research in Nuclear Sciences, BRNS***	116	5,086	2.28
	Department of Atomic Energy, DAE**	100	6,776	1.48
	Ministry of Human Resource Development (MHRD)**	136	1,781	7.64
	Defence Research Development Organisation (DRDO)	94	4,189	2.24
"Nuclear Science & Technology" or "Physics, Nuclear"	Department of Science and Technology	1,061	63,191	1.68
	Department of Atomic Energy, DAE	805	6,776	11.89
	Council of Scientific Industrial Research CSIR, India	689	62,262	1.11
	University Grants Commission, India	576	51,424	1.12

Source: Authors' elaboration based on the methods and data sources described in this chapter, and WS searches.
Note: *These WS categories corresponds to the "unallocated" MI category. **Assumed to be from University Grants Commission. *** Assumed to be from the Board of Research in Nuclear Sciences, BRNS. Estimates for nuclear are added to the Atomic Energy funding found in the Department of Atomic Energy.

Last, in Step 4, we multiplied the institutional percentage of allocation to energy estimated from the WS method by the total RD&D in the UBs for the institutions from WS Step 2.

WS method limitations

There are potential drawbacks to our WS methods, summarized in Table 2.16.

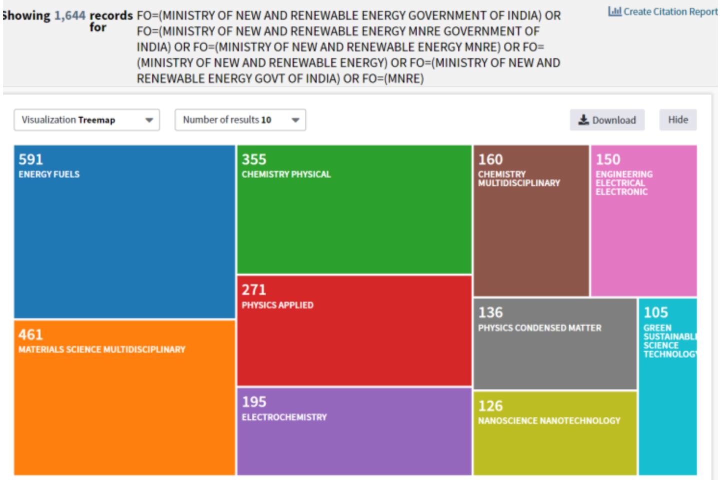
Table 2.16. Limitations to the Web of Science methods described in this section.

Challenge	Description	Result
1	WS does not homogenize funding body names. Sometimes, there are multiple names for one entity, and this may mask its true importance. For example, "DST SERB", "SERB", "Science and Engineering Research Board Serb New Delhi", "SERB New Delhi", "Science and Engineering Research Board", "Science and Engineering Research Board India" and "SERB India" are all considered separate entities, each with less than 20 publications.	Possible underestimation
2	We assume that the proportion of ERD&D per institution is static over time.	Masks changes in importance of ERD&D over time
3	The search only covers publications in India, while Indian institutions publish outside of India too.	Obfuscates true proportion of publications in the different categories, if national and international proportions differ

Source: Authors' elaboration based on the methods and data sources described in this chapter.

To help mitigate Challenge 1 in Table 2.16, we use the top five alternative names for the same institution. As an example, in Figure 2.12, we show the results for the top 5 alternatives to MNRE that came up within the top 50 funding institutions for the energy technology “Fuels & Energy”.

Figure 2.12. Web of Science categories to which the Ministry of New and Renewable Energy contributed.



Source: Authors’ elaboration based on the methods and data sources described in this chapter, and WS searches.

To help mitigate Challenge 2 of Table 2.16, we also considered repeating the exercise at a yearly level to obtain time-disaggregated proportions. However, it would be impossible to attribute publications to the correct funding years because there are lags between investment and output, as discussed in the literature.

Last, we do not consider Challenge 3 to be a major impediment. We believe that this search gives a representative understanding of the relative importance of allocation of expenditure by technologies within institutions.

APPENDIX 2.3. COUNTRY SAMPLES IN REGRESSION ANALYSIS

Some MI countries are not included in the IEA dataset (Table 2.17). While some information on non-IEA MI countries is available through MI documentation, it is incomplete and therefore excluded from this paper and our MI regression sample. The countries in the IEA dataset (and our "all country" sample) that do not participate in MI are in the right-most column.

Table 2.17. Country samples and data availability.

	MI	IEA dataset
Australia	Yes	Yes
Austria	Yes	Yes
Canada	Yes	Yes
Denmark	Yes	Yes
European Union	Yes	Yes
Finland	Yes	Yes
France	Yes	Yes
Germany	Yes	Yes
Italy	Yes	Yes
Japan	Yes	Yes
Korea	Yes	Yes
Mexico	Yes	Yes
Netherlands	Yes	Yes
Norway	Yes	Yes
Sweden	Yes	Yes
The United Kingdom	Yes	Yes
The United State	Yes	Yes
Brazil	Yes	No
Chile	Yes	
China	Yes	No
India	Yes	No
Morocco	Yes	No
Saudi Arabia	Yes	No
UAE	Yes	No
Indonesia	Yes	No
Belgium	No	Yes
Czech Republic	No	Yes
Estonia	No	Yes
Greece	No	Yes
Hungary	No	Yes
Ireland	No	Yes
Luxembourg	No	Yes
New Zealand	No	Yes
Poland	No	Yes
Portugal	No	Yes
Slovak Republic	No	Yes
Spain	No	Yes
Switzerland	No	Yes
Turkey	No	Yes

Sources: Mission Innovation (2020), (IEA 2020b).

APPENDIX 2.4. FUNDING IN CHINA ACCORDING TO MI

Table 2.18 shows ERD&D funding in China for technology categories missing in our source, according to MI.

Table 2.18. China renewables, hydrogen, and cross-cutting RD&D funding (technologies our methods do not differentiate) between 2015-2019 as reported in the 2020 Mission Innovation Country Highlights Report, million 2019 USD.

Year	Renewables	Hydrogen/fuel cells	Other cross-cutting techs/research
2015	831.8	18.9	491.5
2016	710.6	46.3	523.7
2017	1231.3	106.4	636.9
2018	1447.1	125.1	748.9
2019	910.3	651.2	784.4

Source: Mission Innovation (2020), adjusted using World Development Indicators (World Bank 2021a).

APPENDIX 2.5. DISCUSSION OF INCREASES IN US UNALLOCATED FUNDING

The size of RD&D funding reported by the U.S. government unallocated category in their submissions to the IEA RD&D statistics in 2018 was 3.3 billion USD. Since the number is very large, we leverage a more detailed database that keeps track of US investments in public RD&D at the U.S. Department of Energy: Database on U.S. Department of Energy (DOE) Budgets for Energy Research, Development, & Demonstration (1978–2021R) (Gallagher and Anadón 2020). This database was built from the Statistical Tables of Budget Justification documents, similar to the documentation we used for India.

We went through a process of matching funding amounts in both data sources for the United States and suggest that most of the 3.3. billion allocated to this category in 2018 is likely to be attributed as follows: 2.1 billion USD dedicated to the Basic Energy Sciences (BES) program, 418 million USD for the fusion program, and 360 million USD for ARPA-E.

However, the evolution in these categories in the database does not seem to explain the jump of 2.3 USD billion between 2010 and 2015 in the 'unallocated' category in the IEA RD&D database. Instead, we find that BES funding decreased slightly between 2010 and 2015 to 1.9 and 1.8 billion USD, respectively and fusion stayed more or less constant (489 and 493 million USD in 2010 and 2015, respectively).

Changes in ARPA-E funding can only explain a small part of the jump. In 2015 ARPA-E received 360 million USD. In 2010, it received 0 dollars from the normal request and about half of the funding that was secured as part of the stimulus package (around 194 USD). Thus, we suspect that during that period there may have been changes in reporting, which may include changes in categorizations or reporting for relevant projects in Departments other than DOE.

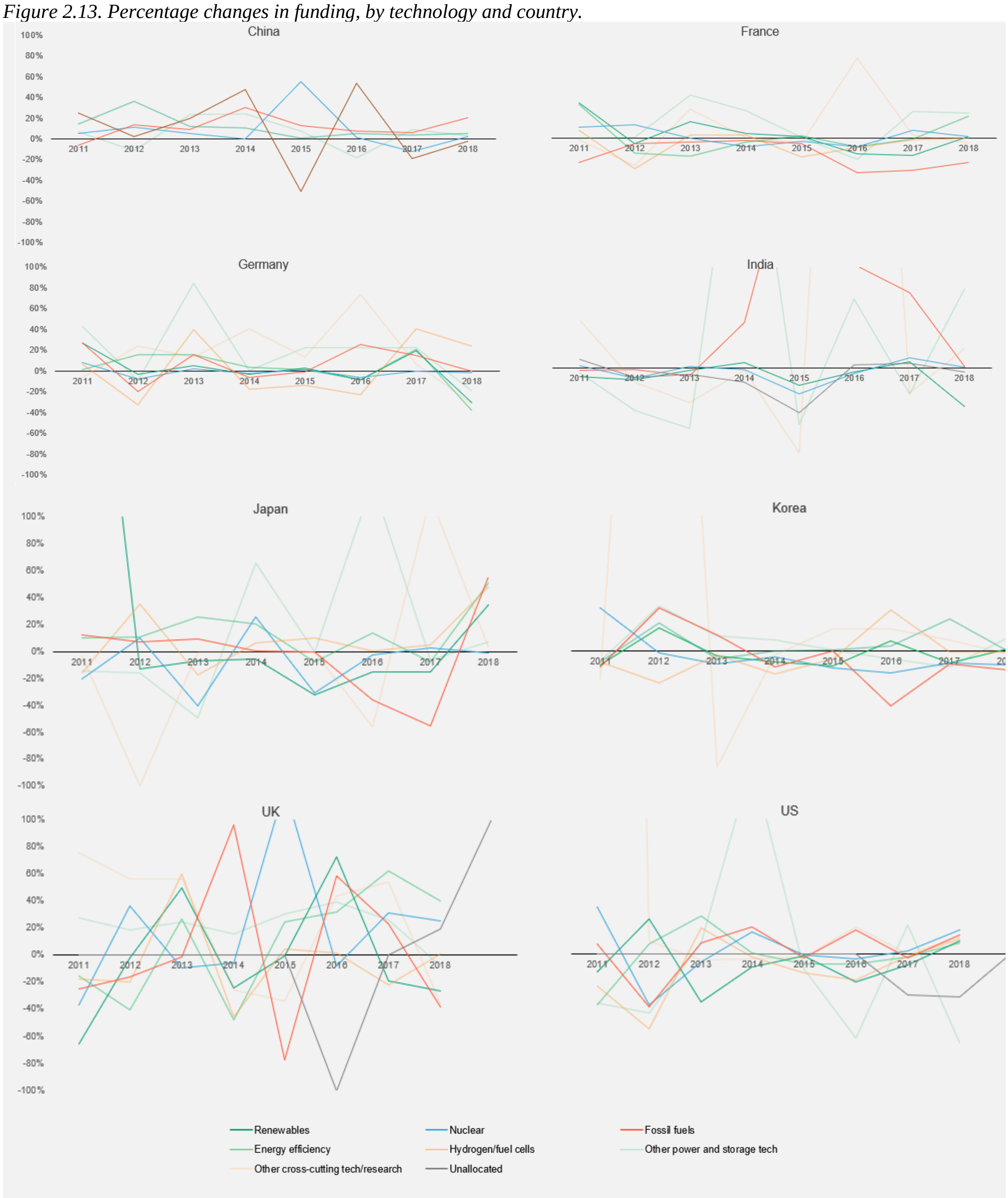
We also used the database to contrast the renewables category with the renewables data reported to the IEA. We find that the datasets are aligned on this in terms of the decrease between 2010 and 2015. The database reports a decrease from 1.1 billion USD in 2010 to 827 million USD in 2015. US funding for renewables RD&D then increased to 928 million USD in 2018. These numbers are of a similar magnitude (and similar trend between 2010 and 2015) but they are somewhat different from those reported in the IEA database: 1.5 billion, 966 million and 769 million in 2010, 2015 and 2018, respectively.

Because the overall trends do not change substantially, we chose to keep the data the United States submitted to the IEA for consistency with other countries.

APPENDIX 2.6. GROWTH RATES BY TECHNOLOGY AND COUNTRY

The panels in Figure 2.13 depict percentage changes of funding by technology after 2010.

Figure 2.13. Percentage changes in funding, by technology and country.



Source: Authors' elaboration based on the methods and data sources described in this chapter, including Ministry of Finance, Government of India (2020a) and International Energy Agency (2020b).

APPENDIX 2.7. DETAILED REGRESSION INPUT

As expressed in the Methods section, we use country FE, or demeaned values, in all our regression specifications. Country FE subtracts the average of each country from every data point, in other words it "demeans" the data, and this helps control for country-specific variation.

Figure 2.14 is a visual representation of the demeaned data, barring three outliers, Poland, Estonia, and Hungary. The datapoints in years 2009-2011 (in red) had FC dummies. The datapoints in years 2016-2018 (in green) had MI dummies. The regression serves to test whether the reds and greens (separately and together) were statistically significantly different from the blues.

Figure 2.14. Demeaned annual percentage changes of spending, by technology (all technology and CP) and country groups (All countries, MI, and M8), excluding outliers. 2009-2011 FC dummies= red; 2016-2018 MI dummies= green. The left column corresponds to total funding; the right column corresponds to clean plus. The rows correspond to All countries, M8, and MI countries, top to bottom.

Source: Authors' elaboration based on the methods and data sources described in this chapter, including Ministry of Finance, Government of India (2020a) and International Energy Agency (2020b).
Note: Excludes Poland, Estonia and Hungary, which are outliers.

APPENDIX 2.8. DETAILED DISCUSSION OF REGRESSION RESULTS

Table 2.19 summarizes the significant coefficients. The table does not include the coefficients from AC with outliers. The text below details and discusses the results.

Table 2.19. Technology, country groups, and coefficients for regressions with significant results.

Reg	Technology	Dummy included in the regression	Country groups	FC dummy	MI dummy
(4)	Total	FC3	All exc. Outliers	0.368**	
(7)	Total	FC3	M8	0.279**	
(8)	Total	FC	MI	0.110*	
(9)	Total	FC2	MI	0.249***	
(10)	Total	FC3	MI	0.373***	
(19)	Clean	FC2	MI	0.231**	
(20)	Clean	FC3	MI	0.370***	
(29)	Clean	MI	M8		0.0904*
(37)	Total	FC3 MI	All exc. Outliers	0.356**	-0.0900
(39)	Total	FC2 MI	M8	0.158**	-0.0157
(40)	Total	FC3 MI	M8	0.310***	-0.0161
(41)	Total	FC MI	MI	0.148***	-0.0333
(42)	Total	FC2 MI	MI	0.280***	-0.0272
(43)	Total	FC3 MI	MI	0.406***	-0.0370
(56)	Clean	FC3 MI	M8	0.248**	-0.0221
(57)	Clean	FC MI	MI	0.147*	-0.122
(58)	Clean	FC2 MI	MI	0.258***	-0.118
(59)	Clean	FC3 MI	MI	0.398***	-0.126*

Source: Authors' elaboration based on the methods and data sources described in this chapter.
Note: FC= 2009-2011, FC2=2009-2010, FC3=2009; MI=2016-2018. ***= <1%, **=<5%, *=<10%.

FC only, 2000-2012. Three variations of FC dummy: FC= 2009-2011, FC2=2009-2010, FC3=2009

- For M8 countries, the change in total funding was positive (0.279) and significant (0.022) only when we limited the dummy to 2009.
- For M8 countries, the change in clean energy funding was insignificant for all lengths of the FC dummy.
- For All countries, the change in total funding was positive (0.93) and significant (0.002) only when we limited the dummy to 2009. It decreases to (0.368 & p-value of 0.012) when we exclude outliers (Poland, Estonia and Hungary).
- For All countries, the change in clean energy funding was positive (1.13) and significant (0.026) only when we limited the dummy to 2009. It decreases and becomes insignificant when we exclude outliers.

MI only, 2012-2018. MI dummy: 2016-2018

- For All countries total funding and clean energy funding, the change in the years after MI is always insignificant. This holds when we exclude outliers.
- For M8 countries and total funding, changes were insignificant. But clean energy funding change was positive (0.09) and significant at the 10% level (p-value of 0.06).
- For MI countries, the change in total funding and clean energy was insignificant.
- For non-MI countries, the change in total funding and clean energy was insignificant.

MI + FC, 2000-2018. Three variations of FC dummy: FC=2009-2011, FC2=2009-2010, FC3=2009. MI dummy: 2016-2018

- For All countries and total funding, FC and MI, FC is significant when it is limited to two and three years (0.44 and 1.08, p-value of 0.04 and 0.00, respectively). Coefficients become (0.1235 and 0.356) and (p-value of 0.26 [note it increased and the coefficient is no longer significant] and 0.016, respectively) when we exclude outliers.
- When we exclude outliers, the same occurs to non-MI, which was significant for one year after the FC (1.85, p-value of 0.005), and is no longer significant without outliers.
- For M8 countries and total funding, coefficients are significant after 2 years and one year after the FC. Coefficients are 0.158 and 0.310 with p-values of 0.026, and 0.001, respectively.
- For MI countries and total funding, the FC was significant for all versions of the FC dummy. The coefficients for the longest to shortest FC dummy were: 0.148, 0.280, and 0.406, with p-values of 0.001, 0.000, 0.000, respectively. MI was never significant.
- For All countries and clean energy funding, the FC was significant one year after the FC, 1.44 (p-value of 0.003); but it becomes insignificant without outliers, (coefficient of 0.16, p-value of 0.93). The same occurs with non-MI (2.64, p-value of 0.012).
- For M8 countries and clean energy funding, there is a significant change in clean energy expenditure one year after the FC (0.24, p-value of 0.46).
- For MI countries and clean energy funding, the FC was significant for all versions of the FC dummy. The coefficients for the longest to shortest FC dummy were: 0.398, 0.258, and 0.147, with p-values of 0.002, 0.003, 0.062, respectively. MI was *negative* and significant (-0.125, p-value of 0.092) when FC was shortest.

Results summary

- In summary, we look at FC alone for All countries*, M8 and MI countries. These three country groups show a significant** change in total funding one year after the FC, and MI countries retained growth longer. The growth rate of All countries in 2009 increased more than M8 and MI, but we need to remember that this analysis can only compare groups with themselves. In other words, All countries increased more compared to themselves than M8 and MI compared to themselves one year after the FC. As opposed to All countries and M8, MI clean energy experienced an increase in funding one and two years surrounding the FC.
- When we look at MI alone, M8 exhibits a very small growth of clean energy funding surrounding MI, while All countries and MI countries do not.
- When we look at FC and MI together, All countries, MI, and M8 exhibit growth in total funding in the year of the FC, with the largest to smallest change (always compared to itself) as follows: MI, All and M8 countries. In MI and M8 countries, the FC remained significant when we extended the FC to two years. It remained significant three years after for MI countries.
- For MI countries and clean energy funding, there are significant effects of all lengths after the FC. Additionally, there is a small decrease surrounding MI when FC dummy is longest. M8 countries significantly increased their spending in clean energy one year after the FC.

Note: *We exclude output with outliers from the summary. **This summary does not differentiate between significance levels, but the preceding text within this Appendix does.

CHAPTER 3: COMPARING THE CAUSAL EFFECTS OF SEVEN ENERGY POLICY INSTRUMENT CATEGORIES ON ENERGY DECARBONIZATION IN 100+ DEVELOPING COUNTRIES 3-7 YEARS AFTER IMPLEMENTATION

Abstract

There is a variety of energy policies, all over the world, aiming to advance one or several environmental, economic, security, or equity policy goals. We offer the first consistent attempt to identify how seven energy policy instrument categories (PICs), representing 75+ policies for energy decarbonization, each individually affect the energy mix across 100+ developing countries over time (three, five, and seven years after implementation).

We apply 2SLS with country interactions and country and time fixed effects over regional panels to account for a host of well-documented issues in existing comparable research. These issues include omitted variables that relate to country and regional characteristics and simultaneity and reverse causality between policy enactment and outcomes. Additionally, we design the variables that represent each of the seven PICs using three indices that help account for the degree of reform and collinearity of policies.

We find that generally the effects of PICs improve with time and that policies that address counterparty risks (those that help improve bankability for private participation, including backstops for government auction guarantees) have the most immediate positive effect on energy decarbonization. We suggest that incumbent forces could be behind the immediately lackluster or negative effects in other PICs and consider the effects that long-term country-specific characteristics, like enforcement, are likely to have on the effects of PICs.

3.1 INTRODUCTION

Countries have enacted a plethora of renewable energy policies at different points in time and in different combinations to advance one or several environmental, economic, security, or equity policy goals. More recently, they are also incentivized by the growing challenge of mitigating climate change. We offer the first comprehensive and systematic assessment of how each of seven policy instrument categories (PICs) individually perform in energy decarbonization over the short to medium term across more than 100 developing countries 3 to 7 years after their implementation.

The PICs are: (1) Legal framework (LF); (2) Planning for expansion (PE); (3) Incentives and regulatory support (IR); (4) Attributes of financial and regulatory incentives (AI); (5) Network connection and use (NC); (6) Counterparty risk (CR); and (7) Carbon pricing and monitoring (CP). We consider the effects of PICs on five inter-related indicators of energy mix (outcomes): (1) fossil fuel energy consumption (FFC); (2) electricity production from fossil fuels (EFF); (3) electricity production from oil sources (EOS); (4) renewable energy consumption (REC); and (5) renewable electricity output (REO), all as a percentage of generation and/or consumption of electricity and/or energy.

Our study mainly engages with two topical literature streams. The first is the literature that evaluates and compares the outcomes of policy instruments (which we refer to simply as “policies”) for energy decarbonization. A recent interdisciplinary systematic review of 10 decarbonization policies pointed to geographical inclusion as a major research gap (Peñasco, Anadón, and Verdolini 2021). We address this gap by leveraging the Regulatory Indicators for Sustainable Energy (RISE) policy database, which is created by the Energy Sector Management Assistance Program (ESMAP) at the World Bank (WB) and which covers more than 130 developing and developed countries.

ESMAP catalogs 75+ policies nested within the seven aforementioned PICs. We operationalize the seven PICs into an index (which we call the RISE index) that is suitable for econometric analysis by attributing weights to the policies as provided to us by ESMAP. We also create two alternative indices, further explained below.

The second literature stream considers the effects of power sector reform (PSR), which we define as a slew of structural changes to the power sector that occurred as a result of the Washington Consensus in the 1980s and 1990s (Besant-Jones 2006). We focus on a sub-stream of the literature that subjects country panel data consisting of policies and their intended outcomes to econometric analysis.

We identify common oversights in the design of PSR studies that use data comparable to ours. These include overlooking (or insufficiently considering) the following: omitted variables that relate to country and regional characteristics (Challenge 1), endogeneity due to simultaneity and reverse causality between policy enactment and outcomes (Challenge 2), lack of accounting for the degree of reform (Challenge 3), and collinearity of policies (Challenge 4) (Bacon 2018). We design our study to systematically engage with each of these challenges in three ways.

First, we reduce the possibility of omitted variable bias (Challenge 1) by, amongst other things, running regressions in six regional panels, and by including time and country fixed effects (FE). Second, to address endogeneity (Challenge 2), we build onto the small body of PSR research (including Cubbin and Stern, 2006; Nagayama, 2009; Urpelainen, Yang, and Liu, 2018; and Sen, Nepal, and Jamasb; 2016) that uses instrumental variables (IVs) through two-stage least squares (2SLS).

To select an appropriate IV, we consider that developing countries are more likely to implement PICs when they exhibit "closeness" to World Bank major donors (MDs) that champion today's good practices, which is how ESMAP describes the RISE dataset (Foster et al. 2018). While achieving perfect identification in cross-country panel regressions is difficult if not impossible, we believe these "closeness" measures are plausibly exogenous to developing countries' energy mix and reduce the endogeneity biases. Our main IV is developing countries' foreign policy political proximity to the major donors (France, Germany, Japan, the United Kingdom, and the United States) as estimated in (Bailey et al. 2017) database on voting in the UN General Assembly. For robustness purposes, we also consider two alternative IVs that measure closeness associated with trade, described in detail in the Methods section.

Third, we design two alternatives to the RISE index to operationalize the PICs. The first index addresses the degree of reform (Challenge 3) because it weighs all policies within each PIC equally. Compared to the default weighting by ESMAP, it is comparatively more sensitive to the number of policies implemented. The second index addresses collinearity of policies (Challenge 4) within each PIC by weighting uncorrelated policies more than those that are highly correlated to others.

These combinations of IVs, indices, and other alternatives further detailed in the Methods section, create 18 "base" regression specifications. We run each of these over the seven PICs, five outcomes, and six regions leading to 3,780 regressions. Additionally, we apply 2SLS country interactions following (Wooldridge 2001), rendering tens of thousands first (S1) coefficients.

When we restrict the sample to the IV regressions that plausibly meet the relevance criterion and are theoretically consistent, we obtain 540 first-stage regressions and 85 second-stage regressions, which constitute the basis of our results.

Analyzing our results suggests that, controlling for time and regional differences, the effects of most policy packages in developing countries are negative 3 years after their enactment. That is, renewable energy policies, counterintuitively result in a higher share of fossil fuel sources in developing countries' energy mix. However, the performance of these policies improves to achieve their goals five and seven years afterward.

We interpret these results as evidence of a combination of the Sailing Ship Effect, where in the short term effects of policies are dampened by incumbent forces (Ward 1967; Gilfillan 1935), and the relative inability of developing countries to secure financing (Egli, Steffen, and Schmidt 2019; Moner-Girona et al. 2021).

A notable exception is the CP policy package, which yields an increase of the renewables in developing countries' energy mix 3 years after implementation. This goes some way in supporting the importance of policies that make projects bankable for private investors, including backstops for government guarantees for auctions. In direct juxtaposition to the rest, the effects of CP tend to moderate over time.

The temporal findings could suggest that some PICs (like CP) may be prerequisites for the others to have their intended effects. However, our methods do not address this question. We suggest that a subsequent analysis could consider interactions between PICs. As we discuss in the Limitations section, this has been increasingly reflected in the interdisciplinary "policy mixes" literature, which spans economics, public policy, and innovation studies (Rogge and Reichardt 2016).

Last, we show that country characteristics are likely to play a large part in the direction of effects and acknowledge the possibility that, while we have conducted extensive checks and sensitivity analysis, our IVs and econometric controls may not sufficiently address other patterns shaping the energy sector in developing countries. These include changes in enforcement capabilities over time, which cannot be controlled by static country FE.

Section 2 of this chapter reviews the literature, Section 3 explains the Methods, and Section 5 presents the Data. Section 5 presents and discusses results while Section 6 considers limitations. Section 7 concludes.

3.2 LITERATURE REVIEW

This literature review has three parts. First, we position our study within the current and broad social science literature that analyzes the effect of individual energy decarbonization policies and their outcomes. We show that there is a dearth of systematic studies on developing countries and discuss the overarching results of the literature relevant to our PICs.

Second, we focus on applied economics studies that study the effects of PSR. This literature is relevant because of the resemblance of the underlying datasets (including the structure, source, and their role in policymaking). Last, we discuss the two existing studies that use the RISE dataset.

3.2.1 Energy decarbonization policy review

Peñasco, Anadón, and Verdolini (2021) conduct a systematic review (SR) of 211 studies that evaluate "the effect of a specific policy instrument [related to energy decarbonization] into a specific outcome" across all the social sciences. Their work is relevant to us because each of our PICs represents a group of related policies, and is not a "policy mix" as per Rogge and Reichardt (2016).

Additionally, we do not look at the interactions between PICs (both policy mixes and interactions are further discussed in the Limitations). Last, although we have chosen five dependent variables for robustness, they all represent the expansion of the share of low carbon energy technologies.

Peñasco, Anadón, and Verdolini (2021)'s SR framework helps show that our paper considers a relatively narrow range of possible outcomes and a comparatively broader range of possible policies. Additionally, their sector and methodological typologies reveal that the sectoral focus and methods of our paper (power sector and quantitative, respectively) are relatively common in the literature. On the other hand, our broad geographical coverage is rare.

After having situated our study within the broader literature, we make use of the INNOPATHS Decarbonisation Policy Evaluation Tool (DPET) and the SR itself to discuss the current state of knowledge on how the policies represented in the seven PICs affect the deployment of low carbon energy technologies.

Range of outcomes and policies in this chapter compared to existing literature

Table 3.1 shows the range of outcomes covered and systematically identified by Peñasco, Anadón, and Verdolini (2021). When compared to the broad social sciences literature, the scope of this study lies squarely within the "technological effectiveness" of PICs.

Table 3.1. Outcomes of energy decarbonization policies studied in social sciences according to an SR by Peñasco, Anadón, and Verdolini (2021).

Criteria	Outcomes	Indicators (examples)	Included in this study
Effectiveness	Environmental effectiveness	GHG emission reductions	No
	Technological effectiveness	Electricity generated with RE	Yes, the share of energy/electricity generated/consumed with RE/FF
Efficiency	Cost-related	Euro saved per kWh	No
	Innovation	Patents	No
Economic co-benefits	Competitiveness	Net job creation	No
Social acceptability	Distributional	Incidence of support costs	No
	Other	Perceived transparency from consumers	No

Based on Figure S2 of Peñasco, Anadón, and Verdolini (2021). Definitions are found in Table SI.2.

In contrast to our relatively narrow outcomes focus, our study covers a significant share of the policy instruments identified by Peñasco, Anadón, and Verdolini (2021).

Table 3.2 shows the classification of policies addressed in their sample of 211 studies. In growing level of specification, policies are divided into three main categories, eight meso-level policy types, and 21 policy instruments. Table 3.2 maps our policies onto their framework and provides examples of PICs in which they are found (the full policy list will be introduced in the Data section). Overall, we consider some (not all) regulatory and economic and financial instruments identified in their review.

Table 3.2. Energy decarbonization policies studied in social sciences according to Peñasco, Anadón, and Verdolini (2021) (first three columns), and whether we include them in this study (last column).

Categories (not to be confused with the categories used in this study)	Meso-level policy types	Policy instruments	Included in this study and example of a PIC in which it is found
Regulatory	Codes/standards/mandates	Building codes and standards	No
		Product standards	No
		Vehicle fuel-economy and emissions standards	No
	Obligation schemes/quotas	RE obligations	Yes, Legal framework for renewable energy (LF); Planning for renewable energy expansion (PE).
Economic and financial instruments	Direct investment	Government procurement	No
		R&D funding	No
	Fiscal/financial incentives	Feed-in tariffs and feed-in premiums (FITS/FIPs)	Yes, Incentives and regulatory support for renewable energy (IR).
		Auctions	Yes, Attributes of financial and regulatory incentives (AI).
		Taxes and tax exemptions	Yes, Carbon pricing and monitoring (CP).
		Grants, subsidies, and other tax allowances	Yes, Incentives and regulatory support for renewable energy (IR).
		Loans and soft loans	No
		User charges	No
	Market-based instruments	GHG emissions allowance trading schemes (ETS)	Yes, Carbon pricing and monitoring (CP).
		Green certificates	No
		White certificates	No
Soft instruments	Performance labels	Comparison labels	No
		Endorsement labels	No
	Information campaigns	By government agencies, government departments	No
	Voluntary approaches	Negotiated agreements (public-private sector)	No
		Public voluntary schemes	No
		Unilateral commitments (private sector)/EMSs	No

Source: Based on Table S2 of Peñasco, Anadón, and Verdolini (2021). Definitions can be found in Table SI.1.

Range of industry, methods, and geographies in this chapter compared to existing literature

Within the 211 publications reviewed by Peñasco, Anadón and Verdolini (2012), the power sector, which is the focus of this article, made up more than 50% of studies. Quantitative studies such as ours made up the largest group (44.1%).

However, international reviews made up only 15.3% of publications, third after national and state/regional studies. Overall, the SR covered 50 countries, with a bias toward the OECD (Peñasco, Anadón, and Verdolini 2021). Instead, we look only at non-OECD and cover about 100 countries (we devote a discussion to country coverage in the Data section).

State of knowledge on effects of the PICs

Last, we consider the state of knowledge on technological effectiveness and policies covered in this paper. Note that it is impossible to review the effects of all 75+ policies on technological effectiveness given space constraints. Therefore, we consider the evidence only for the policies that were mapped onto the SR framework in Table 3.2.

The DPET online interface based on Peñasco, Anadón, and Verdolini (2021) allows us, amongst other things, to search papers along several key characteristics such as (1) policies; (2) outcomes; (3) methods (randomized, observational/quantitative, qualitative, and ex-ante studies); (4) jurisdiction (national, regional, international); and (5) sector (power, building, construction, etc.). We include results from all methodologies and all jurisdictions but concentrate only on the power sector.

Table 3.3 summarizes the effects of the PICs that we mapped onto the SR framework in Table 3.2. Feed-in tariffs and feed-in premiums (broadly, subsidies for renewable energy) boast the highest support, but today, they are losing ground to auctions (competitive bidding processes for private sector investment in renewable energy deployment). While there is relatively less data to assess auctions, it seems like design elements are crucial to success. Of our seven PICS, AI includes several of the design elements thought to be important today, and CR includes the bankability of all private financial investments, including those in auctions.

Table 3.3. Energy decarbonization categories and policies in Peñasco, Anadón, and Verdolini (2021) (first two columns), whether they are covered in this study (third column), and their effect on our outcome of interest, technological effectiveness (last column).

Categories	Policies	Included in this study and example of a Policy Instrument Category in which it is found	Effect on technological effectiveness
Regulatory	RE obligations	Yes, Legal framework for renewable energy (LF)	Inconclusive. 50% of the evaluations report that RPS's have no impact on technology outcomes.
Economic and financial instruments	Feed-in tariffs and feed-in premiums (FITS/FIPs)	Yes, Incentives and regulatory support for renewable energy (IR)	Generally positive. 86% of the evaluations of FITs report a positive effect on technology-related outcomes.
	Auctions	Yes, Attributes of financial and regulatory incentives (AI)	Mixed. 59% report a positive impact, 41% report negative or no impact. Relatively short time series compared to FITs/FIPs. Design is especially important. Due diligence of projects from commercial or investment banks seems imperative, which is related to the Counterparty risk (CR) PIC.
	Taxes and tax exemptions	Yes, Carbon pricing and monitoring (CP)	Generally positive. 75% agreement.
	Grants, subsidies, and other tax allowances	Yes, Incentives and regulatory support for renewable energy (IR)	Same as above.
	GHG emissions allowance trading schemes (ETS)	Yes, Carbon pricing and monitoring (CP)	Mixed. 58% report no impact, 33% positive impact, and 8% negative impact.

Source: Based on Supplementary Information of Peñasco, Anadón, and Verdolini (2021) and DPET database.

3.2.2 Evolving prescriptions for power sector regulation

In contrast with the literature reviewed by Peñasco, Anadón, and Verdolini (2021), PSR related studies cover a more geographies, including developing countries. More importantly, the PSR literature matters to us due to the type of data used and methodological issues it addresses.

Supported and advised by international development organizations and developed country governments, almost half of 150 developing countries initiated PSRs since the early 1990s (Besant-Jones 2006). For our purposes, PSR refers broadly to the implementation of a slew of policies under four key elements: (1) increasing private sector participation; (2) establishing regulation; (3) increasing competition; and (4) unbundling monopolies in the power sector.

Based on neoclassical microeconomic theory, the implementation of PSR was considered to be the panacea to address a range of power sector challenges, including the technical and financial underperformance of utilities, as well as a lack of public financing needed to expand capacity (Besant-Jones 2006; Sen, Nepal, and Jamasb 2016).

Today, the wealth of information on the PSR experiences of more than one hundred countries over more than three decades has allowed for an animated “introspection” in several overlapping disciplines, including political science, development, sociology, and applied economics (Sen, Nepal, and Jamasb 2016). The “introspection” covers a myriad of aspects of PSR, including the mechanisms underlying reform decisions and coercion and conditionality of loans from donors and international development institutions (see Henisz, Zelner, and Guillén (2005); Domah, Pollitt, and Stern (2002); Lee and Usman (2018); Wamukonya (2003); Williams and Ghanadan (2006) for examples of this range). In fact, the literature summarizing theory and power sector impacts of PSR has become rich enough for several reviews, including Jamasb, Nepal, and Timilsina (2015) and Jamasb et al. (2005).

A sub-stream of the PSR literature subjects the supposed benefits of PSR to empirical econometric examination covering a range of both developing and developed countries over various decades using panel datasets with dummy variables as policies, exactly as captured by RISE.

However, note that PSR studies are not interested in climate-related outcomes. Consequently, we refrain from taking up space discussing their conclusions (although we do provide several in a table format). Our main interest is instead on the methods that different authors propose to address potential shortcomings associated with similar datasets. Therefore, in this section, we identify and discuss methodological challenges behind PSR studies and focus on how past studies inform the methods we apply to our data.

Incidentally, we note that the similarities found between PSR studies and RISE is not coincidental. The current structure of ESMAP is organized along the three pillars of the 2015 UN Sustainable Development Goal 7 (SDG7) of Energy Access (EA), Renewable Energy (RE), and Energy Efficiency (EE). ESMAP provides 133 aggregate country “traffic light” scores of red, yellow, and green in a way that is reminiscent of the ESMAP scorecard of the 1990s (World Bank ESMAP 1999) for each pillar. The “traffic light” colors represent the lower, middle, and upper third of scores, normalized to a theoretical minimum of 0 and a maximum of 100. As an example, in 2015 the score ranged from 2 to 90 (Somalia and Germany, respectively).

According to ESMAP, the scores communicate the “strength and breadth of government support for sustainable energy and the actions they have taken to turn that support into reality.” Though today’s UN SDG7 is more holistic than power sector goals of the 1990s (and ESMAP candidly acknowledges that policies exist in an ecosystem that influences their quality and enforcement), the underlying dataset, and its source, are similar to those behind PSR studies.

Methodological PSR challenges relevant to our data and studies that address those challenges

Recently, Rethinking Power Sector Reform, a World Bank knowledge program by ESMAP and the Public-Private Infrastructure Advisory Facility, published five literature review working papers taking stock of lessons learned from several aspects of PSR, including Bacon (2018).

Bacon (2018) is the most recent review of studies that apply regression analysis to evaluate the links between several sub-elements of PSR and utility performance, and as well as broader economic development indicators.

Broadly, Bacon (2018) finds that the literature associates private sector involvement with improvements in sector performance indicators (labor productivity and operational efficiency), though other elements like regulation and competition remain contested. Most importantly, the review identifies 14 overarching conclusions, including challenges related to econometric studies.

Here we summarize the five most relevant methodological design oversights for our study and briefly describe how we address them. A more detailed discussion is found in the Model and methods section.

Some studies tend to overlook important country characteristics (like country income or system size), which might partially determine the success of PSRs (Challenge 1, an issue discussed extensively in (Levy and Spiller 1994)). This can be at least partially addressed by adding adequate control variables or accounting for country and regional effects in the regression specification. Additionally, there may be potential endogeneity between policy enactment and outcomes (Challenge 2) due to reverse or simultaneous causality in the implementation of a reform (eg, the decision to implement reform is influenced by the past performance of the system). IVs can help address this issue.

There is also difficulty in accounting for the degree of reform because the data is usually set up as a country panel of dummy variables. Most studies include only four variables (one for each element of PSR mentioned above – privatization, regulation, competition, and unbundling) represented with a 0 when the element is not enacted, and 1 when the policy is enacted (Challenge 3). We address this issue by aggregating RISE's 75+ variables into three different indices.

Additionally, there may be interaction effects of implementing several policies at the same time (collinearity of the independent variable) (Challenge 4). In the Methods, we explain how we consider the collinearity of policies within categories. However, we do not account for interactions across PICs, like policy mix studies do (which we discuss in the Limitations section).

Last, although not an econometric design problem, Bacon (2018) identifies the lack of quality data on pre-reform and post-reform performance indicators as limiting the accuracy of results (Challenge 5).Our data stretches farther back than the current climate-related objectives. We further discuss our approach to these challenges in the Methods and Data Section.

Studies that address several methodological challenges

Table 3.4 summarizes four studies that address several of the five relevant challenges discussed in this section of the Literature Review.

Table 3.4. Selected power sector reform studies that use instrumental variables (IVs) to address endogeneity (Challenge 2), as well as how they address other challenges.

Author	Objective	Method/data	Vars	Output
Cubbin and Stern (2006), *World Bank Economic Review*	To assess whether a regulatory law and higher quality regulatory governance are associated with superior outcomes in the electricity industry, defined as increases in the rated generation capacity per capita.	Country FE, error correction, and IV regression for robustness. 28 African, Asian, Caribbean, and Latin American countries over 1980–2001.	*Dependent*: Net electricity generation per capita of the population; Installed generation capacity per capita of the population; Net electricity generation per employee in the industry; Electricity generation to average capacity (capacity utilization). *Independent*: Regulatory, a four-component index of regulatory governance in the electricity sector (Elements 1-3 are dummies), 4 is 0-1. Based on Domah, Pollitt, and Stern (2002). *Controls*: Privatization, % of generating capacity owned by private investors; Competition, market share of the three largest generators in the sector; Real GDP/capital (log); Debt payments (% of national income); Industry value-added, (% of GDP) from World Governance Indicators (WDI).	Controlling for privatization and competition and allowing for country-specific FE, both regulatory law and higher quality regulatory governance are positively and significantly associated with higher per capita generation capacity. The results are robust to estimating alternative dynamic specifications (including error correction models), to the inclusion of economy governance political risk indicators, and to controlling for possible endogeneity biases.
Nagayama (2009), *Energy Economics*	To study the relationship of power prices on PSR (Model 1), and PSR on power prices (Models 2-3).	Country FE, ordered probit random effects lagged model, and IV regression (Model 3). 78 countries by power sector structure over 1985-2003. Original dataset.	*Dependent*: Price (Models 2-3); Original power sector transition data using four types: monopoly, single buyer market, wholesale market, and retail market (Model 1). *Independent*: Price (Model 1); Original power sector transition data (Models 2-3) *Controls*: GDP/capita.	High power prices tended to impulse PSR (Model 1). Liberalization rose prices in every region modeled (Model 3).
Sen, Nepal, and Jamasb (2016), *Oxford Institute for Energy Studies Working Paper*	To systematically examine technical, economic, and welfare impacts of individual PSR policies in non-OECD Asian developing economies accounting for cross-country	Country FE and IV regression. 17 non-OECD developing Asian economies over 1990-2013.	*Dependent*: Transmission and distribution losses/capita, GDP/capita, electricity trade/capita, Gini coefficient, Human Development Index *Independent*: Independent reform measures (not indexed); index of political reform (IV) *Controls*: electric power consumption/capital; transparency index; installed capacity/capita.	First, early structural reform measures carried appear to have had a greater influence on the outcomes of electricity reforms in the region. Second, the reform measures associated with positive economic growth appear to be associated with negative effects welfare indicators. Third, country-specific institutional factors have strongly influenced

Author	Objective	Method/data	Vars	Output
	institutional differences.			outcomes in non-OECD Asia.
Urpelainen, Yang, and Liu (2018), *Review of Policy Research*	To investigate the impact of power sector reforms on efficiency in the power sector.	Country FE, IV regression. 184 countries over 1982-2011 based on Erdoğdu (2011).	*Dependent*: T&D losses- % power lost between power generation and actual use, total power generation capacity – ln of installed capacity in megawatts. *Independent*: Extent of regulatory reform, OECD membership dummy, IV-regional power sector reforms (the number of reforms enacted by other countries in that region and the average numbers of reforms that neighboring countries have enacted, with very similar results). *Control*: log of GDP/capita, population, Polity score, ICRG, % population urban, value-added by industrial sector, % of GDP, electricity exports and imports over total electricity production, log net bilateral and multilateral aid.	Each additional reform increases installed capacity in megawatts by 5% and decreases power lost between generation and consumption by 2 percentage points.

Source: Authors' elaboration and work cited in the table.

Cubbin and Stern (2006) analyze the relationship between the quality of regulatory governance and the level of generation capacity per capita for electricity supply industries in 28 African, Asian, Caribbean, and Latin American countries over 1980–2001, a similar time frame to us. They control for privatization and competition using Henisz, Zelner, and Guillén (2005)'s data, and applying Domah's regulatory quality survey from Domah, Pollitt, and Stern (2002).

Due to collinearity between the four independent variables on regulatory characteristics (Challenge 3), they create the "Cubbin-Stern" regulatory index. The index communicates the extent of PSR implementation better than a dummy variable, and in the Methods section of this paper, we call it the "Summation" index. However, the Cubbin-Stern index assumes each component has the same bearing on the outcome of the model (Challenge 4), an issue we also address in our methods.

Based on the model's lag structure, the authors suggest an underlying causal relationship, especially given the use of country FE to control for the myriad of differences that might lead to different country behaviors (Challenge 1). The authors attempt to correct for weak evidence of endogeneity (Challenge 2) by instrumenting the lag of the predicted value of the Cubbin-Stern index, producing similar results.

Nagayama (2009) proposes three models to study the relationship between power prices and PSR using an original dataset that categorizes 78 countries by power sector structure (monopoly, single buyer, wholesale market, or retail market, and combinations where necessary) between 1985-2003. In the second model, Nagayama (2009) proposes that PSR affects power prices, and employs both random and FE (the second would help address Challenge 1).

The author also notes the problem of simultaneity between power prices and PSR (Challenge 2) and uses the political democratic degree index from the Polity IV dataset as an IV. We tried and discarded this IV in earlier versions of this analysis. Urpelainen, Yang, and Liu (2018) argue that these IVs violate the exclusion restriction because democratic governments have an interest in reducing consumer prices.

Urpelainen, Yang, and Liu (2018) investigate the effects of PSR on total power generation capacity and T&D losses using a comprehensive dataset of 184 countries between 1982 (the start of the Chilean power market reform) and 2011 (end of available data). They propose addressing endogeneity (Challenge 2) by using the number (and average number) of reforms enacted by other countries in a country's region as an IV, in addition to time and country FE (Challenge 1) in both 2SLS stages.

Similar to the Cubbin-Stern (and our Summation) index, Urpelainen, Yang, and Liu (2018)'s independent variable is computed as the yearly sum of PSR enacted, by country. The latter is taken from Erdoğdu (2011) who puts forth a dummy panel dataset for eight PSR reforms (such as corporatization of electric utilities and privatization).

One limitation of using the sum of dissimilar reforms by year and country is the inability to distinguish between different types of reforms. Importantly, our approach is an improvement because we group 75+ policies within similar PICs.

3.2.3 Studies that discuss or use the RISE dataset

As primarily a policymaker tool codifying policies related to EA, EE, and RE, RISE has been the main thrust behind three WB institutional policy reports (World Bank 2014; World Bank 2018; Banerjee et al. 2017). RISE data is also used as evidence of policy advancement towards SDG7 by Sustainable Energy for All, an independent international organization established by the UN in 2011.

However, RISE has not been without critics. In an *Energy Research and Social Science* perspective piece, Urpelainen (2018) argues that "the idea of global practices, codified in an elegant and easily understandable scorecard [behind RISE], should be abandoned as largely irrelevant and potentially counterproductive" to the outcomes the SDG7. Urpelainen (2018) contends that impacts depend on the country context, including the governmental capacity to implement them.

However, instead of making normative assumptions of the RISE indicators, our analysis attempts to find causality between PICs and energy decarbonization. As explained, we do not use the scoreboard itself. Instead, we group similar policies into PICs. In that sense, we ignore the question of whether (or not) the policies in RISE should (or should not) be considered global standards. We simply use the dataset to empirically discuss which PICs led to desired incomes, and whether this changed over time after implementation.

In the only existing empirical exercise using RISE data, Foster et al. (2017) take on our perspective. As an overview paper to the Rethinking Power Sector Reform initiative, Foster et al. (2017) use RISE to depict trends in policy implementation globally between 1995-2015. Unlike us, Foster et al. (2017) avoid attempting to establishing a causal connection; instead, they discern trends in economic and political characteristics that may affect policy deployment. Specifically, Foster et al. (2017) use statistical tests of differences in values between country groupings (N-1 two-proportion tests for binary variables, and Analysis of Variance [ANOVA] for continuous variables).

They find that characteristics like geography, income group, power system size, and political economy all influenced the pattern of implemented policies, further supporting the need to use regional groups and country FE, like we do. The authors also find that the spread of policies slowed in the second decade (2005–2015) and experienced some reversal.

3.3 MODEL AND METHODS

We posit a linear relationship between a renewable energy policy x and an energy mix outcome, y in a country c and a year t. Energy sector policies take time to implement, so we assume that policy enaction does not have an immediate effect on the outcome variable and consider three-year, five-year, and seven-year lags, l. Each regression equation can be summarized as follows:

$$y_{c,t} = \alpha_c + \beta x_{c,t-l} + \gamma_t + \varepsilon_{c,t} \qquad \textit{Eq. 3.1}$$

where β is the coefficient of interest, α and γ are the country- and time- FE, and ε is the unobserved error term.

In the following three sub-sections, we describe further specifications: (1) To limit omitted variable bias (Challenge 1), we include time and fixed effects and run the regressions within regions. (2) We address the possibility of reverse or simultaneous causality (Challenge 2) with three different IVs. (3) Finally, we account for the degree of reform and address collinearity, or the fact that multiple policies may act at the same time, by using indices that aggregate PICs in different ways (Challenge 3 and 4).

3.3.1 Addressing omitted variables (Challenge 1)

The literature we cited in our review has posited that country size, income per capita, and other socio-economic variables may play a part in policy outcomes and that some studies fail to consider these omitted variables. For instance, when interest rates are low in the United States, there may be an influx of foreign direct investment in developing countries, and this may vary according to regional characteristics, such as historical (cultural and colonial) ties as well as geographical proximity to the United States and Europe. To mitigate this problem, we control for group characteristics by estimating regression models separately for each World Bank region (Table 3.5).

Table 3.5. Regions and acronyms.

Region	Acronym
East Asia & the Pacific	EAP
Europe & Central Asia	ECA
Latin America & Caribbean	LAC
Middle East & North Africa	MENA
South Asia	SAS
Sub-Saharan Africa	SSA

Sources: Subset of World Bank country categories 2020.

Additionally, we include country FE to control for long-term country-specific characteristics. Each variable used in a country FE regression is transformed to measure a country's deviation from its own average.

We also apply time FE. In time FE, the data is demeaned over each period. Since our estimations are performed separately across regions, the regional average at each point in time will be subtracted from each observation.

Note that country and time FE do not capture non-uniform changes in country-level variables over time, such as the business environment, financing conditions, or enforcement capability.

To obtain comparable estimations of β, which is the coefficient that indicates the effect of the policies over regions and countries, the data is standardized using the z-score. Each variable is therefore rescaled to have a mean of zero and a standard deviation of one.

3.3.2 Addressing simultaneity and reverse causation (Challenge 2)

As discussed in the literature review, panel data analysis on PSR and policy packages has suffered from simultaneity between the independent (policy) and dependent (result of policy) variable of interest, violating classical OLS assumptions and resulting in potentially biased estimators (Challenge 2).

In our case, the enactment of the PICs is at least partially (endogenously) determined by current emissions. In the Literature Review, we discussed several studies that attempted to correct for endogeneity using IVs.

In theory, IVs successfully attribute causality by isolating the non-endogenous portion of the relationship between the independent variable of interest, x, and the dependent variable, y. This is done by using a measurable third variable, z, that affects the enactment of PICs, but not the energy-mix, except through the PICs. The main challenge in implementing this method is to find a suitable IV, a topic we discuss in depth in the upcoming data section.

Two-stage least squares (2SLS) is the most common IV approach and the one we apply in this paper. Stage 1 (Eq. 3.2) consists of regressing the independent variable on our IV, generating a coefficient that predicts the behavior of x based on z.

The behavior of x that is unrelated to z is captured by the error term, ε. Stage 2 (Eq. 3.3) uses the predicted values of x, $\hat{x}$ to estimate its effect on the dependent variable of interest, y (Stock and Watson, 2002).

A typical 2SLS regression model in a panel dataset with country c, time t, an IV z, an independent variable x, and a dependent variable y, is as follows:

$$Stage\ 1\ (S1)\text{: } x_{c,t} = \alpha + \beta z_{c,t} + \varepsilon_{c,t} \qquad \textit{Eq. 3.2}$$

$$Stage\ 2\ (S2)\text{: } y_{c,t} = \theta + \vartheta_c \widehat{x_c} + n_{c,t} \qquad \textit{Eq. 3.3}$$

Where ε and ν represent error terms. Note that lags and/or moving averages of the IV, the independent, or the dependent variables can be added at each stage, depending on the research question and the data.

In our model, we introduce country dummy interaction variables into the two stages of the IV model to obtain 2SLS estimations by country, following Chapter 9 of Wooldridge (2001).

Following the literature (Wooldridge 2001; Stock and Watson 2011) we estimate the model (Eq. 3.1) in the following two stages:

$$x_{c,t} = \alpha_c + \beta z_{c,t} + \sum_{c=1}^{n} \delta_c z_{c,t} D_c + \gamma_t + u_{c,t} \qquad \textit{Eq. 3.4}$$

$$y_{c,t} = \theta_c + \sum_{c=1}^{n} \vartheta_c \widehat{x_{c,t-l}}\, D_c + \sum_{c=1}^{n} \rho \widehat{x_{c,t-l}} + \mu_t + n_{c,t} \qquad \textit{Eq. 3.5}$$

where D is a country dummy variable, $\hat{x}$ is the instrumented policy variable, α, $\theta, \gamma,$ and μ are the country- and time- FE, and u and v are the unobserved error terms.

The key coefficients of interest are the second-stage estimates of policy variables interacted by country fixed effects, ϑ_c.

We restrict our analysis to the sub-set of the second-stage estimates that are likely to satisfy the IV *relevance* condition (i.e., *z* must be strongly correlated with *x*) and the *exclusion* restriction (i.e., *z* only affects *y* through its impact on *x*). Assessing the IV relevance criterion is straightforward by checking the F-statistic of the first-stage regression (Eq. 3.2). As there is no valid statistical test for the exclusion restriction, we keep the first stage estimates that are statistically significant and have theoretically consistent signs.

Stata supports interactions in its ivreg2 command. However, the pre-loaded command did not allow us to extract the F-statistic results of S1. As a result, we manually created the interaction terms and replicated the first stage of each regression.

Additionally, if a researcher is interested in replicating our findings, it is important to note that in our commands, we omitted including the independent variable's base term in S1, and the policy variable's base term in S2. In this way, we avoid having to compare each extracted interacted coefficient with a base term.

An instrumental variable approach is not the only method that can test causality. A differences-in-differences approach, for instance, compares the means of the outcome variable in a group of countries in which a policy was implemented (the treatment group), with the means a group in which the policy was not implemented (the control group). This method may be a possible avenue of further exploration of the impact of policies reviewed in RISE.

The method does not align with our current research question, however. The current research question focuses on the effect of seven PICs. Because PICs are made up of a variety of component policies, they are not applied on a binary basis. Instead, they are applied to varying extents in different countries. The current IV method adequately captures ordinal and continuous changes in the application of each PIC.

3.3.3 Addressing degree of reform and policy collinearity (Challenges 3 and 4)

Our independent variables for regression analysis are measurements of the seven PICs listed in the introduction. The PICs themselves (RISE refers to them as "Headings") and the policies included in each are pre-defined in the dataset. We use the pre-determined PICs to group 75+ policies so that comparisons between them make theoretical, statistical, and practical sense and reflect the extent to which they are used together. In other words, using RISE PICs has the effect of reducing highly dimensional policy data in a manner appropriate for regression analysis and interpretation.

There are different methods to aggregate policies (or operationalize and design) each PIC, with the potential to affect the regression results. Our default option is to use the RISE index, which is based on how ESMAP weighs the policies and is fully described in the Data section. In the next paragraphs, we discuss Challenges 3 (addressing the degree of reform) and 4 (policy collinearity) as well as how alternate PIC policy aggregation methods (or "indices"), can help address these challenges. Note that because a granular discussion of the indices requires a deeper understanding of the RISE database, the Data section contains a detailed description and analysis of each index.

A single binary variable that indicates, for example, the existence of planning for renewable energy expansion, provides limited information about the degree of the effort behind the measure (Challenge 3). However, there is a relative depth to the RISE dataset. For instance, the PE PIC on planning for renewable energy expansion includes general questions like "Does an official renewable energy target exist?" alongside others such as "Is the target legally binding?", "Is the target based on a transparent methodology?", "Is there a renewable energy action plan or strategy to attain the target?", etc. Due to the detail of the RISE dataset, a simple summation (or counting) implemented policies within each PIC is arguably a proxy for the scope of the energy decarbonization policy effort. This is what we capture in the aptly named Summation index.

At the same time, policies within PICs are alike in content and may be implemented at the same time, which may lead to collinearity in our estimations (Challenge 4). Within our running example of the PE PIC, consider the similarity between the two policies: “Does an official renewable energy target exist?” And “Is there a target for renewables in electricity?”. Following the logic in Cubbin and Stern (2006), estimates of the effects of the PICs could be biased upward, depending on the correlation of policies within each group, because they may reinforce one another and work together. Other research has shown that policies could work against each other, but this is more likely to occur across PICs, because of the similarity of policies within them. The Composite index engages with the idea of policy collinearity through correlation analysis.

In summary, we operationalize the seven PICs by using one main index (RISE) and two alternatives, Summation and Composite. RISE is provided to us and the last two engage with the need to address the degree of reform (Challenge 3) and collinearity between policies (Challenge 4) within PICs.

3.4 DATA

3.4.1 Outcome (dependent) variables

We use the World Bank World Development Indicators (WDI) as a source of data for our dependent variables spanning over the last four decades and more than a hundred developing countries. For robustness, we consider five relevant variables (Table 3.6).

We expect that the PICs negatively affect the first three energy mix measures in Table 3.6, which are FCC, EFF, and EOS PICs. On the contrary, we expect the PICs to positively affect the remaining two energy mix measures in Table 3.6, which are REC and REO. To make our estimation results comparable across different specifications we multiply estimated coefficients of interest for the first three energy mix measures by minus one.

Table 3.6. Outcome variables, their units, and their expected relationships with the policy instrument categories (PICs).

	Outcome	Acronym	Unit	Expected PIC relationship
1	Fossil fuel energy (oil, gas & coal) consumption	FCC	Percent of total	Negative
2	Electricity production from fossil fuel (oil, gas & coal) sources	EFF	Percent of total electricity output	Negative
3	Electricity production from oil sources	EOS	Percent of total electricity output	Negative
4	Renewable energy consumption	REC	Percent of total final energy consumption	Positive
5	Renewable electricity output	REO	Percent of total electricity output	Positive

Source: World Bank World Development Indicators (WDI) database 2021.

An in-depth descriptive discussion of the changes of these variables over hundreds of countries and several decades is beyond the scope of this chapter. We offer descriptive statistics in a visual format for each dependent variable over time. These summaries are in Appendix 3.1 because they would take up a substantial amount of space and affect the flow of the main text.

The graphs in Appendix 3.1 include all countries used in our regressions but aggregate over regions due to space constraints. There are patterns over regions that further support the rationale to run the regressions over regions, which we explained in the Methods section dedicated to addressing omitted variable bias. For example, there is a clear difference in all the outcome variables when comparing oil-dominated versus hydro-dominated regions like MENA and LAC, respectively.

3.4.2 RISE dataset

Our explanatory variables are based on the renewable energy policy instrument portion of the novel RISE database created by ESMAP at the World Bank. To create these variables, we use the background data behind the RISE renewable energy "traffic light" indicators that ESMAP has published and updated annually since 2010. Below, we discuss the dataset and explain the three alternative methods, or indices, we designed to create our independent variables.

Introduction to the dataset

The primary dataset contains 75+ policies that are each addressed in two variables: one indicating the existence of the policy through yes/no answer, and the second specifying the year of the first instance of the policy, if applicable. For instance, "Does a legal framework for renewable energy development exist?" and the year for the first legal framework.

When restructuring the primary dataset, we combine the two variables for each policy instrument into one, so that the value changes from 0 to 1 when the first policy was put into place. This creates the country panel dataset needed for the rest of the analysis.

The 75+ policies are classified within seven RISE PICs listed in (Table 3.7). As an example, carbon pricing and monitoring contains two questions (from now on, "questions" and "policies" will be used interchangeably): "Is there a carbon pricing mechanism […] implemented in the country, covering part or all of the country's greenhouse gas emissions?", and "Is there a monitoring, reporting and verification system for greenhouse gas emissions in place?"

Table 3.7. Headings/PICs in RISE.

	Heading/PIC	Acronyms
1	Legal framework for renewable energy	LF
2	Planning for renewable energy expansion	PE
3	Incentives and regulatory support for renewable energy	IR
4	Attributes of financial and regulatory incentives	AI
5	Network connection and use	NC
6	Counterparty risk	CR
7	Carbon pricing and monitoring	CP

Source: RISE website and authors' acronyms.

Primary dataset challenges

Each PIC contains a different number of policies, and sometimes contains clusters of policies. In fact, PICs contain up to three levels of sub-PICs that we call "groups", where the final individual policy/question resides. For instance, IR, on Incentives and regulatory support for renewable energy, contains four groups, with three to five questions each.

Aside from its asymmetric nested structure, there are at least three further challenges to preparing the primary dataset for use. First, we find several different discrepancies between the yes/no and years variables for the same policy. For instance, the policy may be marked as inexistent, but there is a year for the enactment of the same policy. Table 3.8 shows seven discrepancies we found in the primary dataset and describes the algorithm we followed to handle each. This should make it possible for other researchers to recreate our dataset.

Table 3.8. Discrepancies in RISE primary data.

	Type of discrepancy	Dummy*	Year	Decision	Rationale
1	Dummy and year discrepancy	0	Year should not be specified, but is specified	Favored the year’s column	The year column is more specific information than the dummy column. If there is input for the more specific column, then we assume that it has been verified and is correct.
2	Potential dummy and year discrepancy	0	Year should be 0, but it is NA, N/A, not applicable, or missing	Favored the dummy column, treated Year as “0”	We cannot use a year if we do not have it.
3	Dummy and year discrepancy	1	Year should be specified, but is 0	Treated year as NA (“.”)	Treating them as no’s would be incorrect because the reform seems to have been made. However, without a year, we cannot count them in a panel.
4	Dummy and year discrepancy	1	Year should be specified, but is missing	Treated year as NA (.)	Treating years as no’s (with 0) would be incorrect because the reform was made according to the dummy column. However, without a year, we cannot count them in a panel.
5	Year looks suspicious	1	Year seems too old	No action	Some years are very early, examples re.2.1.6 (1895) or re.6.3.1.3 (1923). We give the dataset the benefit of the doubt.
6	Dummy and year discrepancy	NA	Year should be NA, but is specified	Favored the year’s column	The year column gives more specific information than the dummy column. If there is input for the more specific column, then we assume that it has been verified and is correct.
7	Potential dummy and year discrepancy	NA	Year should be NA, but is 0, as if “no”	Favored the dummy column, treated year as NA (“.”)	Seems like the year column was given a “0” because it was “NA” in the dummy column. But we treat missing in the dummy column as “NA”. So, we favored the dummy column.

Source: RISE dataset and authors’ elaboration based on methods described in this chapter.
Note: *Dummy (0=no; 1=yes; blank = NA).

Second, there are occasional continuous variables in the dataset, and variables that cannot be transformed into panel data. These occasional continuous variables disrupt our efforts to address collinearity and reduce the dimensionality of the dataset, as discuss in the Methods sections. Third, there are constant variables that cannot be transformed into panel data. This is the case with several variables within CP.

The final dataset contains binary indicators for 76 policies over a panel of 133 countries (this includes developed and developing countries). Although the dataset starts in 1875, we limit it to 1980-2018, as most policies were not implemented before then. Table 3.9 contains descriptive information for the primary and the final datasets.

Table 3.9. Attributes of the primary and final datasets.

Dataset	Primary	Final
Countries	133	133
Period	1875	1980-2018
Variables	168	76
Policies directly in headings/PICs (final)	-	4
Policies nested once (final)	-	66
Policies nested twice (final)	-	6

Source: RISE dataset and authors' elaboration based on methods described in this chapter.
Note: *"Is there any provision for consultation with the public on the renewable plan?"

Table 3.10 contains a list of all PICs and policies included in our final dataset. The nested structure of the data is preserved in the IDs of each policy where the first digit refers to the PIC and subsequent digits related to different grouping levels.

Final primary dataset

Table 3.10. PICs and policies covered in the RISE dataset, as well as their structure.

Headings/PIC	RISE ID	Our ID	Question
Legal framework for renewable energy (LF)	1.1.1	re_1_1	Does a legal framework for renewable energy development exist?
	1.2.1	re_1_2	Does the legal framework allow private sector ownership of renewable energy generation?
Planning for renewable energy expansion (PE)	2.1.1	re_2_1_1	Does an official renewable energy target exist?
	2.1.2	re_2_1_2	Is the target legally binding?
	2.1.3	re_2_1_3	Is the RE target linked to international commitments (eg. NDC or regional commitment)?
	2.1.4	re_2_1_4	Is the target based on a transparent methodology?
	2.1.5	re_2_1_5	Is there a renewable energy action plan or strategy to attain the target?
	2.1.6	re_2_1_6	Is there any provision for consultation with the public on the renewable plan?
	2.2.1	re_2_2_1	Is there an assessment of the role of renewables in electricity supply?
	2.2.2	re_2_2_2	Is there a target for renewables in electricity?
	2.3.1	re_2_3_1	Is there an assessment of the needs for heating and cooling in buildings and industry in the country and of how renewables can contribute?
	2.3.2	re_2_3_2	Is there a specific target for renewables for heating and cooling?
	2.4.1	re_2_4_1	Is there an assessment of the potential role for renewables in transport including biofuels and electrification?
	2.4.2	re_2_4_2	Is there a specific target for renewables in transport?
	2.5.1	re_2_5_1	Does the renewable plan or strategy estimate the amount of investment necessary to meet the RE target?
	2.5.2	re_2_5_2	Is there an institution responsible for tracking progress in renewable energy development?
	2.5.3	re_2_5_3	Is there any periodic reporting mechanism for renewable energy progress?
	2.5.4	re_2_5_4	Is there a mechanism for adjusting the plan based on reporting of renewable energy deployment?
	2.5.5	re_2_5_5	Is current policy environment conducive to renewable energy deployment?
	2.6.1	re_2_6_1	Is generation and transmission planning integrated?
	2.6.2	re_2_6_2	Is planning for dispatch included in the generation and transmission plan?
	2.6.3	re_2_6_3	Is the generation plan based on a probabilistic approach?
	2.6.4	re_2_6_4	Does the current transmission planning consider renewable energy scale-up?
	2.7.1	re_2_7_1	Does the government endorse and use the solar/wind resource maps and data applicable to their country that are available through the Global Solar Atlas / Global Wind Atlas, or have they published some other solar/wind resource map that conforms to best practice in the last five years?
	2.7.2	re_2_7_2	Has the country carried out geospatial planning or produced zoning guidance to inform the commercial development of the RE resource?
	2.7.3	re_2_7_3	Has the geospatial planning or zoning guidance been carried out according to best practice by i) being undertaken as part of a strategic environmental and social assessment or equivalent process; and ii) by making the outputs publicly available?
Incentives and regulatory support for renewable energy (IR)	3.1.1	re_3_1_1	Does the country offer long term PPA's for renewable electricity production for large scale producers (e.g. via. Feed-in-tariffs, PPA's awarded through auctions etc.)
	3.1.2	re_3_1_2	Does the country offer long term PPA's for renewable electricity production for small scale producers (e.g. via. Feed-in-tariffs, PPA's awarded through auctions etc.)
	3.1.3	re_3_1_3	Does the government publish clear and practical guidance on what permissions are required to develop a RE electricity project?

Headings/PIC	RISE ID	Our ID	Question
	3.1.4	re_3_1_4	Does the government offer other direct fiscal incentives for renewable electricity (e.g. capital subsidies, grants or rebates, investment tax credits, tax reductions, production tax credits, FITs for large producers?)
	3.2.1	re_3_2_1	Does the country provide prioritized access to the grid for RE?
	3.2.2	re_3_2_2	Do RE projects receive priority in dispatch?
	3.2.3	re_3_2_3	Are there provisions to compensate seller if offtake infrastructure is not built in time?
	3.2.4	re_3_2_4	Are there mechanisms to compensate RE projects for lost generation due to certain curtailments after project commissioning?
	3.2.5	re_3_2_5	Is the compensation due because of curtailment actually given out.
	3.3.1	re_3_3_1	Is there a biofuels blending mandate or other obligation to use biofuels?
	3.3.2	re_3_3_2	Are there sustainability criteria which biofuels which contribute to the mandate must meet?
	3.3.3	re_3_3_3	If there is a plan for producing biofuels in the country, has this included an assessment of sustainability impacts (e.g. against the GBEP Sustainability indicators) including an assessment of impacts on food security.
	3.3.4	re_3_3_4	Is there at least one scheme to encourage use of electric/hybrid vehicles? (e.g. Tax benefit to consumers and manufacturers, etc.)
	3.4.1	re_3_4_1	Are there any policies to encourage deployment of any renewable energy heating and cooling technologies?
	3.4.2	re_3_4_2	Are there specific measures (financial support or promotion) designed to encourage the use of renewables in the heating and cooling sectors?
	3.4.3	re_3_4_3	Are opportunities for renewable heat promoted alongside energy efficiency measures in buildings and/or industry?
Attributes of financial and regulatory incentives (AI)	4.1.1	re_4_1_1	Is competition used to ensure large scale RE generation (projects >10MW) is cost competitive (e.g. through auctions for PPA's)?
	4.1.1.1	re_4_1_2_1	Is there a schedule for future bids/auctions available for investors?
	4.1.1.2	re_4_1_2_2	Is there a pre-qualification process to select bidders?
	4.1.2.3	re_4_1_2_3	Are tariffs indexed (in part or in whole) to an international currency or to inflation?
	4.1.1.4	re_4_1_2_4	Are there provisions to ensure full and timely project completion (e.g. bid-bonds, project milestones)
	4.1.1.5	re_4_1_2_5	Are projects awarded through auctions/bids online/on track to be online on stated date?
	4.1.1.6	re_4_1_2_6	Have auctions/bids met stated target for installations?
	4.2.1	re_4_2_1	Can small producers (residential, commercial rooftop PV,etc) connect to the grid?
	4.2.2	re_4_2_2	Are contracts with fixed tariffs available for such producers?
	4.2.3	re_4_2_3	Is there a schedule or clear rules (e.g. capacity based limits) for adjusting the tariff level over time?
	4.2.4	re_4_2_4	Are different tariffs available for different technologies and sizes of the generation plant?
	4.2.5	re_4_2_5	Is there a mechanism to control the capacity built under each tariff?
	4.2.6	re_4_2_6	Are tariffs indexed (in part or in whole) to an international currency or to inflation?
Network connection and use (NC)	5.1.1	re_5_1_1	Does the country have a grid code that clearly specifies connection procedures?
	5.1.2	re_5_1_2	Do the connection procedures meet international best practices?
	5.1.3	re_5_1_3	Does the grid code include measures or standards addressing variable renewable energy?
	5.1.4	re_5_1_4	Are there rules defining the allocation of connection costs?
	5.1.5	re_5_1_5	Is the type of the connection cost allocation policy considered shallow (grid operator pays for connection costs)?
	5.2.1	re_5_2_1	Are there rules that allow electricity customers to purchase power directly from a third party (i.e. an entity other than the designated utility in a service area)?
	5.2.2	re_5_2_2	Do the rules define the size and allocation of costs for use of the transmission and distribution system (e.g. wheeling charges, locational pricing?)
	5.3.1	re_5_3_1	Does the country carry out regular assessments of the flexibility of the electricity grid and the issues relating to renewables integration?
	5.3.2	re_5_3_2	Can renewable energy projects sell into balancing/ancillary services?
	5.3.3	re_5_3_3	Are there rules for exchanging power between balancing areas that penalize variable renewable energy, e.g. through imbalance penalties? (only scored in countries with multiple balancing areas)
	5.3.4	re_5_3_4	Are there provisions in the power exchange rules that allow for plant forecasting? (only scored in countries with multiple balancing areas)
	5.3.5	re_5_3_5	Does the country integrate high quality forecasting for any variable RE resources (either through subscription service or provided by national agencies) into their dispatch operations?
	5.3.6	re_5_3_6	Are dispatch operations being carried out in real time?
Counterparty risk (CR)	6.1.1	**	Are the following financial ratios of the counterparty deemed creditworthy?
	6.1.1.1	**	Current ratio, <1 – 0 in between – scale >= 1.2 – 25
	6.1.1.2	**	EBITDA margin; <0 – 0 in between – scale >= 15% -- 25
	6.1.1.3	**	Debt service coverage ratio; <1 – 0 in between – scale >= 1.2 – 25
	6.1.1.4	**	Days payable outstanding ; >180 – 0 in between – scale <=90 – 25
	6.2.1	re_6_2_1	Is the counterparty underwritten by a government guarantee or are there other mechanisms to ensure credit worthiness (e.g. through a letter of credit, escrow account, payment guarantee, or other)?
	6.2.2	re_6_2_2	Are standard PPAs bankable?
	6.3.1.1	re_6_3_1	Generation, Are the financial statements of the largest utility publicly available in the following categories?
	6.3.1.2	**	Transmission, Are the financial statements of the largest utility publicly available in the following categories?

Headings/PIC	RISE ID	Our ID	Question
	6.3.1.3	**	Distribution, Are the financial statements of the largest utility publicly available in the following categories?
	6.3.1.4	**	Retail sales, Are the financial statements of the largest utility publicly available in the following categories?
	6.3.2.1	re_6_3_2	Generation, If yes, are they audited by an independent auditor for the following categories of utilities?
	6.3.2.2	**	Transmission, If yes, are they audited by an independent auditor for the following categories of utilities?
	6.3.2.3	**	Distribution, If yes, are they audited by an independent auditor for the following categories of utilities?
	6.3.2.4	**	Retail sales, If yes, are they audited by an independent auditor for the following categories of utilities?
	6.3.3.1	re_6_3_3	Generation – Electricity available for sale to end-users, Are the following metrics published in a primary official document (by the utility, regulator or ministry and/or government)?
	6.3.3.2	**	Transmission – Transmission loss rate, Are the following metrics published in a primary official document (by the utility, regulator or ministry and/or government)?
	6.3.3.3	**	Distribution – Distribution loss rate, Are the following metrics published in a primary official document (by the utility, regulator or ministry and/or government)?
	6.3.3.4	**	Retail Sales – Bill collection rate, Are the following metrics published in a primary official document (by the utility, regulator or ministry and/or government)?
	6.3.4	re_6_3_4	Is the utility operating an incidence/outage recording system (or SCADA/EMS with such functionality)?
	6.3.5	**	Is the utility measuring the SAIDI and SAIFI or any other measurements for service reliability?
	6.3.5.1	**	Are the measurements reported to the regulatory body?
	6.3.5.2	**	Are the measurements available to public?
Carbon pricing and monitoring (CP)	7.1	re_7_1	Is there a carbon pricing mechanism (eg carbon tax, emissions trading scheme) implemented in the country, covering part or all of the country's greenhouse gas emissions?)
	7.2	re_7_2	Is there a monitoring, reporting and verification system for greenhouse gas emissions in place?

Source: RISE dataset and authors' elaboration based on methods described in this chapter.
Note: **Do not contain the year, cannot be used in a panel format.

Discussion on using pre-determined RISE PICs

Having introduced the data structure of the RISE dataset and its components, we challenge our use of the pre-determined RISE PICs as the base from which to build our independent variables by creating a dendrogram visualization.

Dendrograms are widely used to find homogeneous groups in observations, or in our case, policies, that differ from each other. They can help the researcher to identify the structure of the data or to group variables based on their similarity. The results of the dendrogram support our methodological choice to groups policies within the PICs that were provided to us in the dataset.

To depict how the policies relate to one another, we first create a dissimilarity (1-similarity) matrix based on the Jaccard coefficient. In brief, the Jaccard coefficient (Eq. 3.6) is the proportion of occurrences in which both variables (policies) take a value of one in the panel dataset, over the occurrence of all other combinations, except both variables taking a value of zero.

$$Jaccard\ coefficient = a/(a+b+c) \qquad \textit{Eq. 3.6}$$

Table 3.11. Variables in the Jaccard coefficient.

	Var1, 1	Var1, 0
Var2, 1	a	b
Var2, 0	c	d

Source: Jaccard (1908).

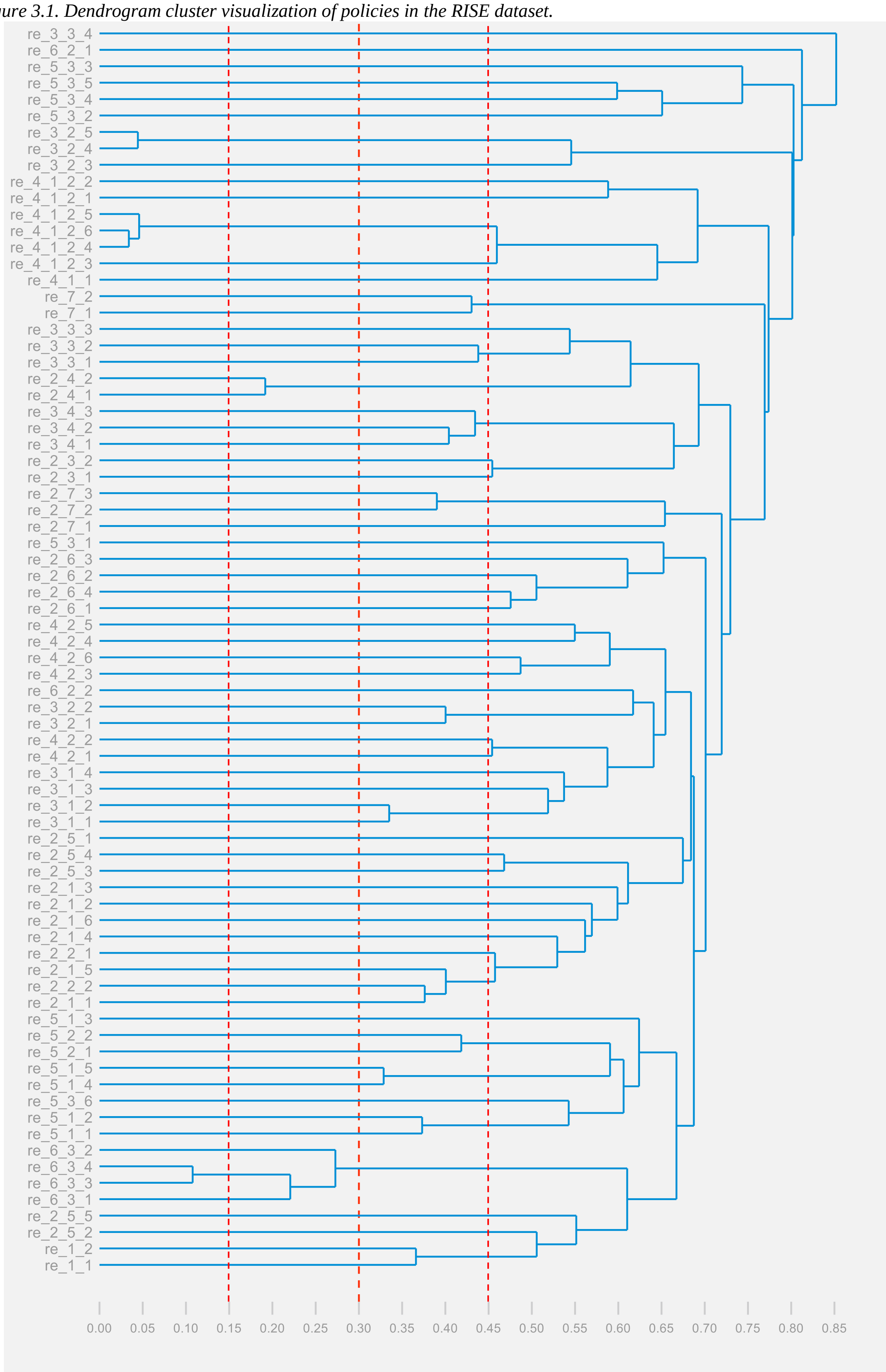
We then systematically merge similar policies into groups, creating an agglomerative hierarchical clustered visualization. In the resulting dendrogram, each policy is placed along the y-axis and is connected to other policies via a horizontal line that ends at their corresponding similarity value. The shorter the lines, the more similar the policies.

The shape of dendrograms changes according to the method linking groups. The methods pertinent to binary data are single, complete, and average linkages. Single (nearest neighbor or minimum) linkage defines the distance between two clusters as the minimum distance found for any pair of policies that includes one case from each cluster (Yim and Ramdeen 2015). Complete (farthest neighbor and maximum) considers the furthest distance between pairs of cases. In short, single and complete linkages rely on the smallest or largest distance that can be found between pairs of cases to define the distance between two clusters, respectively. Last, the Unweighted Pair-Group Method with Arithmetic Mean linkage averages the distances between cases in each cluster.

Each method has its limitations. Single linkage may produce “chaining”, in which several clusters are joined because one of their cases is within proximity of a case from a separate cluster. However, in complete linkage, outlying cases prevent close clusters from merging. We choose the third method, average linkages, as in theory it provides a compromise between single and complete linkage (Yim and Ramdeen 2015; Greenacre and Primicerio 2013). At the same time, it is important to keep in mind that some information is lost in all three linkage methods. Taking a bottom-up approach helps reduce the influence of information lost in creating linkages across groups.

In Figure 3.1, the three vertical lines dashed red lines allow the reader to visually compare dissimilarities. In our case, the dendrogram helps further support the idea that policies within PICs are most alike to each other, and not most alike to policies in other PICs. Overall, it supports our theoretical rationale to operationalize the independent variables (PICs) using the structure that was pre-determined by the dataset we acquired.

Figure 3.1. Dendrogram cluster visualization of policies in the RISE dataset.



Source: RISE dataset and authors' elaboration based on methods described in this chapter.

3.4.3 PICs indices (independent variables)

As described in the Methods section, we create three different indices to operationalize the PICs for regression analysis. This section discusses the three indices in detail. The end of the section provides a visualization that compares the PICs based on each index. For robustness, Appendix 3.2 considers and discards Principle Component Analysis (PCA) as a last alternative to reduce dimensionality of the dataset.

RISE index

The first alternative is what we call the RISE index reported by ESMAP. The RISE index sums policies within policy groups over the entire dataset. Since we are interested in running regressions at the PIC level, we aggregate policies within groups but stop short of summing groups across different PICs. While the RISE index weighs policy groups equally, each group itself contains a different number of policies. Therefore, in the RISE index, the number of policies in each group affects the weight given to each policy . For instance, when there are four policies in a group, each of them is worth 25 percent, and when there are two policies, each is worth 50 percent. This arbitrary aspect of weighing the policies within groups is part of our motivation to seek alternative methods to create indices that will be used as our independent variables.

Summation index

The first alternative to the RISE index is to create an index that sums the enacted policies at each point in time. Such an index, which we will call the "Summation index," has been tried before and discussed in our literature review (Cubbin and Stern 2006). The Summation index weighs all policies equally within PICs.

Composite index

Last, we propose a third, "Composite index," which is based on correlation analysis. The Composite index first reduces dimensionality by dropping highly correlated variables so that highly collinear policies are not counted several times over. It then sums the remaining variables by Heading.

There are several ways to approach the task of isolating and merging similar variables through correlation. We design and compare two methods that apply to our analysis, which we entitle the "Survival" and "Average" methods. We use the phi statistic, which is suitable for truly dichotomous variables.

In the "survival" method we assume that keeping one of two highly correlated policies retains enough information to represent both. We start the exercise at the most disaggregated group level. At this level, we keep one of each highly correlated policies. We then compare any 'surviving' policies against the ones that reside at higher aggregation levels within the same PIC. When there are no highly correlated policies left in a PIC, we attribute the same weight to each. For instance, if there are four uncorrelated policies left in a given PIC, each policy is weighted 0.25 when a country implements it.

An alternative is to use group averages. We first obtain phi statistics for all pairs within a PIC and compute the average phi statistic for that PIC. When the average phi statistic is higher than a predetermined cutoff, the PIC variable is computed as the average of the policies at each point in time. However, if the phi statistic is below the cutoff, we repeat the exercise by sub-groups. In that case, we sum the averages within subgroups to create the final PIC variable.

By definition, averaging correlated policies at any point in time retains more information than the survival method, but it may obscure underlying disparities in the averaged variables. Specifically, using group averages fails to identify policies that are different from others in their group. This drawback seems to nullify the point of the analysis, which is to count sufficiently different policies separately. Therefore, we implement the Survival method.

In sum, the "Composite" index is composed of two steps. First, we reduce dimensionality through correlation analysis of policies over the entire dataset with a p value<0.05. We disregard highly correlated variables so that highly collinear policies are not counted several times. Second, we sum the variables that "survived" the first step, by PIC.

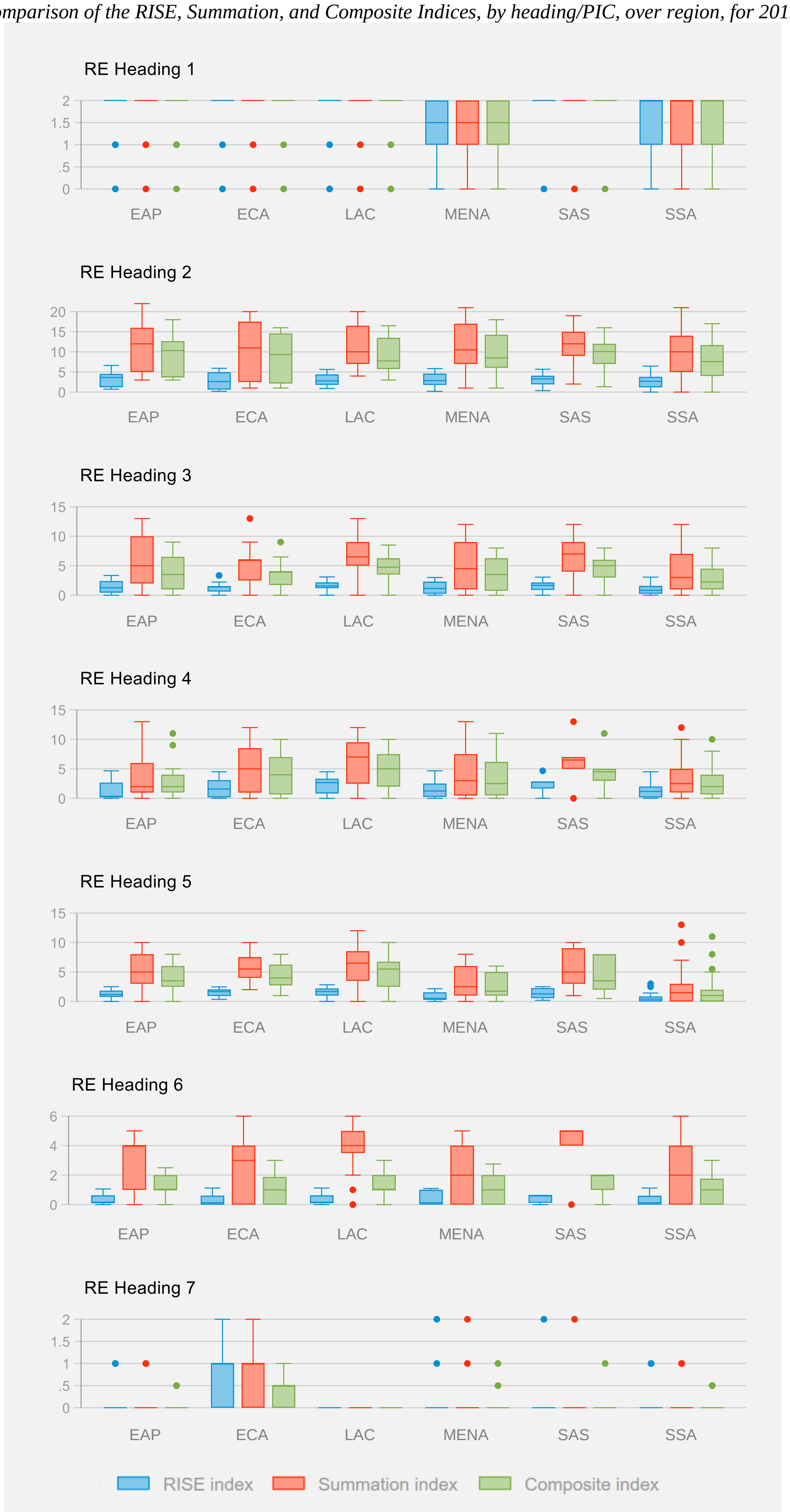
An important factor for the composite index is the cut-off used to determine "high" correlation. We further discuss this in Appendix 3.3.

Index Summary

Each independent variable is a representation of the policies within the seven PICs. PICs include thematically and statistically-related policies. Both policies and packages are predetermined in the original RISE dataset. We use three different methods to aggregate the policies and create three alternative PIC indices: the RISE, the Summation, and the Composite indices. Appendix 3.4 compares the final weights given to each policy in the RISE versus Composite index (this is unnecessary for the Summation index, which weighs all policies equally).

Because we are working in a panel format, each country has three versions of each of the seven independent variables, over several decades. Figure 3.2 provides a visualization comparing the three indices across all PICs. Each boxplot represents the distribution of an index by PIC and region. Since showing all years between 1980-2018 is too unwieldy, we only display 2015. The RISE index is shown in blue, the Summation index is in red, and the Composite index is in green.

Figure 3.2. Comparison of the RISE, Summation, and Composite Indices, by heading/PIC, over region, for 2015.



Source: RISE dataset and authors' elaboration based on methods described in this chapter.

The visualization clearly shows that all indices yield the same distribution across countries for the first PIC, or RE heading 1. In all other cases, the RISE index tends to have the smallest ranges overall while the Summation index has the biggest ranges.

PICs one and seven depict the smallest ranges, with a minimum of zero and the maximum is two. We expect the relatively small ranges because PICs one and seven contain fewer policies.

3.4.4 Instrumental variables

The main challenge in implementing the IV method in any analysis is to find a suitable IV. The IV must be uncorrelated with the dependent variable, Y_i, except through its effect on the endogenous variable, X_i. This is known as the *exogeneity* condition. Additionally, the IV must satisfy the *relevance* condition. This means that it Z_i must be correlated with X_i.

To propose suitable IVs, we take advantage of international political economy aspects highlighted in the rich literature on PSR that spans several decades and regions. We posit that countries are more likely to implement regulatory energy policies when they display a relatively higher level of closeness with developed countries that champion increased private sector participation when extending loans related to power markets, which broadly satisfies the *relevance* condition.

The conditionality of reform for loans is discussed in existing research. For example, in a comprehensive study of governance in power and telecommunications sectors, Henisz, Zelner, and Guillén (2005) argue that "the domestic adoption of market-oriented reforms is strongly influenced by international pressures of coercion and emulation […in] as many as 205 countries and territories between 1977 and 1999 [with] the coercive effect of multilateral lending from the IMF, the World Bank or Regional Development Banks […] increasing over time."

We consider two channels that could indicate closeness to the World Bank major donors (MDs, which are France, Germany, Japan, the United Kingdom, and the United States). These two channels are: (1) similarity in foreign policy; and, (2) connection through trade. We then pinpoint three measurable ways through which this rapport may be measured and evidenced over time. Table 3.12 summarizes the chosen IVs, which we describe and support in the paragraphs that follow.

Table 3.12. Summary of IVs that capture relations with major donors.

Changes in closeness to donors may be reflected through	IV	Supported in	Data source
Foreign policy	Closeness to the MDs through UNGA voting	Bailey et al. (2017)	Affinity of Nations dataset by Bailey et al. (2017)
Trade	Relative trade value aggregates	Rufín (2003)	UN Comtrade (United Nations Statistics Division (UNSD) 2020)
	Trade agreements in place		European Commission, trade agreements in place (European Commission 2021)

Source: Authors' elaboration based on the methods described in this chapter and the sources in the table.

Like in the previous section on outcome variables, we produce figures of the descriptive statistics of the three IVs over time. With the flow of the chapter in mind, the visualizations can be found in Appendix 3.5. For the figures showing United Nations General Assembly (UNGA) and trade aggregate IVs, it is necessary to aggregate over regions due to the large scope of our data, so the figures inevitably mask underlying changes at the country level.

Importantly, we consider the possibility that it may take time to implement policies following an increase of closeness measured through our IV. Therefore, we use a moving average of five years of the IVs. Although bilateral relationships can be relatively slow to change, changes of administration in democracies may result in more abrupt changes, so we also consider a moving average of three years. The Results section compares the outcomes of the two different moving averages.

Foreign policy instrumental variable

To represent changes in foreign policy preferences, we use the dyadic (country to country) dataset behind the Affinity of Nations index by Bailey et al. (2017). The authors use a dynamic ordinal spatial model on a single dimension to estimate state preferences toward the U.S.-led liberal order, as reflected through UNGA voting. They refer to this measure as the *Ideal Point Index*.

The *Ideal Point Distance*, on the other hand, is the difference between the Ideal Points for all country dyads that participate in the UNGA (e.g., France and Gabon). The Ideal Point Distance, therefore, suggests the difference between the preference for the U.S.-led liberal order for any two countries in any given year.

It is important that the dataset does not simply provide a measure of similarity in all voting, and instead produces an estimate of the distance of voting towards a specific topic, or the U.S.-led liberal order. Anchoring the content of the estimates in one topic helps address the issue that the World Bank MDs do not always vote the same as each other. Additionally, note that while the U.S.-led liberal order is related to the Washington Consensus and relevant regulatory measures in our dataset, we are instead interested in identifying changes in closeness to our MDs, and to be able to do this over time.

To understand how preferences in our sample changed in comparison to the five MDs over time, we sum the Ideal Point Distance between each country and the five MDs at a yearly frequency.

Last, since we want a *closeness* indicator rather than a *distance* indicator (we want our IV to be positively associated with relative closeness to the MDs), we multiply the summed Ideal Point Distance by negative one.

Trade instrumental variables

Rufín (2003) discusses how “countries imitate their trade-related peers.” To capture changes in closeness through trade we compute the percentage of aggregate trade value that corresponded to exchange with the MDs, for each country, by year. The data is based on the comprehensive bilateral trade dataset UN Comtrade published by the UN Statistics Division.

We also generate a panel dataset on the existence of Trade Agreements with the EU. The source of the data is the EU Commission’s “current state of play” agreements in place. The variable is binary and takes on a 1 for all the years after a trade agreement comes into force. If there is no trade agreement, the variable is 0 for the entirety of the time series.

3.4.5 Country coverage

Our literature review shows that previous literature has centered on developed countries. This illuminated the direction of our work and one of our contributions is the focus of our analysis on developing countries.

Moreover, we have to exclude developed countries from our regression analysis due to the rationale behind our IVs. The logic behind our selected instruments relies on the conditionalities that developed countries can impose on developing counterparts to implement power sector reforms and renewable energy policies. Hence, it would be inconsistent to include them. As a result, our country sample excludes European Union members, Australia, Norway, Great Britain, Japan, Korea, and Switzerland.

Table 3.13 provides a list of all the countries in the RISE dataset, and whether they are included in the regressions. On two occasions, we excluded a developing country available in RISE because of inconsistent or missing WDI data.

Table 3.13. Countries in the RISE dataset, organized by the regions previously introduced, and whether they are included in the regression analysis of this chapter.

Count	Country	Reg	Kept	Count	Country	Reg	Kept	Count	Country	Reg	Kept
1	Cambodia	East Asia & Pacific (EAP)	1	49	Australia	OECD	0	92	Afghanistan	South Asia	1
2	China		1	50	Austria		0	93	Bangladesh		1
3	Indonesia		1	51	Belgium		0	94	India		1
4	Lao PDR		1	52	Canada		0	95	Maldives		0, missing data
5	Malaysia		1	53	Chile		1, moved to LAC	96	Nepal		1
6	Mongolia		1	54	Czech Republic		0	97	Pakistan		1
7	Myanmar		1	55	Denmark		0	98	Sri Lanka		1
8	Papua New Guinea		1	56	Finland		0	99	Angola	Sub-Saharan Africa (SSA)	1
9	Philippines		1	57	France		0	100	Benin		1
10	Singapore		1	58	Germany		0	101	Burkina Faso		1
11	Solomon Islands		1	59	Greece		0	102	Burundi		1
12	Thailand		1	60	Hungary		0	103	Cameroon		1
13	Vanuatu		1	61	Ireland		0	104	Central African Republic		1
14	Vietnam		1	62	Israel		0	105	Chad		1
15	Armenia	Europe & Central Asia (ECA)	1	63	Italy		0	106	Congo, Dem. Rep.		1
16	Azerbaijan		1	64	Japan		0	107	Congo, Rep.		1
17	Belarus		1	65	Korea, Rep.		0	108	Côte d'Ivoire		1
18	Bulgaria		0, EU member	66	Netherlands		0	109	Eritrea		1
19	Croatia		0, EU member	67	New Zealand		0	110	Ethiopia		1
20	Kazakhstan		1	68	Norway		0	111	Ghana		1
21	Kyrgyz Republic		1	69	Poland		0	112	Guinea		1
22	Romania		0, EU member	70	Portugal		0	113	Kenya		1
23	Russian Federation		1	71	Slovak Republic		0	114	Liberia		1
24	Serbia		1	72	Spain		0	115	Madagascar		1
25	Tajikistan		1	73	Sweden		0	116	Malawi		1
26	Turkey		1	74	Switzerland		0	117	Mali		1
27	Turkmenistan		1	75	United Kingdom		0	118	Mauritania		1

Count	Country	Reg	Kept	Count	Country	Reg	Kept	Count	Country	Reg	Kept
28	Ukraine		1	76	United States		0	119	Mozambique		1
29	Uzbekistan		1	77	Algeria	Middle East & North Africa (MENA)	1	120	Niger		1
30	Argentina	Latin America & Caribbean (LAC)	1	78	Bahrain		1	121	Nigeria		1
31	Bolivia		1	79	Egypt, Arab Rep.		1	122	Rwanda		1
32	Brazil		1	80	Iran, Islamic Rep.		1	123	Senegal		1
33	Colombia		1	81	Jordan		1	124	Sierra Leone		1
34	Costa Rica		1	82	Kuwait		1	125	Somalia		1
35	Dominican Republic		1	83	Lebanon		1	126	South Africa		1
36	Ecuador		1	84	Morocco		1	127	South Sudan		0, missing data
37	El Salvador		1	85	Oman		1	128	Sudan		1
38	Guatemala		1	86	Qatar		1	129	Tanzania		1
39	Haiti		1	87	Saudi Arabia		1	130	Togo		1
40	Honduras		1	88	Tunisia		1	131	Uganda		1
41	Jamaica		1	89	United Arab Emirates		1	132	Zambia		1
42	Mexico		1	90	West Bank and Gaza		1	133	Zimbabwe		1
43	Nicaragua		1	91	Yemen, Rep.		1				
44	Panama		1								
45	Paraguay		1								
46	Peru		1								
47	Uruguay		1								
48	Venezuela, RB		1								

Source: RISE dataset and authors' elaboration.

3.5 RESULTS

In this section, we present the results and robustness tests of the empirical specification (Eq. 3.4 and Eq. 3.5) estimated over six regions, five dependent outcomes, seven policy variables, three IVs, two IV moving averages, and three aggregation indices.

Altogether we estimate 3,780 regressions, to which we also apply country interactions. This renders thousands of S1 coefficients that constitute the foundation of the analysis in this section, summarized in Table 3.14.

Table 3.14. Regression specifications resulting from the Methods and Data sections of this chapter.

Base or other specification	Variable	Options
Base	IVs	1. Affinity the MDs through UNGA voting (main) 2. Affinity with the MDs through trade (alternate 1) 3. Affinity with the MDs through EU trade agreements (alternate 2)
Base	Moving averages for IV	1. 5 years moving average (main) 2. 3 years moving average (alternate)
Base	Indices to quantify our independent variables	1. RISE (main) 2. Composite (alternate 1) 3. Summation (alternate 2)
Other	Regions	1. East Asia & the Pacific (EAP) 2. Europe & Central Asia (ECA) 3. Latin America & Caribbean (LAC) 4. Middle East & North Africa (MENA) 5. South Asia (SAS) 6. Sub-Saharan Africa (SSA)
Other	Dependent variables (indicators of the energy mix)	1. Fossil fuel energy consumption % of total, (FFC) 2. Electricity production from fossil fuels (oil, gas & coal sources), % of total (EFF) 3. Electricity production from oil sources, % of total (EOS) 4. Renewable energy consumption, % of total final energy consumption (REC) 5. Renewable electricity output, % of total electricity output (REO)
Other	Independent variables (PICs)	1. Legal framework for renewable energy (LF) 2. Planning for renewable energy expansion (PE) 3. Incentives and regulatory support for renewable energy (IR) 4. Attributes of financial and regulatory incentives (AI) 5. Network connection and use (NC) 6. Counterparty risk (CR) 7. Carbon pricing and monitoring (CP)

Source: Authors' elaboration based on the methods and data sources described in this chapter.

S1 results

As per standard practice, we define the S1 of 2SLS as significant when it has a p-value at or below 5% and an f-statistic above 10 (Stock and Watson 2011). Additionally, for theoretical relevance, the relationship between the IV and the endogenous variable must be positive (i.e., closeness to donors increases the likelihood of adopting a renewable energy policy).

Table 3.15 is ordered by based specifications that, in addition to being significant at a p-value of 0.05 with an f statistic of at least 10, had the sign we theorized for the .

We were puzzled by the number of S1 coefficients that fulfilled the relevance condition and had a negative coefficient. For instance, these are 244 (784-540) when we use a moving average of 5, the UNGA affinity IV, and the RISE index. A negative coefficient would seem to indicate that implementing decarbonization policies is less likely when countries are linked to the MDs through UNGA voting and trade.

Table 3.15. Eligible S1 coefficients for base specifications; green is higher, red is lower.

Index	IVs	Moving average	Significant, f>10	Significant, f>10, positive
Rise	UNGA aff.	5	784	540
Rise	UNGA aff.	3	698	516
Composite	UNGA aff.	5	713	479
Composite	UNGA aff.	3	656	471
Summation	UNGA aff.	5	703	471
Summation	UNGA aff.	3	640	449
Summation	EU agreements	5	262	194
Rise	EU agreements	5	248	180
Rise	EU agreements	3	245	177
Composite	EU agreements	5	243	175
Summation	EU agreements	3	242	174
Composite	EU agreements	3	240	172
Rise	Trade w. donors	3	953	31
Rise	Trade w. donors	5	934	28
Composite	Trade w. donors	3	914	25
Summation	Trade w. donors	5	907	24
Composite	Trade w. donors	5	885	23
Summation	Trade w. donors	3	897	21

Source: Authors' elaboration based on the methods and data sources described in this chapter.
Note: Column four indicates the number of coefficients with a p-value below 5% and an f-statistic above 10. Column five contains the same information filtered for coefficients with a positive sign.

While the exogeneity of the second stage estimates cannot be established with certainty, we perform additional robustness tests to establish the validity of chosen instrumental variables. One established finding in the economics literature is that "getting similar results from alternative instruments enhances the credibility of instrumental variable estimates" (Murray 2006).

Our empirical approach allows us to conduct a formal test of the differences in the S2 estimates resulting from different IVs. We regress a vector of estimated S2 coefficients for each of the five energy mix outcomes, on dummies for each of the IVs, PICs, indices.

Table 3.16 shows the estimated regression results. Only for one of the five energy mix outcomes (electricity production from oil sources, EOS) did we observe statistically significant differences between the S2 estimates obtained from affinity through UNGA and the other two IVs. For all other energy mix outcomes, there are either no statistically significant differences across estimated S2 coefficients and the three chosen IVs, or the differences are only marginally significant.

Admittedly, this exercise would be strongest if performed over three IVs with different underlying justifications. Still, our IVs do represent two different channels (foreign policy and commercial trade) by which coercion and emulation take place. These results give us greater confidence that our S2 estimates do indeed reflect the causal outcome of decarbonization policy reforms.

Table 3.16. IV exogeneity robustness regression test.

	(1) FCC	(2) EFF	(3) EOS	(4) REC	(5) REO
IV: EU Agreements	0.27	0.78**	1.85	-0.43	-0.22
	(0.16)	(0.34)	(1.44)	(0.30)	(0.24)
IV: Affinity through bilateral trade	0.79	6.34*	4.23***	-0.15	-1.27*
	(0.67)	(3.27)	(0.72)	(0.42)	(0.67)
Policy: Planning for renewable energy expansion	-1.11*	-2.95***	-2.5*	1.8**	3.06**
	(0.57)	(0.93)	(1.48)	(0.68)	(1.33)
Policy: Incentives and regulatory support for RE	-0.33	-1.02	-1.02	0.21	1.16
	(0.69)	(1.06)	(1.56)	(0.44)	(0.94)
Policy: Attributes of financial and regulatory incentives	-0.47	-0.9*	-0.95	0.73	2.21*
	(0.33)	(0.52)	(0.87)	(0.73)	(1.13)
Policy: Network connection and use	-0.14	-0.39	1.38	0.74**	2.19**
	(0.33)	(0.39)	(1.00)	(0.35)	(0.89)
Policy: Counterparty risk	0.15	0.47	0.73	-0.26	0.51
	(0.36)	(0.96)	(1.86)	(0.44)	(0.84)
Policy: Carbon pricing and monitoring			-0.45	0.81***	1.68**
			(0.84)	(0.29)	(0.80)
Index: Composite	-0.22**	-0.1	-0.98**	0.67**	.99**
	(0.08)	(0.30)	(0.46)	(0.32)	(0.38)
Index: Summation	-0.05	0.14	-0.28	-0.09	0.02
	(0.07)	(0.23)	(0.45)	(0.12)	(0.14)
Constant	-0.62*	-1.65***	-3.61***	0.24	-0.2
	(0.33)	(0.50)	(0.84)	(0.36)	(0.88)
Observations	707	717	726	947	923
R-squared	0.071	0.146	0.075	0.01	0.055
Country Fixed Effects	YES	YES	YES	YES	YES

Source: Authors' elaboration based on the methods and data sources described in this chapter.
Notes. FFC= Fossil fuel energy consumption % of the total; EFF= Electricity production from fossil fuels (oil, gas & coal sources), % of the total; EOS= Electricity production from oil sources, % of the total; REC: Renewable energy consumption, % of total final energy consumption; REO= Renewable electricity output, % of total electricity output. Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

We also perform Kruskal-Wallis H tests to determine whether there is a statistically significant difference between the number of eligible S1 results obtained by using any of the indices, IVs, and IV moving averages above. The Kruskal-Wallis H test is sometimes also called the "one-way ANOVA on ranks," and it is applicable here because it is impervious to the normality assumption.

The results shown in Table 3.17, (left) suggest that despite our hypothesis that different ways of tallying policies within PICs would make a difference in the regressions, there was no significant difference between the three indices in the number of eligible S1 regressions. The choice of IV does make a significant difference in the number of eligible S1 regressions Table 3.17, (middle). However, as shown in Table 3.16, these first-stage differences do not consistently affect the second-stage estimates themselves. Last, there is no significant difference in the number of eligible output when comparing moving averages of 3 and 5 periods for our IVs Table 3.17, (right).

Table 3.17. Kruskal-Wallis H tests for the three options in the regression base specifications: Indices, IVs, and IV moving averages.

Indices	IVs	IV moving averages
chi-squared = 0.880 with 2 d.f. probability = 0.6440 chi-squared with ties = 0.881 with 2 d.f. probability = 0.6437	chi-squared = 15.158 probability = 0.0005 chi-squared with ties = 15.174 probability = 0.0005	chi-squared = 0.195 with 1 d.f. probability = 0.6588 chi-squared with ties = 0.195 with 1 d.f. probability = 0.6587

Source: Authors' elaboration based on the methods and data described in this chapter.

Based on the outcomes of the tests above, we continue our analysis with the base combination that yields the highest number of eligible and positive S1 coefficients. This choice increments the probability of having a larger sample of S2 coefficients to analyze.

The S2 analysis in the following paragraphs uses the following S1 base specification: (i) the RISE index; (ii) the IV based on affinity through United Nations General Assembly voting; and (iii) the IV moving average of 5 years. Of the 1902 first-stage regressions in the chosen empirical specification, 28 percent (or 540 coefficients) are eligible for the second-stage estimation.

S2 results overall

The S2 coefficients represent the effect of the seven PICs on the five outcomes, by country, through the UNGA IV. As explained in the Methods, the input data was standardized and the relationship is measured in units of standard deviation distance from the mean so as to be comparable across policy packages and energy mix outcomes.

Overall, only 15.7 percent (or 85 coefficients) of the estimated second-stage regressions meet the statistical significance threshold of p-value < 0.10. In other words, the vast majority of reforms had no measurable impact. A mere 4.8 percent (or 26 coefficients) of the estimated second-stage regressions are positive and statistically significant, so the majority of policies that had an impact were harmful to decarbonization.

Consistent with the literature on the energy sector reform in developing countries (Foster and Rana 2020; Jamasb, Nepal, and Timilsina 2017; Jamasb et al. 2005), these results point to the low effectiveness of renewable energy policies to achieve decarbonization of energy mix. They are also consistent with several of the studies identified by Peñasco, Anadón, and Verdolini (2021) that was summarized in Table 3.3 of the Literature Review.

Appendix 3.6 summarizes the number of available coefficients for analysis by PIC and the energy mix outcomes. There are no significant regressions for CO2 pricing and monitoring, likely because of limited application to the countries in our sample.

Figure 3.3 plots a scatter of the coefficients by PIC (horizontal axis) and outcome (color), for the SSA region and a lag of 3. As expected, the figure suggests that coefficients related to different outcomes for the same country tend to cluster together. This is due to the inherent similarity of the outcome variables, chosen for robustness. We have circled three country examples: Kenya, Eritrea, and Angola.

We take a moment to note that of our three fossil fuel variables, only one of them (electricity from oil sources) excludes natural gas. However, in some of the countries that we study, natural gas may have been considered a transition fuel. Therefore, lumping gas in with other fossil fuels could theoretically be driving the pessimistic results.

Figure 3.3 helps us consider this possibility. As shown in the figure, the results of the PICs on fossil fuels (red) and renewables (blues) tend to all cluster together. Thus, a potential misclassification of natural gas is unlikely to be driving the counterintuitive results.

Figure 3.3. S2 coefficients of outcomes by country tend to cluster. Scatter of S2 coefficients for SSA region including country labels, by PICs (x-axis) and outcomes (colors). S2 lag 3.

Source: Authors' elaboration based on the methods and data described in this chapter.
Note: LF=Legal framework; PE= Planning for expansion; IR=Incentives and regulatory support; AI=Attributes of financial and regulatory incentives; NC=Network connection and use; CR= Counterparty risk. AGO=Angola; BEN= Benin; CIV=Cote d'Ivoire; ERI=Eritrea; KEN=Kenya. To avoid an overpopulated graph, we show one region only. Regression specification: RISE index, UNGA affinity IV with five years moving average.

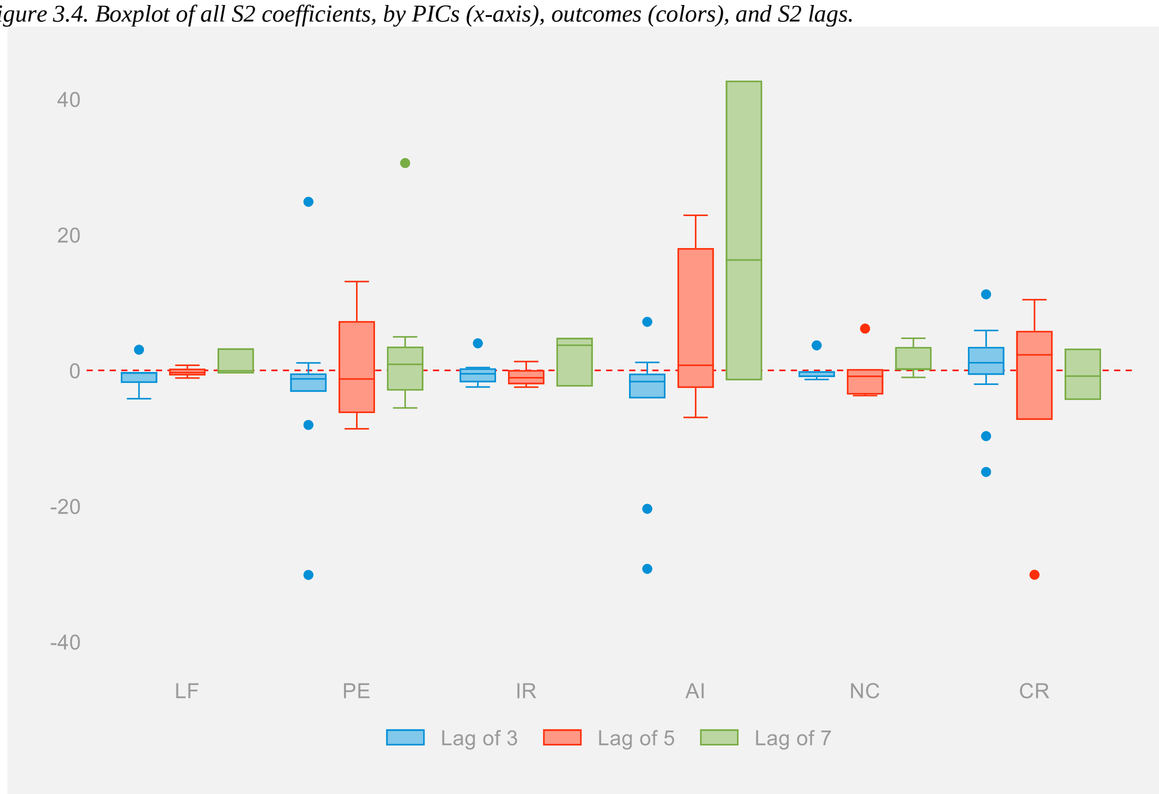
To avoid biasing the plots towards the countries for which there are several coefficients by PIC, we keep only one outcome coefficient at random by PIC and country in all subsequent figures and analyses, keeping 53 coefficients of which only 32% are positive. Appendix 3.7 shows that more than half pertain to the SSA region, and that lower and lower-middle income countries are equally represented.

S2 results, over PIC and time

In addition to the default lag of 3 years, we consider the possibility that the effect of each PIC changes with time and analyze lags of 5 and 7 years. Figure 3.4 shows distributional boxplots of the effects of each PIC aggregated across all regions. Appendix 3.8 provides the coefficients.

Patterns from Figure 3.4 and Table 3.18, which summarizes the means of estimated second-stage coefficients across packages, regions, and income categories, show that all policy packages except for CR had consistently higher average effects over time. Moreover, PE, IR, AI, and NC overcome negative medians seven years after their implementation (Figure 3.4 and Table 3.18).

Figure 3.4. Boxplot of all S2 coefficients, by PICs (x-axis), outcomes (colors), and S2 lags.



Source: Authors' elaboration based on the methods and data sources described in this chapter.
Note: LF=Legal framework; PE= Planning for expansion; IR=Incentives and regulatory support; AI=Attributes of financial and regulatory incentives; NC=Network connection and use; CR= Counterparty risk. Regression specification: RISE index, UNGA affinity IV with five years moving average.

Table 3.18. Average effect of PIC, by S2 lag.

Policy instrument category (PIC)	3	5	7
Legal framework (LF)	-0.66	-0.25	0.90
Planning for expansion (PE)	-2.20	0.48	3.02
Incentives and regulatory support (IR)	-0.30	-0.92	2.04
Attributes of financial and regulatory incentives (AI)	-5.35	5.48	19.17
Network connection and use (NC)	-0.08	-0.43	1.48
Counterparty risk (CR)	0.38	-2.24	-0.67

Source: Authors' elaboration based on the methods and data described in this chapter.
Note: Regression specification: RISE index, UNGA affinity IV with five years moving average.

Unlike other policy packages, we note that CR has the only positive median and mean closest to implementation (lag 3). Its median is higher in lag 5, too (except when compared to attributes of financial and regulatory incentives). CR includes government guarantees or other means to ensure the creditworthiness of projects procured through auctions or otherwise.

One interpretation is that mitigating CR could have comparatively immediate effects. Another is that CR positively influences outcomes while supporting other PICs that take more time to have the intended outcomes. Either way, this result gives credence to the idea that policies that address the bankability of private investment in renewable energy are crucial for energy decarbonization.

Challenging the S2 results over time

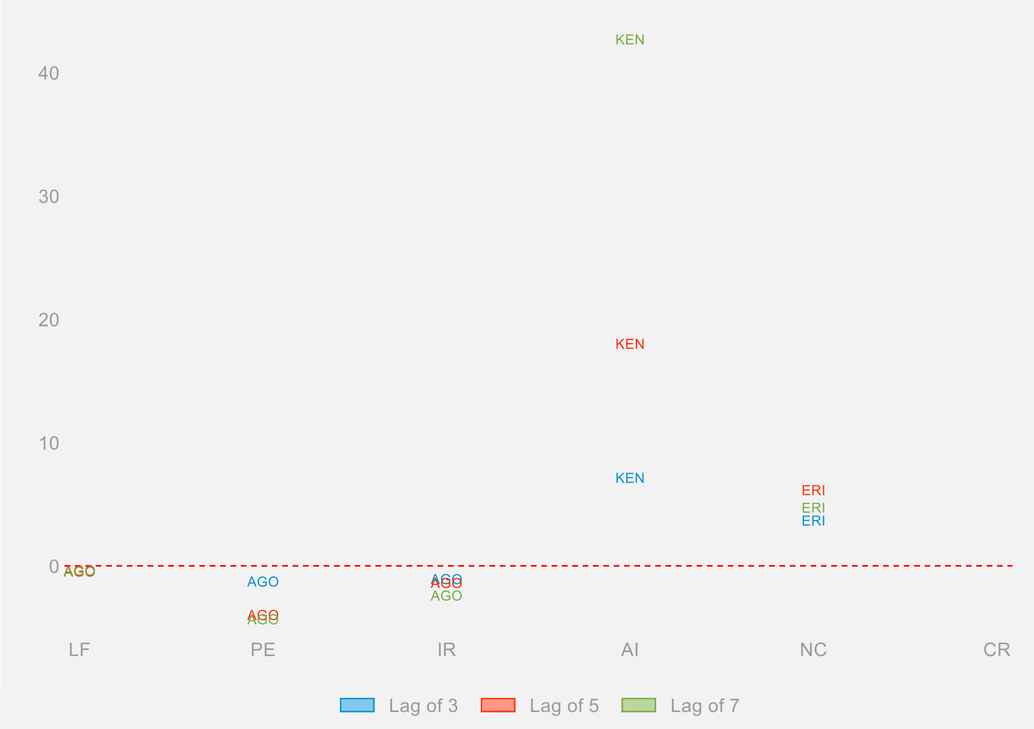
Observe that our analysis of the S2 results across time relies on the assumption that methods such as country FE and regional panels were truly able to remove all country-specific characteristics from the data, making cross-country comparisons possible. Otherwise, the country sample by PIC is not homogenous across all lags and the interpretation of results is weaker. For instance, there are coefficients related to LF for Ghana only in lag 3 and for Peru only in lag 5.

We therefore challenge our results by narrowing the comparison only to countries for which there are significant coefficients in all three lags. There are only nine countries that fulfill this criterion. (Figure 3.5) plots SSA, (Figure 3.6) plots all the other regions.

The results in the restricted sample with the relaxed assumption about our methods still point to a temporal dimension of effects across PICs. Examples of consistent improvements by PIC are evidenced in AI and IR for Kenya and Ukraine, respectively.

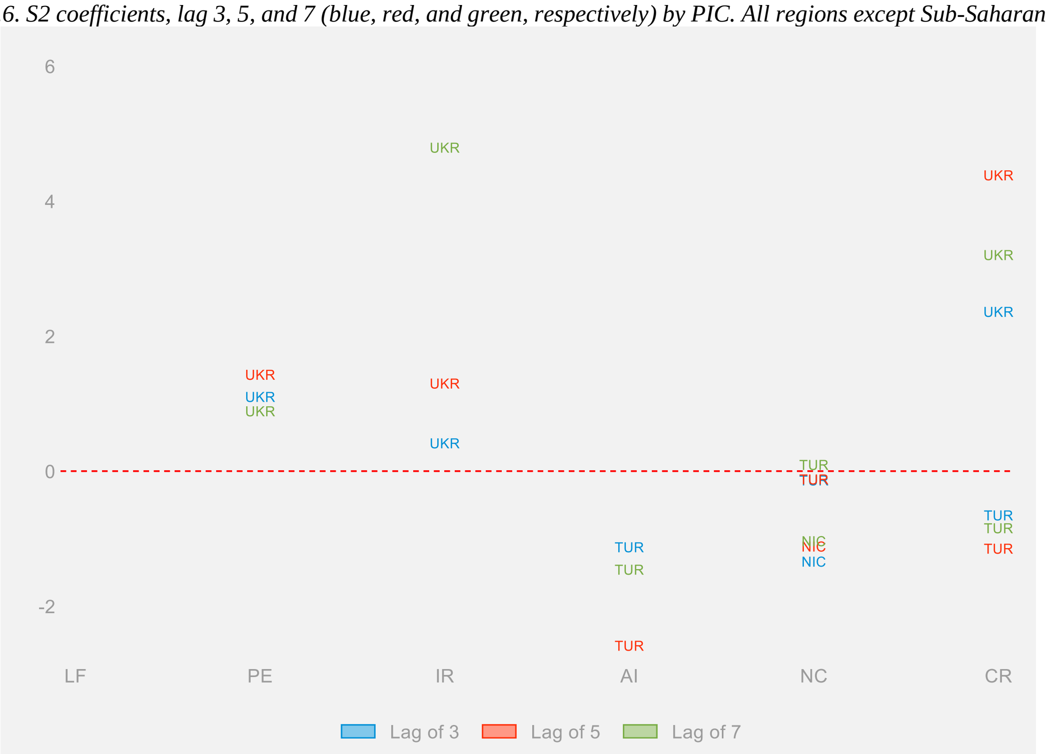
Unfortunately, the small size of the data sample restricts us from reasonably averaging over PICs separately. However, if we average the effects of all PICs in this sample, we see increases over time (0.73,1.72, 3.83 in lags 3, 5, and 7, respectively). The result holds even when we remove AI for Kenya, which is relatively higher than the rest (in this sample, averages are 0.14, 0.24, 0.29 in lags 3, 5, and 7, respectively).

Figure 3.5. S2 coefficients, lag 3, 5, and 7 (blue, red, and green, respectively) by PIC. Only Sub-Saharan Africa.



Source: Authors' elaboration based on the methods and data described in this chapter.
Note: LF=Legal framework; PE= Planning for expansion; IR=Incentives and regulatory support; AI=Attributes of financial and regulatory incentives; NC=Network connection and use; CR= Counterparty risk. To avoid an overpopulated graph, we show one region only. AGO=Angola; KEN=Kenya; ERI=Eritrea; NIC=Nicaragua; TUR=Turkey; UKR=Ukraine.
Regression specification: RISE index, UNGA affinity IV with five years moving average. We separate SSA from all other regions to avoid an overpopulated graph.

Figure 3.6. S2 coefficients, lag 3, 5, and 7 (blue, red, and green, respectively) by PIC. All regions except Sub-Saharan Africa.



Source: Authors' elaboration based on the methods and data described in this chapter.
Note: LF=Legal framework; PE= Planning for expansion; IR=Incentives and regulatory support; AI=Attributes of financial and regulatory incentives; NC=Network connection and use; CR= Counterparty risk. To avoid an overpopulated graph, we show one region only. AGO=Angola; KEN=Kenya; ERI=Eritrea; NIC=Nicaragua; TUR=Turkey; UKR=Ukraine.
Regression specification: RISE index, UNGA affinity IV with five years moving average. We separate SSA from all other regions to avoid an overpopulated graph.

3.6 DISCUSSION

Achieving climate goals worldwide requires a sound understanding of how effective different decarbonization policies are, including in developing countries that are relatively understudied. We shed light on these important issues by conducting a thorough systematic assessment of how variation in decarbonization policy affects changes in the developing countries' energy mix. Specifically, we address the following questions: How do the effects of seven major PICs on the deployment of clean energy technologies compare in developing countries? And, how do such effects change from the short to medium term after implementation, by policy category?

The literature on PSR includes several studies applying comparable methods to similar datasets. Our data leverages highly disaggregated decarbonization policy indicators collected by the World Bank, and we account for the degree of reform and potential collinearity between policies by testing different PIC aggregation methods (indices). Additionally, we include time and country FE and run the regressions within regions to limit omitted variable bias. To address reverse or simultaneous causality between policies and the energy mix, we exploit different sources of arguably exogenous variation in decarbonization policies using three separate IV.

Overall, we estimate thousands of indicator-instrument-outcome-level FE regressions over the panel of more than 100 developing countries over four decades. The scope of our data allows us to concentrate the analysis on developing countries, helping breach the geographical gap on the analysis of decarbonization policy (Peñasco, Anadón, and Verdolini 2021).

We evaluate the robustness of indicators' measurement, the quality of the IVs, and significance and direction of estimated policy-level coefficients. The results show no major measurement differences based on the alternatives for aggregation (indices). This allows us to conclude that the aggregation method used by the World Bank is robust to potential under- and overweighting problems and does not result in major double-counting or significant loss of other relevant information. Additionally, we find no major differences in the second-stage estimates by IV, which adds robustness to our identification approach.

Our findings of the effects of PICs on decarbonization outcomes in developing countries are quite pessimistic. Only one-sixth of the PICs coefficients have even modest statistical significance, and most of them have the sign opposite to what one would expect. All in all, as they stand, these results seem to suggest that, at least within 3-7 years studied, decarbonization policies in developing countries fail to deliver on their goals of reducing the share of fossil fuels in their energy mix.

The findings are not out of scope based on Peñasco, Anadón, and Verdolini (2021)'s work on developed countries. They may be driven by a host of interrelated issues in developing countries, including and culminating in an inability to secure finance (Egli, Steffen, and Schmidt 2019; Moner-Girona et al.

2021), despite the crucial role it plays in decarbonization (Buchner et al. 2019; Steckel et al. 2017; IRENA and Climate Policy Initiative (CPI) 2020; Macquarie et al. 2019).

The importance of securing finance is in line with our results surrounding the counterparty risk PIC. Indeed, it is the only PICs that yields an increase of renewables in developing countries' energy mix three years after implementation. This result again ties in with existing research. According to the review by Peñasco, Anadón, and Verdolini (2021), "due diligence of projects from commercial or investment banks" is crucial for the success of auctions (see Table 3.3 of this chapter) in developed countries.

In addition to the relatively positive effects of policies that address counterparty risk, there is some further basis for optimism, as the effectiveness of PICs improves over time overall. We posit that the Sailing Ship Effect (Ward 1967; Gilfillan 1935) could be a potential driver for these dynamics, wherein the short-term effects of renewable energy policies are dampened by incumbent fossil fuel technologies.

Despite our efforts to identify the causal relationship between PICs and decarbonization, our analysis is limited by the extent that our methods, through IVs and controls, can address other patterns shaping the energy sector in developing countries. These include, for example, changes in enforcement capabilities over time, which cannot be controlled by static country FE.

Another limitation potentially driving the results is that our IVs may not completely fulfill the exclusion criteria. In that case, closeness to major donors as measured through foreign policy and trade IVs could have affected policies outside the power sector. Those non-power sector policies may in turn have had some effects on the energy mix. Nevertheless, we were unable to find alternative instruments and data that covered the breadth of geography, power sector policy, and outcomes that our research questions entailed. Further research may be able to consider other instruments, especially if the analysis is narrower in scope.

Future research could apply our methods to convert RISE data into a panel dataset and to create and evaluate different indices. Future studies might want to use the World Bank WDI dataset to study electricity from coal and natural gas separately. The World Bank WDI also provides a breakdown of electricity from hydropower and "modern renewables," whereas we bundle them together. Last, there is also an indicator for electricity from nuclear power.

Last, the possibility of findings driven by interrelated factors (for instance, the effect of CR on other PICs) evidences the limitations of our analysis which does not allow for interactions between PICs. The evolving interdisciplinary analytical framework of policy mixes spearheaded by Rogge and Reichardt (2016) may help address this limitation. It is a descriptive conceptual framework about how policies and the policy-making process can be understood and is appropriate for social science research questions in multiple fields that consider a range of interacting policies. The limited empirical work in energy based on this framework includes Schmidt and Sewerin (2019), who analyze policy mixes in nine developed countries (although their study does not consider policy interactions).

3.7 Conclusion

We offer the first comprehensive and systematic assessment of how each of seven policy instrument categories individually affect energy decarbonization. Our analysis covers just over 100 developing countries 3 to 7 years after policy implementation and helps breach the literature gap of coverage for developing countries.

While the results of the effects of PICs on decarbonization are pessimistic overall, they suggest improvements over time (3-7 years), and the relative immediate strength of policies that account for counterparty risk. Therefore, our analysis contributes further evidence to the notion that climate finance in developing countries is paramount and supports the importance of industrialized countries fulfilling their climate finance commitments under the Paris Agreement.

We find several venues for future research. Future research could study the same outcomes comparing over regions and income levels, which was beyond our research question on the PICs themselves. Additionally, while we establish the limited effectiveness of the PICs in achieving decarbonization in developing countries, the causal mechanism of this result remains unclear. Studies that utilize less aggregate data at the developing countries' industry level may elucidate the effects of unobserved factors such as, for example, the extent to which PICs are enforced and how industry players respond to these policies.

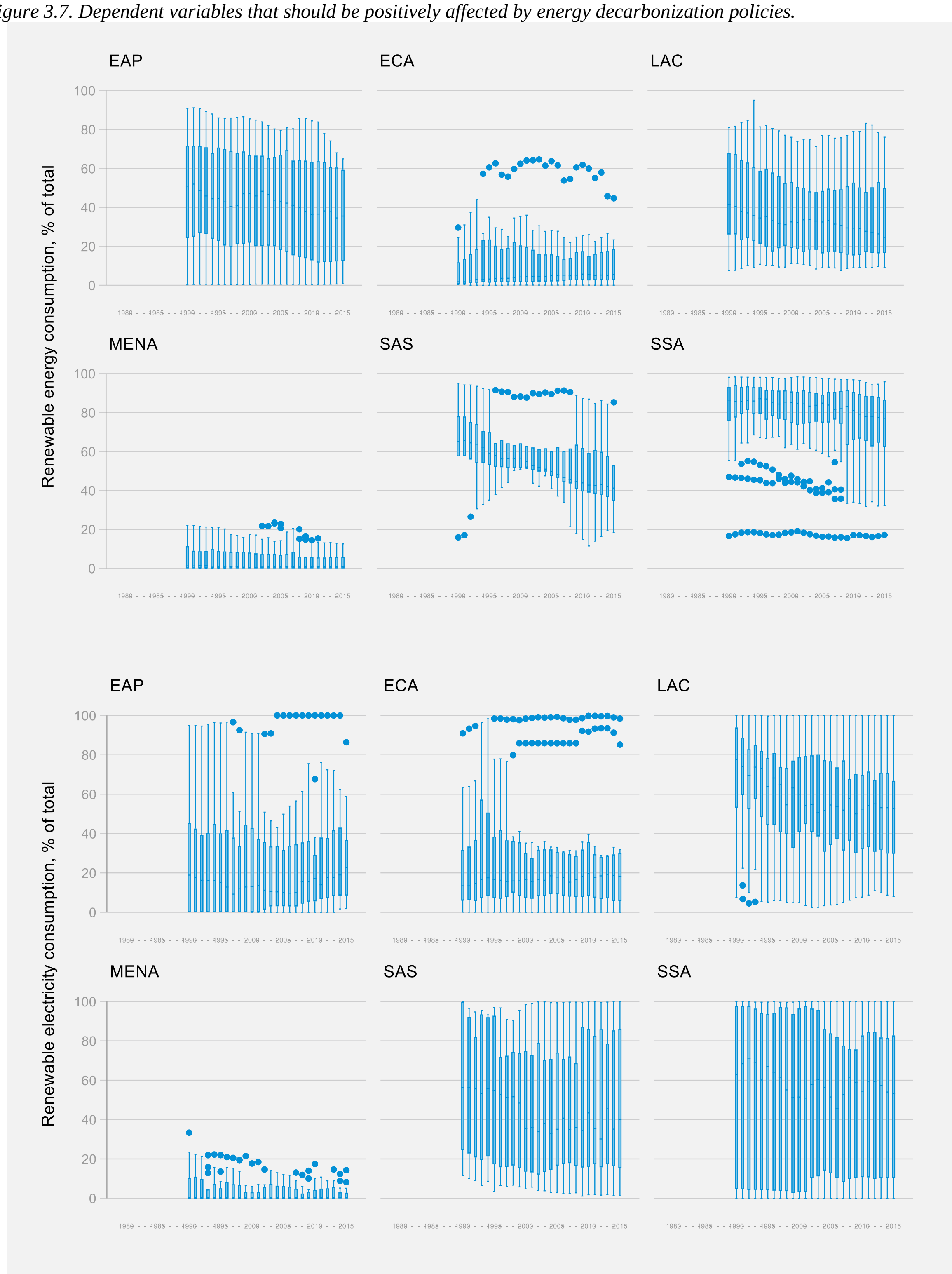
Another important direction for future research is to study the macroeconomic effects of PICs, including implications for productivity, entry and exit, the turnaround of capital stock, and constraints to adoption of low carbon energy technologies.

Last, our results point to the possibility of complementarity and interaction between PICs. Rogge and Reichardt (2016)'s policy mix framework would be a pertinent future sub-stream to which the dataset could be applied.

APPENDIX 3.1. OUTCOME VARIABLES, DESCRIPTIVE STATISTICS

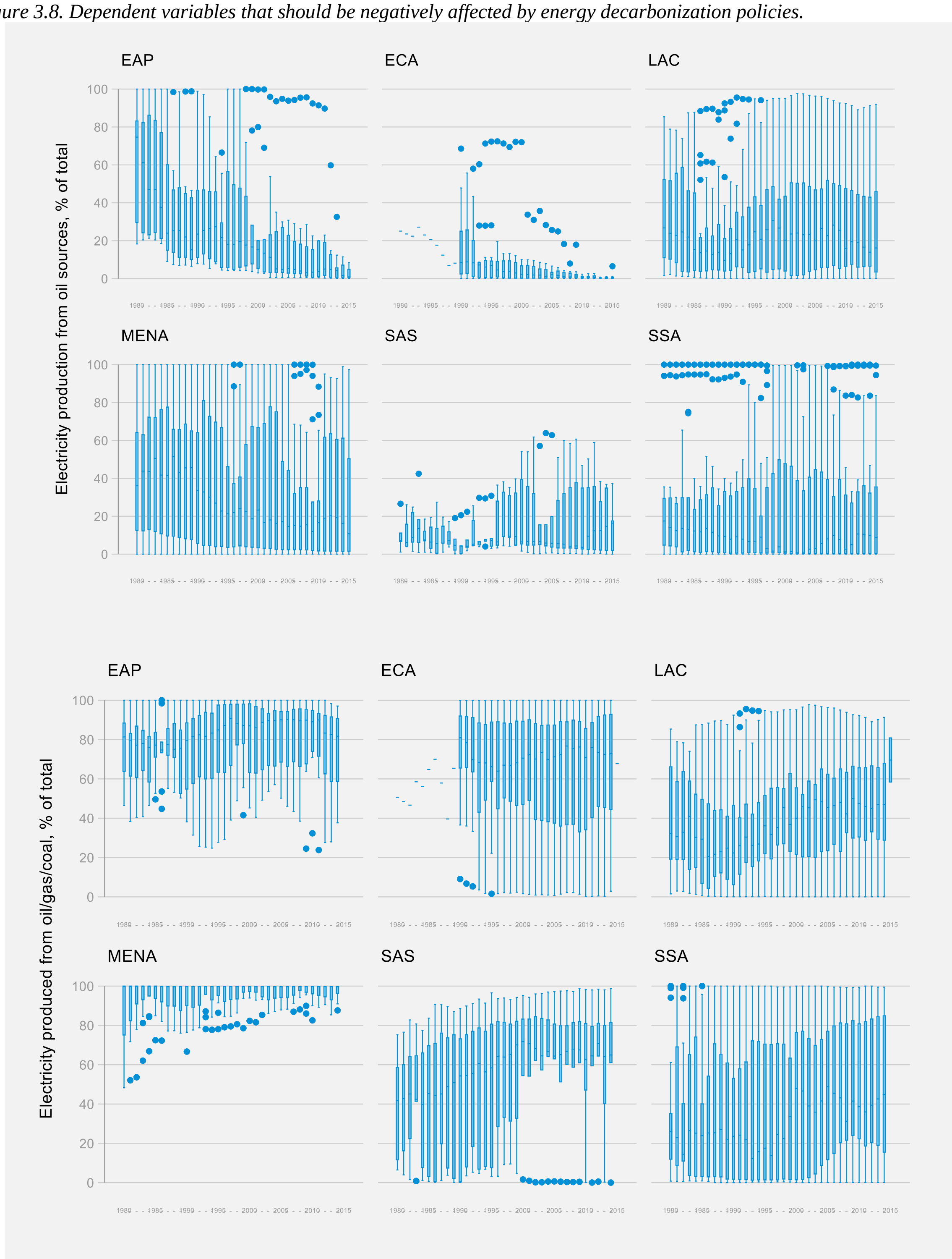
Figure 3.7 and Figure 3.8 And provide an overall view of the dependent variable over time. Due to the scale of the data used in this paper, it is expected that country-level specifics are overlooked in these visualizations. The figures are meant to provide an aggregate summary, over all regions.

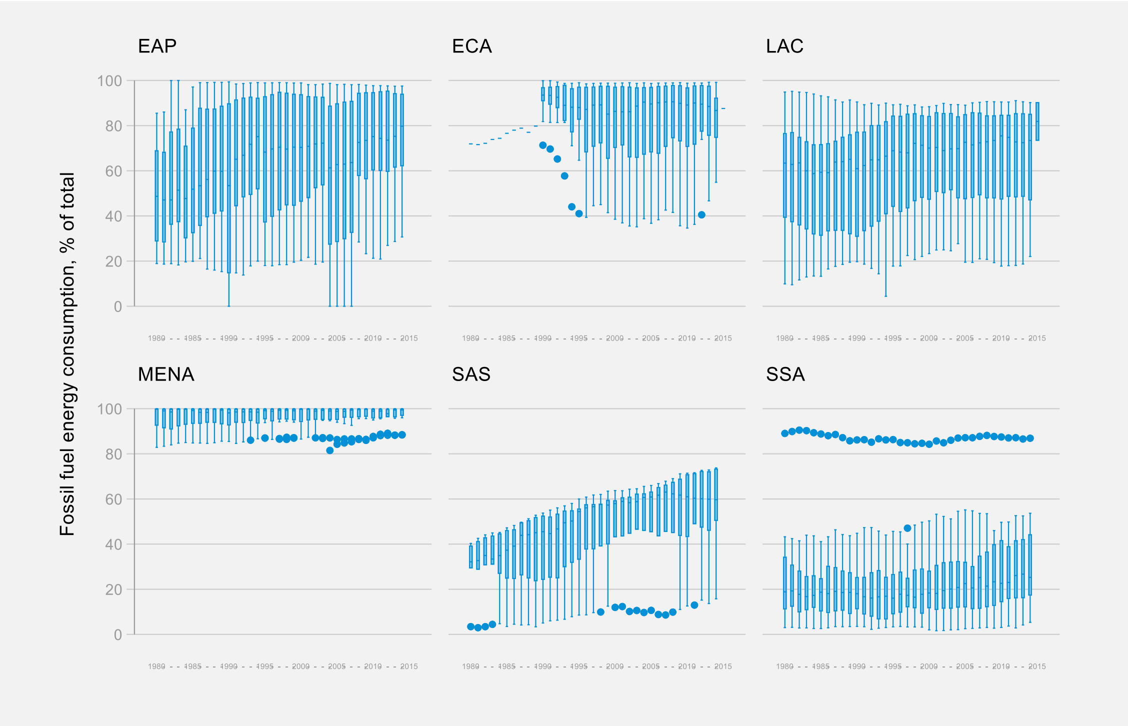
Figure 3.7. Dependent variables that should be positively affected by energy decarbonization policies.



Source: World Bank WDI database and authors' elaboration based on the methods described in this chapter.

Figure 3.8. Dependent variables that should be negatively affected by energy decarbonization policies.





Source: World Bank WDI database and authors' elaboration based on the methods described in this chapter.

APPENDIX 3.2. PRINCIPLE COMPONENT ANALYSIS (PCA)

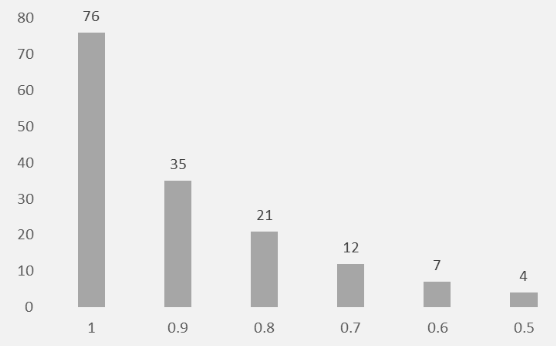
Principal component analysis (PCA) is a method used to reduce dimensionality in large datasets. Cubbin and Stern (2006) apply in the PSR context . PCA makes use of how variables relate to each other in their correlation matrix, summarizing the directions in which the data is dispersed (Eigenvectors) and the relative importance of the directions (Eigenvalues). Based on the input, PCA creates the same number of new variables ("components") but orders them in decreasing amount of information contained. Using only the first few computed components, it is possible to both reduce dimensionality of the dataset and retain its information (Brems 2017).

The default PCA analysis uses a Pearson correlation matrix. Technically, the phi statistic is suitable for truly dichotomous variables like ours. However, the phi statistic is equivalent to Pearson's rho (Pearson's rho=sqrt (chisquare/N)) in a 2x2 contingency table, and the output is equivalent to Cramer's V, Spearman's rho, and Pearson's correlation (Warner 2007). Another option is to create a tetrachoric correlation matrix and input that into the PCA analysis. However, a tetrachoric correlation matrix assumes an underlying normal distribution, which does not apply to our data.

Figure 3.9 (left) summarizes the number of components that explain 0.5-0.9 of the variation of all policies when we ignore the PICs they are in. At the 0.6 level, there are fewer components than there are RISE PICs. Nevertheless, it is hard to justify the use of PCA because its components lack meaning, which is essential to our research question. This is exactly the problem that Cubbin and Stern (2006) run into when running regressions with output from PCA analysis. They find that the principal components are impervious to interpretation.

PCA is therefore useful only when variables subjected to it do not need to be understood separately. In our case, it makes sense to run a PCA within PICs. Figure 3.9 (right) summarizes the number of components needed to explain each PIC, depending on the amount of variability of the data we would like to keep. We find that PCA retains too many components and loses too much information compared to the RISE and Summation indices.

Figure 3.9. Number of components needed (y-axis) to explain the proportion of information (color); Overall (left), by heading/PIC (right)



	Components	Reduction, %
0.5	11	87%
0.6	15	82%
0.7	21	75%
0.8	30	65%
0.9	48	48%

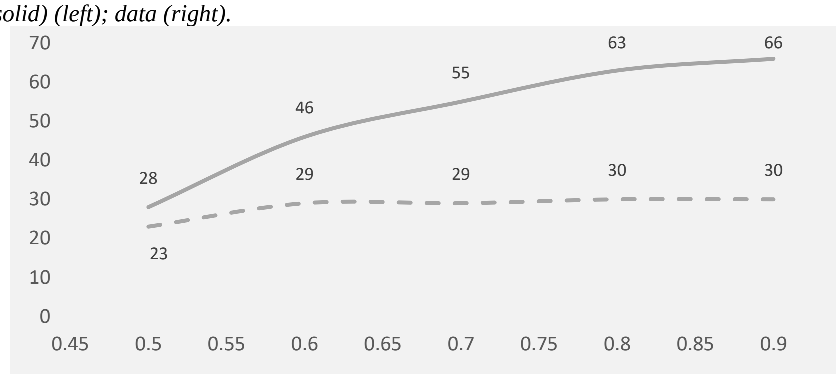
Source: RISE dataset and authors' elaboration based on methods described in this chapter.

APPENDIX 3.3. PICS, COMPOSITE INDEX CORRELATION CUT-OFFS

An important determinant of the behavior of results of both the Survival and Average correlation methods is the cut-off for what should be considered a sufficiently “high” enough correlation. The trade-off is between retaining information or nearing the recreation of the Summation index, where each policy is weighed the same.

As an additional robustness check, we run the analysis (disregarding headings/PIC) at cut-off levels between 0.5-0.9 for both methods to see whether there is an embedded tipping point in the data that minimizes cutting data and maximizes information retention. Figure 3.10 suggests the higher the cut-off, the more variables we keep, which is expected. However, there also does not seem to be a unilaterally optimal cut-off point, which would have occurred if increasing the cut-off point did not alter the aggregate number of variables retained by the analysis, especially for the Survival method. We therefore choose the middle-of-the-road cutoff of 0.7.

Figure 3.10. Number of variables/groups/headings remaining (y-axis), by cut-off point (x-axis), Survival method (dashed), Average method (solid) (left); data (right).



Source: RISE dataset and authors’ elaboration based on methods described in this chapter.

Both the Average and Survival methods may mask and compound errors. On average, at the p=0.05 level, five out of every 100 correlations erroneously fail to reject the null hypothesis, a Type II error. If these variables are carried into the subsequent rounds, then the possibility of rejecting the null hypothesis is carried with them.

APPENDIX 3.4. PICS, RISE VS COMPOSITE INDEX WEIGHTS

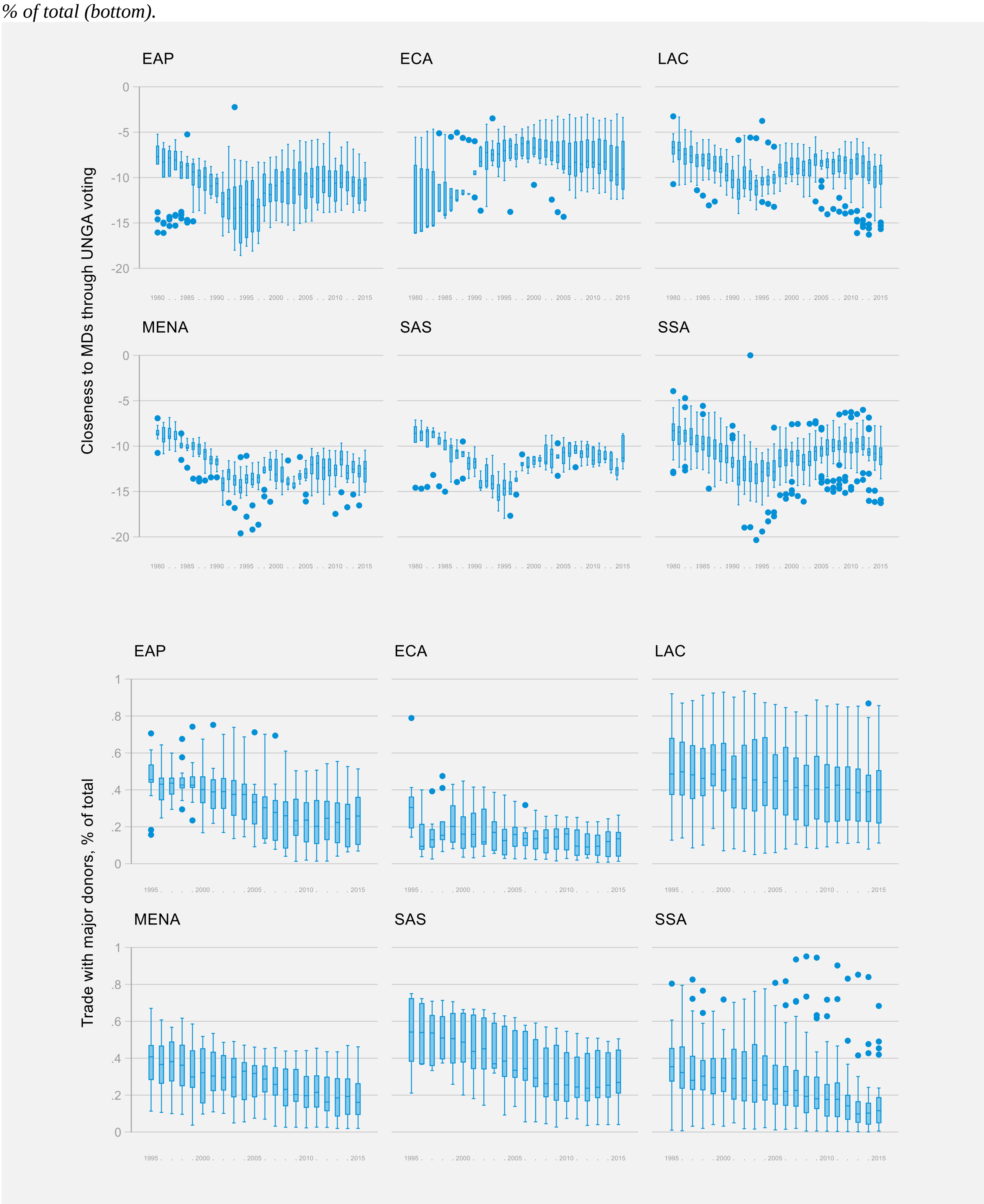
Table 3.19. RISE and Composite index weights used to create the PIC (independent) variables in the PIC column.

PIC	Our ID	Composite	RISE	PIC	Our ID	Composite	RISE
Legal framework for RE	re_1_1	1	1	Network connection and use	re_5_1_1	0.5	0.2
	re_1_2	1	1		re_5_1_2	0.5	0.2
Planning for renewable energy expansion	re_2_1_1	0.333	0.167		re_5_1_3	1	0.2
	re_2_1_2	1	0.167		re_5_1_4	0.5	0.2
	re_2_1_3	1	0.167		re_5_1_5	0.5	0.2
	re_2_1_4	1	0.167		re_5_2_1	1	0.5
	re_2_1_5	0.333	0.167		re_5_2_2	1	0.5
	re_2_1_6	1	0.167		re_5_3_1	1	0.167
	re_2_2_1	1	0.5		re_5_3_2	1	0.167
	re_2_2_2	0.333	0.5		re_5_3_3	1	0.167
	re_2_3_1	1	0.5		re_5_3_4	1	0.167
	re_2_3_2	1	0.5		re_5_3_5	1	0.167
	re_2_4_1	0.5	0.5		re_5_3_6	1	0.167
	re_2_4_2	0.5	0.5	Counterparty risk	6.1.1	**	**
	re_2_5_1	1	0.2		6.1.1.1	**	**
	re_2_5_2	1	0.2		6.1.1.2	**	**
	re_2_5_3	1	0.2		6.1.1.3	**	**
	re_2_5_4	1	0.2		6.1.1.4	**	**
	re_2_5_5	1	0.2		6.2.1	1	0.5
	re_2_6_1	1	0.25		6.2.2	1	0.5
	re_2_6_2	1	0.25		6.3.1.1	0.25	0.03125
	re_2_6_3	1	0.25		6.3.1.2	**	**
	re_2_6_4	1	0.25		6.3.1.3	**	**
	re_2_7_1	1	0.333		6.3.1.4	**	**
	re_2_7_2	0.5	0.333		6.3.2.1	0.25	0.03125
	re_2_7_3	0.5	0.333		6.3.2.2	**	**
Incentives and regulatory support for renewable energy	re_3_1_1	0.5	0.25		6.3.2.3	**	**
	re_3_1_2	0.5	0.25		6.3.2.4	**	**
	re_3_1_3	1	0.25		6.3.3.1	0.25	0.03125
	re_3_1_4	1	0.25		6.3.3.2	**	**
	re_3_2_1	0.5	0.2		6.3.3.3	**	**
	re_3_2_2	0.5	0.2		6.3.3.4	**	**
	re_3_2_3	1	0.2		6.3.4	0.25	0.03125
	re_3_2_4	0.5	0.2		6.3.5	**	**
	re_3_2_5	0.5	0.2		6.3.5.1	**	**
	re_3_3_1	0.5	0.25		6.3.5.2	**	**
	re_3_3_2	0.5	0.25	Carbon pricing and monitoring	re_7_1	0.5	0.5
	re_3_3_3	1	0.25		re_7_2	0.5	0.5
	re_3_3_4	1	0.25				
	re_3_4_1	0.5	0.333				
	re_3_4_2	0.5	0.333				
	re_3_4_3	1	0.333				
Attributes of financial and regulatory incentives	re_4_1_1	1	Not scored				
	re_4_1_2_1	1	0.167				
	re_4_1_2_2	1	0.167				
	re_4_1_2_3	1	0.167				
	re_4_1_2_4	0.333	0.167				
	re_4_1_2_5	0.333	0.167				
	re_4_1_2_6	0.333	*				
	re_4_2_1	1	0.167				
	re_4_2_2	1	0.167				
	re_4_2_3	1	0.167				
	re_4_2_4	1	0.167				
	re_4_2_5	1	0.167				
	re_4_2_6	1	0.167				

Source: RISE dataset and authors' elaboration based on methods described in this chapter.
Note: *Not scored; **Do not contain the year, cannot be used in a panel format.

APPENDIX 3.5. INSTRUMENTAL VARIABLES, DESCRIPTIVE STATISTICS

Figure 3.11. Closeness to major donors through UNGA voting (top); Closeness with major donors through trade, 1995-2015, % of total (bottom).



Source: Author's elaboration based on Bailey et al. (2017) (top); UN Comtrade via the CEPII BACI dataset (bottom).

Table 3.20. Trade agreements in place with the EU Commission.

Country	Year in place	Country kept in sample
Armenia	1999	1
Azerbaijan	1999	1
Canada	2017	0
Switzerland	1980	0
Chile	2003	1
Côte d'Ivoire	2016	0
Comoros	2014	0
Colombia	2013	1
Costa Rica	2013	1
Dominican Republic	2008	1
Algeria	2005	1
Ecuador	2013	1
Egypt	2004	0
Ghana	2016	1
Guatemala	2013	1
Honduras	2013	1
Israel	2000	1
Jamaica	2008	1
Jordan	2002	1
Japan	2019	0
Kazakhstan	2016	1
Korea	2015	0
Lebanon	2006	1
Morocco	2000	1
Madagascar	2012	1
Mexico	2000	1
Mozambique	2016	1
Nicaragua	2013	1
Norway	1994	0
Peru	2013	1
Singapore	2019	1
Solomon Islands	2020	1
El Salvador	2013	1
Serbia	2013	1
Tunisia	1998	1
Turkey	1995	1
Ukraine	2016	1
South Africa	2016	1
Zimbabwe	2012	1

Source: EU Commission website.

APPENDIX 3.6. S2 COEFFICIENTS BY PIC AND OUTCOME

Table 3.21 shows the number of S2 eligible coefficients, by PIC and outcome, for the default lag of 3. There are no significant regressions for CP (CO_2 pricing and monitoring), likely because of limited application to the countries in our sample. In lag 3, CP and AI PICs are clear leaders by the number of output coefficients.

Table 3.21. Number of S2 eligible coefficients, by PICs and outcomes, lag 3. Higher numbers are green, lower are red.

PIC	FFC	EFF	EOS	REC	REO	Total
Legal framework		1		3	2	6
Planning		2	1	5	2	10
Inc/reg. support	5	1		1	5	12
Attributes of fin/reg inc	5	6	1	4	3	19
Network conn. & use	6	4	1	2	2	15
Counterparty risk	5	6	3	3	6	23
Co2 price & mon.						0
Total	21	20	6	18	20	85

Source: Authors' elaboration based on the methods and data described in this chapter.
Note: Regression specification: RISE index, UNGA affinity IV with five years moving average.

APPENDIX 3.7. S2 COEFFICIENTS FOR ANALYSIS, BY REGION AND INCOME GROUP

Table 3.22. Coefficients for analysis, by region.

WB region	Total S2	Positive S2
SSA	37	11
EAP	4	1
ECA	9	4
LAC	2	0
MENA	1	1
SAS	0	0
Total	53	17

Source: Authors' elaboration based on the methods and data sources described in this chapter.

Table 3.23. Coefficients for analysis, by World Bank income group.

WB Income classification	Total S2	Positive S2
Lower income	23	8
Lower middle income	23	8
Upper middle income	7	1
Total	53	17

Source: Authors' elaboration based on the methods and data sources described in this chapter.

APPENDIX 3.8. S2 COEFFICIENTS FOR ANALYSIS

Table 3.24. S2 coefficients with a p-value <0.1 with a positive S1 coefficient with a p-value<0.05 and an f-statistic>10.

Country code	PIC number	PIC	Region	Lag 3	Lag 5	Lag 7	Income group
AFG	re_6	CR	SAS		-7.289		LI
AGO	re_1	LF	SSA	-0.425	-0.379	-0.462	LM
AGO	re_4	AI	SSA	-2.175			LM
AGO	re_2	PE	SSA	-1.26	-3.966	-4.32	LM
AGO	re_5	NC	SSA		-3.714		LM
AGO	re_3	IR	SSA	-1.061	-1.369	-2.39	LM
BEN	re_3	IR	SSA	-0.72			LI
BEN	re_2	PE	SSA	-0.45			LI
BEN	re_5	NC	SSA	-0.99	-0.875		LI
BEN	re_4	AI	SSA	-3.487	-2.23		LI
BEN	re_6	CR	SSA	-9.693			LI
BFA	re_2	PE	SSA	-1.58			LI
BLR	re_5	NC	ECA			0.141	UM
CIV	re_2	PE	SSA	-30.15			LM
CIV	re_6	CR	SSA	5.697	-30.13		LM
CMR	re_3	IR	SSA	-2.435			LM
CMR	re_5	NC	SSA	-0.971			LM
CMR	re_4	AI	SSA	-0.747			LM
CMR	re_1	LF	SSA	-0.286			LM
ERI	re_3	IR	SSA	0.186	0.298		LI
ERI	re_5	NC	SSA	3.686	6.156	4.734	LI
ETH	re_6	CR	SSA	2.039	5.823		LI
GHA	re_1	LF	SSA	-1.838			LM
GHA	re_4	AI	SSA	-20.41			LM
GHA	re_5	NC	SSA			3.45	LM
GHA	re_3	IR	SSA		-0.813		LM
GTM	re_2	PE	LAC			4.941	UM
HND	re_3	IR	LAC			3.703	LM
HND	re_4	AI	LAC		22.86		LM
HND	re_2	PE	LAC			3.495	LM
IND	re_5	NC	SAS		0.186		LM
JOR	re_6	CR	MENA	0.213			UM
KEN	re_6	CR	SSA	3.461	10.42		LM
KEN	re_1	LF	SSA			3.234	LM
KEN	re_4	AI	SSA	7.156	18.02	42.7	LM
KEN	re_2	PE	SSA		13.09	30.56	LM
KHM	re_6	CR	EAP	5.883	2.291		LM
KHM	re_1	LF	EAP		0.752		LM
KHM	re_2	PE	EAP	-3.15			LM
MLI	re_3	IR	SSA		-2.326		LI
MNG	re_4	AI	EAP			16.27	LM
MOZ	re_6	CR	SSA	2.228			LI
NIC	re_5	NC	LAC	-1.338	-1.114	-1.035	LM
PER	re_5	NC	LAC	-0.731	-3.558		UM

Country code	PIC number	PIC	Region	Lag 3	Lag 5	Lag 7	Income group
PER	re_6	CR	LAC			-4.356	UM
PER	re_1	LF	LAC		-1.126		UM
PER	re_2	PE	LAC			-5.535	UM
PHL	re_6	CR	EAP	-0.237			LM
PNG	re_2	PE	EAP	-1.106			LM
RWA	re_1	LF	SSA	-4.178			LI
RWA	re_3	IR	SSA	-2.45			LI
RWA	re_4	AI	SSA	-29.26			LI
RWA	re_2	PE	SSA			-2.988	LI
RWA	re_6	CR	SSA	-2.035			LI
SLE	re_1	LF	SSA	3.042			LI
SLE	re_2	PE	SSA	24.85			LI
SRB	re_2	PE	ECA			0.891	UM
SRB	re_3	IR	ECA		-1.752		UM
SRB	re_4	AI	ECA	-4.124	-6.939		UM
SRB	re_1	LF	ECA		-0.26	-0.0761	UM
TGO	re_3	IR	SSA	3.989			LI
TGO	re_6	CR	SSA	11.21			LI
TUR	re_1	LF	ECA	-0.271			UM
TUR	re_5	NC	ECA	-0.135	-0.12	0.0946	UM
TUR	re_2	PE	ECA			-0.753	UM
TUR	re_6	CR	ECA	-0.653	-1.146	-0.843	UM
TUR	re_4	AI	ECA	-1.125	-2.584	-1.457	UM
TZA	re_3	IR	SSA		-2.471		LI
TZA	re_6	CR	SSA	-14.97			LI
TZA	re_2	PE	SSA	-8.044	-8.614		LI
UGA	re_6	CR	SSA	-0.187			LI
UGA	re_4	AI	SSA	-0.487			LI
UGA	re_3	IR	SSA	-0.287	-0.212		LI
UKR	re_4	AI	ECA	1.175	3.733		LM
UKR	re_2	PE	ECA	1.102	1.43	0.889	LM
UKR	re_6	CR	ECA	2.362	4.384	3.203	LM
UKR	re_3	IR	ECA	0.415	1.3	4.794	LM

Source: Authors' elaboration based on the methods and data described in this chapter.
Note: Regression specification: UNGA IV; 5 year moving average; RISE index. LF=Legal framework; PE= Planning for expansion; IR=Incentives and regulatory support; AI=Attributes of financial and regulatory incentives; NC=Network connection and use; CR= Counterparty risk. KEN=Kenya; ERI=Eritrea; CIV=Cote d'Ivoire; AGO=Angola; BEN= Benin. AFG=Afghanistan; AGO=Angola; BEN=Benin; BFA= Burkina Faso; BLR=Belarus; CIV=Cote d'Ivoire; CMR=Comoros; ERI=Eritrea; ETH=Ethiopia; GHA=Ghana; GTM=Guatemala; HND=Honduras; IND= JOR=Jordan; KEN=Kenya; KHM=Cambodia; MLI=Mali; MNG=Mongolia; MOZ=Mozambique; NIC=Nicaragua; PER=Peru; PHL=Philippines; PNG=Papua New Guinea; RWA=Rwanda; SLE SRB=Serbia; TGO=Togo; TUR=Turkey; TZA=Tanzania; UGA=Uganda; UKR=Ukraine.

Chapter 4: The evolution of trade in 30 energy technology materials spanning traditional and clean technologies and its implications

Abstract

Deep energy decarbonization will require a shift in the materials used in energy technologies, or energy technology materials (ETMs). Many existing ETM studies are motivated by perceived supply chain vulnerabilities or potential reserve shortages from the point of view of importers of ETMs. The effect of changing demand on exporters of materials is relatively less explored, but still relevant to competitiveness, growth, and other economic priorities that coexist with climate change goals in both developing and developed countries.

We ask whether there are ETM products (and product groups) that exhibit characteristics in growth, volatility, and importer and exporter concentration in trade value and volume from 1999-2018 that are beneficial to exporters, and what the policy implications of these metrics may be. The product groups we study are: clean and traditional materials, and unrefined and refined materials.

To do this, we systematically isolate and categorize 30 relevant traded products in UN Comtrade, an open-access dataset of bilateral trade flows spanning more than two decades, five thousand products, and almost all countries. The product codes and product group definitions can be re-used by other researchers willing to undertake an ETM study with trade data. We establish the direction of each metric that benefits exporters and identify and interpret existing trade trends, employing parametric and non-parametric inferential statistical methods where appropriate.

We find that, of the 30 products, lithium carbonate (used in rechargeable batteries) exhibits the most beneficial metrics for exporters over time. Additionally, among other results, clean energy and refined materials are disproportionately represented in the high-performing products for exporters, compared to traditional and unrefined materials that developing countries tend to export more frequently. Although there are some subtleties, if trends continue, the results make a case for directed policy attention towards enhancing clean and refined ETM trade and capabilities in developing countries, although we discuss other policy options.

4.1 Introduction

By 2050, the “Middle of the Road” Shared Socioeconomic Pathway used as input to the IPCC 6th Assessment Report conservatively predicts that modern renewables will grow to about 10% of world energy supply from about their current 6%. Oil and gas will stay relatively constant, from about 57 to 58% (Riahi et al. 2017). As a result, even without accounting for Paris Agreement targets, oil and gas are likely to cede relative magnitude in world trade to *materials* (a general term that refers to the matter from which a thing is or can be made) for technologies that convert primary renewable sources (wind, solar, etc.) into secondary energy sources (electricity, heat, etc.), such as Rare Earth Elements (REE) for wind turbines. If we were to align with the Paris Agreement, then the Sustainable Development Scenario of the IEA predicts that oil and gas will need to decline to just over 20% of total energy supply (IEA 2020d), thereby reinforcing the change to occur in energy technology materials (ETM) markets.

Climate goals coexist and interact with other policy priorities. These include boosting economic competitiveness and development, as well as maintaining fiscal sustainability (Anadón, Chan, et al.

2016; IPCC 2001; Mazzucato 2018; IMF 2019), in which a country's export base plays a central role. For the first time, we use trade data to interpret changes in the value and volume of traded *products*, defined as materials that cross country boundaries, and product groups along ETM supply chains. We ask: How have the characteristics of growth, volatility, and importer and exporter concentration in trade value and volume evolved for the products in the two decades between 1999-2018? What are the products (and product groups) that exhibit characteristics that are more beneficial to exporters?

In line with the policy priorities discussed, we interpret the trends from the point of view of main exporters and include both developed (defined here as those that are classified as both World Bank high-income and OECD members) and developing countries in our analysis, overall between 1999-2018 and comparing Decade 1 (1999-2008) and Decade 2 (2009-2018). We look in detail at major exporters, defined as those either within the top five in total value for a certain good during the 20 years, or those included in the cumulative top 90% of exporters, whichever comes first.

Considering the Paris Agreement targets, the related literature on supply chains, availability, and geopolitics of EMTs is blossoming. We frame our study within three inter-related existing ETM research streams: (1) Criticality studies (e.g. Erdmann and Graedel (2011), Achzet et al. (2013)); (2) Reserve and resource models (e.g. Speirs et al. (2014) and Olivetti et al. (2017)); and (3) Resource governance (e.g. Lee et al. (2020), and Sovacool (2019)).

The first stream is focused on understanding the extent to which developed countries may face challenges of *mineral* (defined by the United States Geological Survey, USGS, as "naturally occurring inorganic elements or compounds with an orderly internal structure and characteristic chemical composition, crystal form, and physical properties" (USGS 2021)) supply for their own industrial activity. The second is concerned with modeling reserves and resources necessary for different energy decarbonization scenarios. Data used for both streams includes production, consumption, reserves, and prices at international exchanges. The third stream discusses the complex relationship between exports and governance. To our knowledge, our work is the first one to ask whether there are existing discernable trade patterns over ETM products that can guide the intersection between climate, energy, and industrial policy for countries.

To this end, we first systematically identify 17 materials from the existing ETM literature and map these onto 30 traded products available in UN Comtrade, a comprehensive open-access dataset of bilateral trade flows spanning more than two decades, five thousand products, and hundreds of countries (UNSD 2020). While the dataset is already widely used, to the best of our knowledge it has not been employed to study the evolution of trade in traditional and clean ETMs over time, except in a study by Galeazzi, Steinbuks, and Cust (2020) (topically related but not part of the dissertation and presented and summarized in the introductory chapter of this dissertation), and a descriptive industry report by UN Comtrade (only on products related to lithium-ion batteries and only 2010 onwards, from the point of view of importers and criticality) (UNCTAD 2020). The product code list may therefore be useful to other researchers willing to undertake subsequent ETM studies as broad as ours with trade data.

Having identified relevant UN Comtrade products, we categorize them according to their: 1. Role in energy decarbonization (Classification 1) and 2. Level of refinement (Classification 2). Under Classification 1, products are either Clean Energy Materials (CEMs) or Traditional Energy Materials (TEMs, or those that facilitated the energy paradigm of the 19th and 20th centuries). We place platinum group metals in TEMs due to their historical role in internal combustion engines, though we acknowledge and discuss their future uses under CEMs. Under Classification 2, products are either raw ore and concentrates (Ocs, defined as "the naturally occurring material from which a mineral or minerals of economic value can be extracted" (USGS 2016), or refined metals and chemicals (MCs). We compare groups within the same classification (CEMs versus TEMs and Ocs versus MCs), or the same group over time (CEMs in Decade 1 versus CEMs in Decade 2).

Classification 2 shows how our perspective expands existing literature, which is mostly focused on minerals. We consider that each ETM is related to a range of traded products that involve different country exporters along the way. For example, an increase in the demand for "cobalt" for use in lithium-ion batteries will impact trade in minerals (unrefined cobalt ores and concentrates), and a range of refined chemicals derived from cobalt (cobalt oxide/hydroxide and cobalt metal). While existing literature discusses the implications related to the Democratic Republic of the Congo, (a major exporter of unrefined cobalt ores), we show that Europe and China surpass it in exporting cobalt chemicals, and include this in our discussion.

As the first study using historical trade data in the ETMs literature over all countries, we analyze and compare the following metrics: average of yearly growth rates of trade value, the volatility of growth in trade value, and the importer and exporter market concentration in trade volume (akin to the export and import market concentration index. We also identify major exporters by product, defined above. For the average growth and volatility analysis, we use parametric and nonparametric tests of statistical significance to gauge whether the differences in these metrics between groups and over time may be due to chance. For the importer and exporter concentration and major exporters analysis, we study changes over time dynamically (i.e., Decade 2 minus Decade 1).

Finally, we synthesize the results. Our interpretation of the results rests on the assumption that exporters benefit from exporting products that display high growth but low growth volatility in trade value (Renner and Wellmer 2019; McCullough and Nassar 2017). Exporters also benefit when products are highly concentrated over exporters (supply) and unconcentrated by importers (demand) in value. We discuss these assumptions with greater nuance in the Literature Review and Methods sections.

Our main results suggest that overall changes that occurred between Decades 1 and 2 have been unfavorable to exporters of ETMs. Growth rates were generally lower in Decade 2, and the statistical tests we ran to compare these metrics overall and within groups (e.g., CEMs in Decade 1 versus CEMs in Decade 2) imply that the differences are unlikely to be due to chance. In the Discussion, we consider why this might be and how this differs from what we expected given the existing literature. Additionally, in the dynamic analysis of concentration, there was an overall change towards exporter dispersal and importer concentration, exactly the opposite of what would benefit major exporters.

Second, CEMs are disproportionately represented in the products with high growth rates in Decade 2, a trend that mostly benefits developed countries. Our exporter analysis confirms existing literature indicating that major developed exporters of TEMs tend to be major exporters in other ETM products. However, developing TEM exporters tend to have less export diversification. This brings to the fore the importance of continued efforts in strengthening governance and capabilities for large developing TEM exporters.

We also take a sub-sample of top-performer "notable" products. The sub-sample combines those with high growth during Decade 2, favorable importer and exporter concentration during 1998-2018, and favorable changes in importer and exporter concentration in the dynamic analysis. We find that MCs are overrepresented within "notable" products (as well as in the smaller group of top growth products in Decade 2). Additionally, our exporter analysis supports existing literature on industrialization and development, showing that developed countries tend to specialize in MCs (Behrens et al. 2007). Therefore, in line with the result pertaining to TEMs above, this leads us to argue that without coordinated, holistic, and sustained policy, it is likely that developed countries will benefit disproportionally from trade in ETMs in the transition towards decarbonized energy.

Third, we further identify the specific major exporters that stand to benefit the most from the trends in notable products: 1. The European Union (EU), because it is a major exporter in all the notable products (which is expected given the size of the trading bloc); 2. China, because it holds the highest average market share rank across all notable products; and 3. The United States (US), which plays a higher role in the notable products than in the overall sample, although we discuss subtleties. Of the 30 products, lithium [carbonate] exhibits the most beneficial trade patterns, putting its major exporters (Chile, Argentina, the European Union, and China) in a favorable position as energy decarbonization continues.

Our conclusions support the broader existing literature on the importance of efforts to create managed co-benefits of energy decarbonization in developing countries (Deng et al. 2018). We note that trade is only one of several issues related to ETMs. We encourage further research to explore the connection of ETM trade with topics such as the human rights implications of mining and domestic recycling that are outside the scope of our research questions.

Section 2 reviews relevant ETM literature and lays out the research questions; Section 3 details the methods we employ; Section 4 reviews the data; Section 5 presents the results; Section 6 presents the results; Section 7 discusses the results and limitations, and Section 7 concludes.

4.2 LITERATURE REVIEW

We consider three interrelated existing streams of research: 1. Criticality studies, 2. Reserve and resource models, and 3. Resource governance, and conclude with the key research questions that emerge as a result.

Given that the three literature streams span national security, supply chains (management and industrial organization), resources and reserves (geology), and governance, the papers and reports across these areas refer to different but related terms (like materials, raw materials, minerals, non-fuel minerals, raw minerals, commodities, metals, minor metals, major metals, etc.). A useful discussion comparing the listed terms can be found in Chapter 1 of the *Critical Materials Handbook* by Gunn (2014). To keep the review manageable and focused, we refer to materials and minerals using the definitions provided in the introduction. When necessary, we introduce and define new terms used in specific studies.

4.2.1 Criticality assessments: focus on vulnerability to supply disruptions

In the past decade, the need to understand the dynamics and implications of decarbonization on energy technology supply chains has become increasingly clear. In 2010, China honored existing export quotas for rare earth elements (REE) due to a conflict with Japan, and the world saw the price impacts of an interruption of ETMs (the underlying factors are more complex and discussed in detail in Renner and Wellmer (2019)). The disruption galvanized policy attention to ETMs, amongst other things, to the creation of the U.S. Department of Energy Critical Materials Institute in 2013 to "assure supply chains of materials critical to clean energy technologies" (Speirs, Houari, and Gross 2013).

Though they have been used for decades outside of the premise of the energy transition, "criticality" assessments dominate the ETM literature (Glöser et al. 2015). These assessments evaluate "the economic and technical dependency on a certain material, as well as the probability of supply disruptions, for a defined stakeholder group within a certain time frame" and tend to plot materials on a 'criticality matrix' where the risk of disruption in supply is plotted against the impact of that disruption (Schrijvers et al. 2020; Brown 2018). Such visualizations serve as an "early-warning" device and advise policymakers on priorities for basic research and development in material substitutes, processing, exploration, recycling, and more (Gunn 2014; Graedel et al. 2015; McCullough and Nassar 2017).

Criticality studies have usually been commissioned by institutions in large developed countries and each has its own methods (Speirs, Houari, and Gross 2013). Examples include National Research Council (2008) and Department of Energy (2011) in the United States; and Resnick Institute (2011) and European Commission (2010) in the European Union, although there are more "international" perspectives, like UNCTAD (2020) on lithium-ion batteries.

ETM criticality assessments are also published in peer-reviewed journals. As opposed to government reports, peer-reviewed criticality assessments often: 1. Expand the geographical focus, 2. Compare results between assessments, and 3. Evaluate the suitability of different methodologies. These include Erdmann and Graedel (2011), Achzet et al. (2013), Dewulf et al. (2016), Brown (2018), Glöser et al. (2015), Zhang, Kleit, and Nieto (2017), and Nuss et al. (2014).

Measuring concentration

Although the methods behind criticality studies are diverse, there are some unifying themes. For instance, criticality assessments assume that high production concentration increases the risk of supply disruption for importers. The rationale is that exporter market power and competition for access between importers may cause prices to rise or become more volatile, making investments and future planning costly (De Groot et al. 2012).

Concentration is also a focus of this dissertation chapter. However, as opposed to criticality studies, we use export quantity instead of production, because that is what is possible with our data. Observe as well that we take the opposite (exporter) perspective because we are interested in finding product characteristics that are beneficial for major exporters. We assume that a high exporter concentration translates to greater market power allowing for exporters to set terms of trade, as per standard trade theory (although to capture benefits, this must be coupled with stable growth in export value, which we discuss further in the Methods section).

Based on a methodological review for all markets by Acar and Bhatnagar (2003), Brown (2018) applies and compares seven concentration metrics by decades over the past century in five materials (fluorspar, lithium, coal, copper, and nickel). The aim is to understand what concentration metrics researchers on should use.

Brown (2018)'s central argument is that "simple" metrics compared over decades should be the best practice in criticality assessments. We also apply simple metrics here. Metrics tend to communicate more information than other more sophisticated concentration metrics calculated at only one point in time, as is often practiced in criticality assessments. Brown's results are summarized in detail in Table 4.1.

Table 4.1. Summary and comparison of concentration metrics used in criticality studies and evaluated in Brown (2018).

Index	Metric and reference	Description	Brown (2018) discussion	Calculated
1	Number of producers	The number of existing producers	**Does not consider** the size of producers relative to the total amount produced.	Calculated for the HHI, but not discussed
2	Percentage of the dominant producer	Percentage of the dominant producer	**Can only communicate** information on the largest producer.	Calculated and displayed, but only for the exporter analysis
3	Concentration ratio	Sums the market share (percentage of total) of the top producers	**Naturally closer to 100% when there are fewer producers**. Increasing the number of producers included in the calculation will result in higher percentages so the selection of how many is particularly important. Brown (2018) finds it is similar to the HHI (see next line).	Calculated and displayed, but only for the exporter analysis
4	Hirschman-Herfindahl Index (HHI) based on Hirschman (1945) and (Herfindahl 1951)	Sums the square of the market share of each market player.	**Fully discussed in the Methods section**. It is sensitive to the number of producers, and the result should be compared to the minimum possible for the number of players in the market. Monopolistic=0.25; Less concentrated=lower, minimum depends.	Calculated as a measure of concentration
5	Normalized Hirschman - Herfindahl Index (HHI*)	Normalizes the HHI to the number of players.	**Does not adequately capture changes** in the number of producers. Where the number of producers changes over time, there is a clear disadvantage to using HHI*. Monopolistic=1; Complete competition=0.	No
6	Kwoka's Dominance Index (Kwoka 1977)	Sum of the squares of market share differences when producers are ranked by size.	Measures 'inequality' in the size of companies within a market. **Like HHI, it is sensitive to the number of producers**, and the result should be compared to the minimum possible for the number of players in the market. High inequality=1; equality=lower	No
7	Entropy measure of diversification	Sum of the multiplication of the market share of each producer by the logarithm of that market share, multiplied by negative one	Compared to the rest, **measures diversity, not concentration**. Like HHI, it is sensitive to the number of producers, and the result should be compared to the maximum possible for the number of players in the market. High diversity=maximum; low diversity=0.	No

Source: Author's elaboration based on Brown (2018).

As noted in the right-most column of Table 4.1, we calculate and/or discuss Indices 1-3 in this chapter, but outside the context of concentration. For the purposes of concentration, we use the most popular concentration metric, the un-normalized Herfindahl-Hirshmann index (HHI) (Index 4 in Table 4.1). It is less specialized than Kwoka's Dominance Index and the Entropy Measure of Diversification (Indices 6 and 7 in Table 4.1). The HHI also captures more information than, and has a high correlation to, the Concentration Ratio that Brown (2018) endorses (Index 3 in Table 4.1).

The ETM literature widely uses the HHI in criticality reports. As examples, see European Commission (2010, 2014), and Habib, Hamelin, and Wenzel (2016), who map primary ferrous, non-ferrous, precious, and specialty metals production in 1994 and 2013, finding a shift from developed economies to developing economies over this time period. We fully explain the application of the HHI in the Methods section of this chapter.

4.2.2 Resource/reserve assessments and market models

Another complementary ETM research stream deals with the availability and distribution of physical availability (resources), commercially viable resources (reserves), and production.

The Energy Transition Institute (2017) and Gruber et al. (2011) are examples of the large literature on resource assessments comparing estimates of future demand with the physical availability of ETMs.

As opposed to resource assessments, reserve assessments consider economic variables like production ability and recyclability. Examples of reserve assessments in the ETM space include Speirs et al. (2014) and Olivetti et al. (2017). Conclusions vary, Reuter et al. (2014) and Weil et al. (2018) conclude that lithium and/or cobalt markets could face supply constraints, but find these alleviated under time-varying assumptions of technology innovation in materials recycling or the development of substitute technologies. Others, like Narins (2017) take a more nuanced approach, pointing to the importance of the quality, not the quantity of metals, deeming there is the possibility of short, if not long-term, supply disruptions.

World Bank (2017) calculates the material demand expected to achieve the 2 degree, 4 degree, and 6 degree global warming targets for many technologies. Amongst other analyses, World Bank (2020) presents the results of an estimation of global demand growth to 2050 by ETM, according to the IEA Sustainable Development Scenario (SDS), with at least a 50% chance of limiting the average global temperature increase to 2°C by 2100. The difference between World Bank (2017) and World Bank (2020) and many other assessments that attempt to predict demand (e.g. Watari et al. (2019)) is that like us they consider the role that all world regions will play in supplying materials for all renewable energy technologies.

Note that while resource, reserve, and demand assessments may aid in short-term public and private sector planning, the economics literature on exhaustible resources has successfully posited in theory and subsequent empirical analysis that demand and supply do not exist independently of each other. In a study of mineral imbalances over the last 100 years, Renner and Wellmer (2019) find that “short-term market imbalances are generally neutralized by a dynamic reaction on the demand side via substitution, efficiency gains or technological change.”

Along these lines, some studies have estimated the future demand and supply of ETMs dynamically. Methods include spatial-temporal multi-product allocation, partial equilibrium models, and agent-based models. For instance, Zhang, Kleit, and Nieto (2017) present a bottom-up analysis of rare earth flows using agent-based modeling, which features interacting but autonomous agents in complex systems.

Other relevant work includes Labys and Yang (1991), Macal and Hill (1985), and Andriamasinoro and Angel (2012). These empirical and focused assessments show that while geopolitical supply risk should attract some concern from specific governments and industries, globally and in the long run, price signals and technological advances often circumvent physical shortages.

This result does not necessarily undermine criticality assessments, but highlights their role in "early-warning" screening (McCullough and Nassar 2017). Indeed, Solow (1974) notes that exhaustible resource pricing, demand, and supply depend on the "ease with which other factors of production […] can be substituted for exhaustible resources in production". And, while technological innovation is notoriously hard to predict, moments of acute prices can spur innovation within firms, in a process called "induced innovation" where "a change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind—directed to economizing the use of a factor which has become relatively expensive" Hicks (1932). Therefore, an example of endogeneity between innovation and perceived (or real) bottlenecks are the very efforts by developed countries to identify and substitute away from the materials that are most "critical."

Long-term evidence for induced innovation in the broader energy sector exists too. Fouquet (2015) uses 500 years of data for non-renewable energy resource use in the United Kingdom and finds that innovation, due to price increases, appears as the ultimate non-exhaustible resource. Popp (2002)'s seminal paper finds a strong and positive impact of energy prices on innovation.

Overall, while criticality, resources, reserves, and forecasting studies have contributed to an understanding of dynamics behind several ETM markets and actions that can help prepare supply chains for short-term disruptions, there is evidence that market forces tend to lead to innovation and bypass long-term shortages (Renner and Wellmer 2019). Our work contributes to our understanding of what countries are poised to benefit from energy decarbonization by assuming this endogeneity and focusing instead on relative benefits across different geographies from trade trends in ETMs in general and groups of ETMs (with a particular focus on CEMs vs TEMs and Ocs versus MCs) between 1998-2018.

4.2.3 Resource governance

Governance, defined as "the traditions and institutions by which authority in a country is exercised […including] the capacity of the government to effectively formulate and implement sound policies" (World Bank 2021b) is central to and imbedded in ETM criticality literature. That literature infers that countries with low governance can generate supply shocks in importer countries (Bazilian 2018). Vulnerability to supply shocks leads Ali et al. (2017) to suggest a need for "environmental diplomacy" and a "planetary policy for metals."

Renner and Wellmer (2019) question the “seller’s market” narrative. They find that “neither high country concentration nor poor governance seem to have a substantial or lasting impact on market balance” except in some contained examples with limited market impacts. They even find a “tendency of diminishing volatility with increasing country concentration.”

Instead, they posit that demand-side volatility has had noxious effects on exporters themselves. Demand-side price volatility interacts with the infamous Dutch Disease (in which, amongst other effects, real exchange appreciation from resource exporters weaken the country’s export competitiveness and industrial sectors) (Frankel 2012). Therefore, the importance of effective ETM governance can: (1) be framed around the benefits it provides to exporters; and, (2) links to the larger literature on governance in resource-rich countries.

Common policy suggestions include export diversification and turning mining (unrefined products, Ocs) into manufacturing (including refined products, MCs). However, challenges include a lack of skilled labor and technological gaps, in addition to the macroeconomic challenges discussed above (Frankel 2012; Renner and Wellmer 2019). Other options include establishing a local industry around the extractive sector and using it for skilled knowledge development and an expansion of services (Renner and Wellmer 2019).

Renner and Wellmer (2019) make a distinction between minor metals (e.g., gallium, which may occur alone or coupled with others) and coupled elements (e.g. rare earth elements and platinum group metals that occur together in deposits), on the one hand, with major metals (e.g. copper, lead, zinc, and tin) on the other. In the case of minor and coupled elements, volatility and technological change may fail to translate into long-term demand, and fiscal returns from export taxes and royalties may be the extent of resource benefits to exporters.

Despite the issues that the burgeoning ETM literature has already touched upon, there is (yet) no study that attempts to answer questions on the changing characteristics of growth, volatility, and importer and exporter concentration in trade value and volume across the technologies that will play a role in energy decarbonization using historical data between 1999-2008, identifying patterns over groups and products.

The relationship between governance and institutional capacity and the evolution of competitiveness and exports is a rich area of literature. While this study does not try to explain the drivers behind the trends, it lays the groundwork for future governance research by trying to explain the key patterns that may be linked and driven by various governance characteristics.

4.3 METHODS

Our methods consist of four parts. First, we refer to the existing ETM literature to select the most relevant energy technology materials according to pre-set requirements. Second, we match the key materials to the list of traded products (another non-trivial task). Third, we generate the product groups according to Classifications 1 and 2 introduced above. Fourth, we calculate the metrics for the analysis subject them to robustness checks with statistical tests.

4.3.1 Selecting relevant ETMs

The ETM literature covers a vast set of materials, and the selection of ETMs included in each study is a function of the subject of analysis (for instance US criticality assessments select the ETMs that are relevant to US industry). World Bank (2020) is our main source of eligible ETMs. This is because the publication considers a wide range of energy technologies, it has a global outlook, and it is timely.

While World Bank (2020) contains several analyses, the most relevant to us is an estimation of global production growth to 2050 by ETM, according to the IEA Sustainable Development Scenario (SDS), with at least a 50% chance of limiting the average global temperature increase to 2°C by 2100. Table 4.2 summarizes estimates for growth of demand in 2050 in comparison to 2018as well as the relevant energy technologies for each ETM.

To focus on the materials most likely to play a non-negligible role in the coming decades, we follow two criteria. Criterion 1: materials with an estimated non-negligible increase in annual demand, defined as at least 30%. Criterion 2: materials used in more than five technologies. Criteria 1 and 2 identify 13 materials located above the horizontal line in Table 4.2. The technologies in which the materials are found are marked in green.

These two criteria ensure that our sample is comprehensive (Criteria 1 alone leads to eight materials) while excluding materials with negligible changes and roles in energy decarbonization. If we were to increase the stringency of the criteria, for instance increase Criteria 1 to 50%, the results would not change drastically. In that case, we would exclude neodymium. This is a rare earth element that is included in the sample through another route, explained below.

Table 4.2. Materials analyzed in World Bank (2020), including their projected annual demand from energy technologies as a percent of 2018 annual production, the technologies in which materials are used, and whether they were selected (green) or not selected (grey).

Number	Materials	Estimated percentage change 2018-2050*	Count of technologies (excluding coal)	Wind	Solar PV	CSP	Hydro	Geothermal	Energy storage	Nuclear	Gas	CCS	Coal (excluded)
1	Graphite	494	1						✓				
2	Lithium	488	1						✓				
3	Cobalt	460	3						✓		✓	✓	✓
4	Indium	231	2		✓					✓			
5	Vanadium	189	3						✓	✓			✓
6	Nickel	99	8	✓	✓		✓	✓	✓	✓	✓	✓	✓
7	Silver	56	3		✓	✓				✓			
8	Neodymium	37	1	✓									
9	Lead	18	5	✓	✓		✓		✓	✓			
10	Molybdenum	11	7	✓	✓		✓	✓		✓	✓	✓	✓
11	Aluminum	9	5	✓	✓				✓	✓	✓		✓
12	Copper	7	9	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
13	Manganese	4	6	✓			✓	✓	✓		✓	✓	✓
14	Chromium	1	8	✓			✓	✓	✓	✓	✓	✓	✓
15	Titanium	0	5				✓	✓		✓	✓		✓
16	Iron**	1	2										
17	Zinc**		5	✓	✓		✓		✓	✓			

Source: Adapted from World Bank (2020) Tables 3.1 and B.2.
Note: *2050 projected production from energy technologies to achieve under 2DS*, % of 2018 annual production. ** Information for iron and zinc are incomplete in the source. CCS= carbon capture and storage.

We extend our ETM sample past World Bank (2020) in several important ways and identify a total of 17 materials, shown in Table 4.3. First, observe that the World Bank (2020) excludes some ETMs (like rare earth elements including dysprosium, cadmium, tellurium, selenium, gallium) covered in other publications such as National Research Council (2008) and Department of Energy (2011) based on the United States. We include these materials in our analysis because of the way trade data is aggregated, fully explained below.

Second, note from Table 4.2 that World Bank (2020) considers minerals that are crucial for the use of oil, gas, and coal technologies (including carbon capture and storage), but not fossil fuels themselves. Due to our research question on the different groups of ETMs, we include oil and gas in our analysis. We exclude coal for two reasons: (1) the IEA SDS shows a marked phase-out of coal in several regions in accordance with government policies, and this decline is larger than the decline of other fossil fuels; and, (2) in comparison to other materials in this section, coal tends to be consumed domestically and the SDS forecasts that trade will decrease even further due to large coal regions primarily in Asia, led by India and China, prioritizing internal demand (International Energy Agency (IEA) 2020d).

Last, we expand the materials used for oil and gas by considering platinum group metals (PGMs), which consist of platinum, palladium, rhodium, iridium, ruthenium, and osmium. While PGMs have a variety of uses today, half of their use is in catalytic converters for internal combustion engines. A smaller use of PGMs is as catalysts to create high-octane gasoline for cars from crude oil (Renner and Wellmer 2019). They also help improve the quality of hydrocarbons through processes like hydro processing and hydrocracking (Shaffer 2015). Throughout the text, we acknowledge and consider the fact that PGMs are also present in hydrogen fuel cells. Eventually they could become CEMs.

As the following sections will demonstrate, our ETM selection process makes it possible for us to explicitly compare trade trends between CEMs and TEMs across countries, as well as between refined and raw materials. In turn, it allows us to extract conclusions of short to medium-term impacts (or winners and losers) from the energy transition given historical trends as measured by key trade indicators.

Table 4.3. Final materials selection. Check=Sourced from World Bank (2020). X=Explained in the text.

Number	Materials	Sourced from World Bank (2020)
1	Graphite	✓
2	Lithium	✓
3	Cobalt	✓
4	Indium	✓
5	Vanadium	✓
6	Nickel	✓
7	Silver	✓
8	Neodymium	✓
9	Lead	✓
10	Molybdenum	✓
11	Aluminum	✓
12	Copper	✓
13	Manganese	✓
14	Rare earth elements	X
15	Oil	X
16	Gas	X
17	Platinum group metals	X

Source: Author's elaboration based on the methods described in this chapter and World Bank (2020).

4.3.2 Selecting trade products and generating product groups

Methods for selecting relevant trade data

As briefly discussed in the introduction, we define materials as descriptive categories that contain a range of physically traded products.

When materials are traded, national custom offices log and classify them according to several pre-established international and national product nomenclatures. The UN Statistics Division (UNSD) gathers and standardizes self-reported annual customs data from over 170 countries since 1995 using two international trade product nomenclatures: the Harmonized System (HS) and the Standard International Trade Classification (SITC) (UNSD 2020). In this study, we use the HS nomenclature because it provides a more disaggregated product differentiation for our materials compared to the SITC.

The HS nomenclature is updated every four to five years to keep up with technological and other changes. In addition to compiling yearly data, the UNSD also converts the data reported in the most recent nomenclature into each previous nomenclature. Therefore, the longest data series is reported in the first HS version, called "HS 1992." The agency then converts all data reported by customs offices into metric tons (quantity) and current US dollars (USD) using exchange rates from customs offices (value). The data is accessible to all through the United Nations International Trade Statistics Database, also called UN Comtrade.

Despite the invaluable information provided by UNSD, data reported by customs is not checked for errors. There are several discussions of the size and effects of such errors. The methods of the Terms of Trade indicators used in the Integration and Trade Department of the Inter-American Development Bank contain an in-depth review of trade data errors (Galeazzi 2015). Additionally, in UN Comtrade, import data is reported in CIF format (which includes cost, insurance, and freight), and export data is reported in FOB (free on board) format. Usually, the researcher chooses the data format most aligned with the research question (here, we would use FOB).

A second database, the Database for International Trade Analysis (BACI), published yearly by the Center for Prospective Studies and International Information (CEPII), reconciles importer and exporter declarations into freight on board (FOB) import values and weights the data by the reliability of its exporter (Gaulier and Zignago 2012), using differences between CIF and FOB to fix several issues in UN Comtrade data. Like UNSD, BACI provides the value of trade in thousands of current USD and the quantity in metric tons. Their longest nomenclature version is HS 1992, and the latest 2020 dataset ranges from 1995-2018. We, therefore, employ BACI as the direct data source.

BACI's dataset contains more than 1.5 million observations that reflect more than five thousand products, over more than 150 countries and more than 20 years. Selecting the relevant trade products for our study requires an explanation of the available typologies in the HS product classification system and a systematic identification of relevant product groups, described next.

The HS uses six digits to classify traded products. As an example, HS code 282520 refers to lithium oxide and hydroxide. While developed countries tend to disaggregate products into eight (and even 10) digits, data beyond six-digit HS codes is not comparable across countries. It becomes necessary to use only one country's data at a time or else harmonize across the developed countries that report data at that level, which would restrict the data only to developed countries. To the extent that we wish to define varieties as importers from a world demand, this option is not useful to us.

From left to right, each two-digit pair classifies a good in increased detail. In our running example for lithium hydroxide and oxide, the first two digits (also referred to as a *chapter*), 28, indicate "inorganic chemicals; organic and inorganic compounds of precious metals; of rare earth metals, of radio-active elements and of isotopes." Chapters themselves are aggregated into the broadest possible product categories, *sections*. There 21 sections, ranging from Live Animals (Section 1) to Works of Art and Antiques (Section 21).

To narrow the scope of analysis, we first identify HS sections that correspond to our materials. These are: (1) mineral products; (2) chemicals or allied industries; (3) precious or semiprecious stones and metals; and, (4) base metals. Sections relevant to our analysis are summarized in Table 4.4. Table 4.4 also includes their chapters.

Table 4.4. HS Sections and chapters containing the materials we identified in the literature.

HS Section	Section summary	HS Chapter	Section summary
5	Mineral products	25	Salt; sulfur; earths and stone; plastering materials, lime and cement
		26	Ores, slag and ash
		27	Mineral fuels (oil, gas), mineral oils and products of their distillation; bituminous substances; mineral waxes
6	Chemicals or allied industries	28	Inorganic chemicals; organic or inorganic compounds of precious metals, of rare-earth metals, of radioactive elements or of isotopes
14	Precious or Semiprecious Stones, Precious Metals	71	Natural or cultured pearls, precious or semi-precious stones (diamond, etc.), precious metals (silver, gold, platinum, palladium etc.), metals clad with precious metal, etc.
15	Base metals and articles of base metals	74	Copper and articles thereof
		75	Nickel and articles thereof
		76	Aluminum and articles thereof
		78	Lead and articles thereof
		72-83	Rest of base metals, incl. iron and steel, zinc, tin, etc.; cermets and articles thereof

Sources: Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).

The four relevant sections contain a total of 18 HS chapters for further review. We use a UN Comtrade search functionality to identify products related to the materials in the ETM literature. The process allows us to break each HS chapter into its component products. For example, the next two digits in our running example, 25, indicate "hydrazine and hydroxylamine and their inorganic salts; other inorganic bases; other metal oxides, hydroxides and peroxides." The final two digits, 20, indicate "lithium oxide and hydroxide."

We identify 30 trade products that contain references to the materials chosen from Table 4.4. Table 4.5 summarizes their codes and descriptions.

As we described above, the more HS digits, the more specialized the product. However, the more specified the product, the fewer trade flows, and the less data available for the analysis. Therefore, we used the minimum level of aggregation to sufficiently define a product.

For example, 2709 is a 4-digit product that sufficiently defined "Crude oil" from others in its Chapter (27) of "Mineral products." However, it is necessary to use 6-digits, 282520, to identify lithium chemicals from the rest in its group. Overall, we have 19 four-digit HS and 11 six-digit HS products, placed in the top and bottom of Table 4.5, respectively.

Table 4.5. Selected UN Comtrade 4 and 6-digits products that correspond to materials identified in the literature.

Count	Chapter	HS Code	Harmonized System product description
1	25	2504	Graphite powders and flakes
2	26	2602	Manganese ores and concentrate
3		2603	Copper ores and concentrates
4		2604	Nickel ores and concentrates
5		2605	Cobalt ores and concentrate
6		2606	Aluminum ores and concentrate
7		2607	Lead ores and concentrate
8		2613	Molybdenum ores and concentrate
9		2615	Niobium, tantalum, vanadium, and zirconium ores and concentrates
10	27	2709	Crude oil
11		2711	Natural gas
12	28	2822	Cobalt chemical (oxide and hydroxide)
13		2846	Compounds, inorganic or organic, of rare-earth metals, of yttrium or of scandium, or of mixtures of these metals in unwrought, powder and waste and scrap form
14	74	7401	Copper matte
15	75	7501	Nickel matte
16	76	7601	Aluminum unwrought
17	78	7801	Lead unwrought
18	81	8105	Cobalt mattes and other intermediate products of cobalt metallurgy, unwrought cobalt, powders and waste and scrap
19		8112	Beryllium, chromium, germanium, vanadium, gallium, hafnium, indium, niobium (columbium), rhenium and thallium metals; unwrought, waste and scrap, other than unwrought, including not elsewhere specified
20	26	261610	Silver ores and concentrates
21		261690	Rhodium, platinum and palladium (platinum group metals, PGM) ores and concentrates, and other precious metals
22	28	280530	Earth-metals, rare and scandium and yttrium, whether or not intermixed or interalloyed
23		282520	Lithium chemicals (oxide and hydroxide)
24		282530	Vanadium oxides and hydroxides
25		283691	Lithium chemicals (carbonate)
26	71	710691	Silver unwrought
27		711011 and 711019	Platinum unwrought, powder and semi-manufactured
28		711021 and 711029	Palladium unwrought, powder and semi-manufactured
29		711031 and 711039	Rhodium unwrought, powder and semi-manufactured
30	81	810291	Molybdenum unwrought, waste and scrap

Sources: Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).

It is crucial to note that, while the HS nomenclature is usually more detailed than the materials identified in the ETM literature, the typology is a model, or abstraction, of the physical product space. Because of this, the HS nomenclature sometimes fails to differentiate products into the materials we identified. In the example used in the previous paragraphs, HS 282520, contains two types of lithium chemicals, oxide and hydroxide. As a result, it is impossible to differentiate between these two products in trade data. In practice, this is usually not a major issue. Both types of lithium are precursors for materials in the same energy technologies (UNCTAD 2020).

As another example, while dysprosium and neodymium are sometimes referred to separately in the ETM literature, the HS nomenclature groups several rare earth elements together (see 2846 and 8112 in Table 4.5). Therefore, as mentioned previously, our analysis includes all rare earth elements, despite World Bank (2020) excluding some of them.

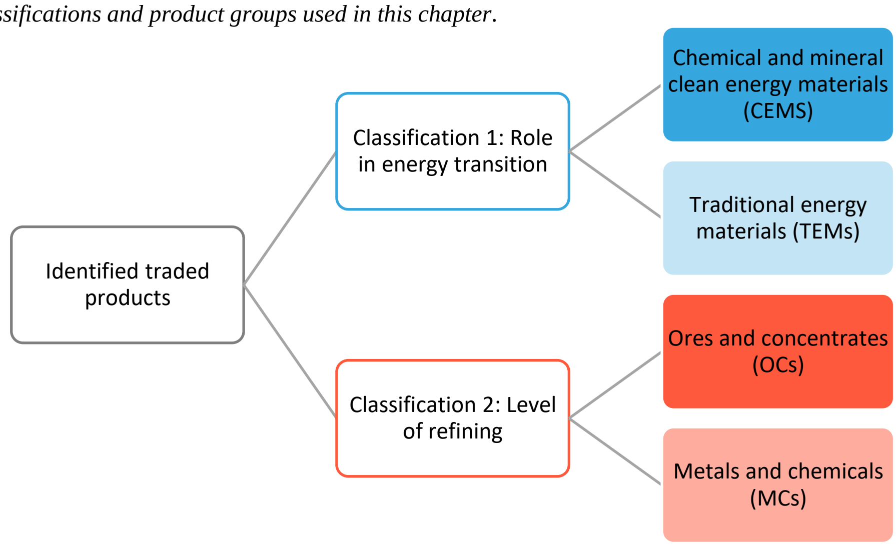
Last, some of the identified materials are so diverse that they exist in dozens of 4 to 6 digit HS products. This is the case for copper, nickel, aluminum, and lead. In fact, each of these has its own HS chapter, and includes several derivative products. To keep our analysis manageable and focused, we keep only mattes (an unrefined stage) and no other associated derivative products such as scraps and alloys of these metals.

Generating product groups

Apart from looking at trade trends overall and by individual products, we look at groups of products.

We first classify products according to their role in the energy transition (Classification 1): Chemical and Mineral Clean Energy Materials (CEMs) versus Traditional Energy Materials (TEMs). In Classification 2, we classify products according to their level of refinement: Ore and Concentrates (Ocs), versus refined Metals and Chemicals (MCs). This is summarized in Figure 4.1.

Figure 4.1. Classifications and product groups used in this chapter.



Source(s): Authors' elaboration based on the methods described in this chapter.

As we discussed in the Introduction and the Literature Review, we have not seen a division of the materials into unrefined versus refined products. This leads to a relevant clarifying question regarding Classification 2: Should MCs (like cobalt chemicals from China) theoretically display the same trends as their inputs (like unrefined cobalt from the Democratic Republic of the Congo)?

Consider that an increase in prices of raw materials may spur increased efficiency, recycling through induced innovation (discussed in the Literature Review), and stockpiling. This is especially true if the origin of a raw mineral is perceived to be an area of supply risk, like the Democratic Republic of the

Congo (Lee et al. 2020). Indeed, the perceived supply risks of ETMs that spurred the criticality literature have also materialized into efforts by governments and private firms to localize and vertically integrate suppliers. Such an effort includes, for instance, the U.S. *Federal Strategy to Ensure Secure and Reliable Supplies of Critical Minerals* "with the intention of progressing toward mineral independence" (Lee et al. 2020).

As a result, the relationship between Ocs and their respective MCs may not easily be summed through a simple linear correlation and can be studied separately. In the Discussion section, we acknowledge another potential issue with our scope. An analysis of each market (for instance, lithium carbonate and not lithium oxide/hydroxide) is relevant but beyond the scope and research questions posed in this chapter. Overall, the distinction between MCs and Ocs remains valid.

We refer to product descriptions in Table 4.5, from UN Comtrade, as the main source in the categorization of products, shown in Table 4.6, following the same colors as Figure 4.1. CEMs make up 80% of the products according to Classification 1. Ocs make up 40% of products according to Classification 2.

Table 4.6. Product, HS codes, and groups. Following the colors in Figure 4.1, Clean Energy Materials (CEMs) are blue, Traditional Energy Materials (TEMs) are light blue; Ores and concentrates (Ocs) are red, Metals and chemicals (MCs) are light red.

Count	Chapter	HS Code	Harmonized System product description	CEMs (1) or TEMs (2)	Ocs (1) or MCs (2)
1	25	2504	Graphite powders and flakes	1	2
2	26	2602	Manganese ores and concentrate	1	1
3		2603	Copper ores and concentrates	1	1
4		2604	Nickel ores and concentrates	1	1
5		2605	Cobalt ores and concentrate	1	1
6		2606	Aluminum ores and concentrate	1	1
7		2607	Lead ores and concentrate	1	1
8		2613	Molybdenum ores and concentrate	1	1
9		2615	Niobium, tantalum, vanadium, and zirconium ores and concentrates	1	1
10	27	2709	Crude oil	2	1
11		2711	Natural gas	2	1
12	28	2822	Cobalt chemical (oxide and hydroxide)	1	2
13		2846	Compounds, inorganic or organic, of rare-earth metals, of yttrium or of scandium, or of mixtures of these metals in unwrought, powder and waste and scrap form	1	2
14	74	7401	Copper matte	1	2
15	75	7501	Nickel matte	1	2
16	76	7601	Aluminum unwrought	1	2
17	78	7801	Lead unwrought	1	2
18	81	8105	Cobalt mattes and other intermediate products of cobalt metallurgy, unwrought cobalt, powders and waste and scrap	1	2
19		8112	Beryllium, chromium, germanium, vanadium, gallium, hafnium, indium, niobium (columbium), rhenium and	1	2

Count	Chapter	HS Code	Harmonized System product description	CEMs (1) or TEMs (2)	Ocs (1) or MCs (2)
			thallium metals; unwrought, waste and scrap, other than unwrought, including not elsewhere specified		
20	26	261610	Silver ores and concentrates	1	1
21		261690	Rhodium, platinum and palladium (platinum group metals, PGM) ores and concentrates, and other precious metals	2	1
22	28	280530	Earth-metals, rare and scandium and yttrium, whether or not intermixed or interalloyed	1	2
23		282520	Lithium chemicals (oxide and hydroxide)	1	2
24		282530	Vanadium oxides and hydroxides	1	2
25		283691	Lithium chemicals (carbonate)	1	2
26		710691	Silver unwrought	1	2
27	71	711011 and 711019	Platinum unwrought, powder and semi-manufactured	2	2
28		711021 and 711029	Palladium unwrought, powder and semi-manufactured	2	2
29		711031 and 711039	Rhodium unwrought, powder and semi-manufactured	2	2
30	81	810291	Molybdenum unwrought, waste and scrap	1	2

Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; Ocs=ores and concentrates; MCs=metals and chemicals.

4.3.3 Trade value growth and volatility

Exporters prefer for their exports to experience a growth in value over time and to expand the number of products that they export, with the promotion of exports being a key role for government departments and ministries in many countries around the world. For example, the UK Department for International Trade aims to "enable the UK to trade its way to prosperity […] by helping businesses export […] opening up markets, and championing free trade" (Department for International Trade 2018).

To capture the importance of growth in trade value , we average annual growth rates in value (the "average growth rate"). While annual growth is the most disaggregated time unit our data allows, it also allows us to capture longer-term trends instead of shorter-term cycles driven, for example, by seasonality or speculation (Renner and Wellmer 2019). We calculate the average of value growth rates separately over twenty years (1999-2018) and over two ten-year periods (1999-2008 and 2009-2018, Decade 1 and Decade 2, respectively).

The growth in export value is important regardless of the differences in prices across products. Note that although their prices tend to be lower, unrefined products can be more profitable on a per unit basis than refined products, depending on the cost of production by product and exporter.

Also note from our description of trade data above that *value* is defined as price times quantity. Therefore, the data already captures the endogeneity between prices and quantity that we discussed in the Literature Review. Additionally, trade literature tends to make a distinction between large and small players, where large (small) set (and accept) trade terms, respectively. We assume that the major exporters in our dataset have already affected the value of the products that were traded, and that this point does not affect their preference for growth in traded value.

There is a nuance to the notion that exporters prefer export value growth, however. For exporters to reap long-term benefits, export increases must be stable. Amongst other detrimental effects, if the increase in the value of exports is driven by volatile increases in prices, importers may invest in product recycling, efficiency, or alternative sources. Such changes can be irreversible and are detrimental to exporters (Habib et al. 2016; Renner and Wellmer 2019). The importance of keeping prices accessible and stable stands in direct contradiction to some high-profile policy decisions, such as the Democratic Republic of the Congo declaring cobalt a 'strategic' mineral and nearly tripling its royalties in 2018 (Reuters 2018).

We consider the advantage of stability to exporters by using a straightforward measure of volatility, the standard deviation (SD). The SD is defined as the square root of the average of the squared differences from the mean. Metrics using the mean and SD have already been used to study the volatility of ETM in McCullough and Nassar (2017), but have been applied to prices and not trade values.

We display the continuum of growth rates and volatility for all groups and products in graphs and tables in the main text and appendixes. We also focus on products that stand out in either metric, and especially on those that are high growth and low volatility. We focus on products that are among the top 20% (top quintile) products in either metric because the metric is broad enough to capture more than only potential outliers, but low enough to allow us to focus on top-performers. In the Discussion section, we focus on the products that stand out in the most recent decade and also discuss how this heuristic can affect our results.

Tests of statistical significance

In the analysis of trade value growth and volatility, we attempt to compare whether changes over groups or decades are statistically significantly different from one another. For this, we employ parametric and non-parametric paired and unpaired tests.

To compare the growth and volatility metrics over groups within the same Classification (for instance TEMs versus CEMs in Decade 1), we use two statistical tests for unmatched data. Specifically, we employ: (1) The Wilcoxon rank-sum test (often used as an alternative to the Student's t-test) and (2) the Nonparametric equality-of-medians test. Both tests are non-parametric inferential statistical methods, which means that amongst other characteristics, they do not assume anything about the underlying distribution of the data. This allows it to be applied to data that is not approximately normally distributed, or in small samples such as ours.

The two-sided Wilcoxon rank-sum test (also known as the Mann–Whitney two-sample statistic) tests whether two samples are likely to come from the same population using the following hypotheses:

H0: The two independent samples are from populations with the same distribution

H1: The two populations are not equal

Rejecting the H0 (when the p-value > 0.05) means that there is evidence the two populations have different distributions. If we obtain a p-value greater than 0.05 in this test, we can assume that there is a difference between the metrics of groups within a classification, for instance, a difference between growth rates of groups in Classification 1 (CEMs versus TEMs). We use the "ranksum" function in Stata (StataCorp 2021).

Tests that compare two groups that contain different items (as opposed to comparing the same items over time) have lower statistical power (StataCorp 2021). Therefore, we supplement the Wilcoxon rank-sum test with the Nonparametric equality-of-medians test. It tests the following hypotheses:

H0: The *k* number of samples were drawn from populations with the same median

H1: At least one sample was drawn from a population with a different median

In this case, rejecting the H0 (when the p-value > 0.05) implies that there is evidence the two populations have different medians. Like above, if we get a p-value greater than 0.05 in this test, we can assume that there is a difference between the metrics of groups within a classification, for instance, a difference in the volatility of growth rates of groups in Classification 2 (Ocs versus MCs). We use the "median" function in Stata (StataCorp 2021).

Over decades within the same group, we make a different comparison. Here, we compare items within the same groups over time, for instance lithium carbonate within CEMs in Decade 1 versus lithium carbonate within CEMs in Decade 2. This allows us to use a paired test. If differences between pairs are normally distributed, it is possible to use the paired Student's t-test on the equality of the means (a two-sample case of ANOVA), with the following hypotheses:

H0: The samples have equal means

H1: The samples have different means

Rejecting the H0 (when the p-value > 0.05) implies that there is evidence the two populations have different means, with the same implications as described for the previous two tests. We employ a Shapiro-Wilk test to confirm normality ("swilk" in Stata), and the "ttest" function (StataCorp 2021).

4.3.4 Export and import quantity concentration

Following the literature we reviewed, we calculate the popular un-normalized Herfindahl–Hirschman Index (HHI-index) over exporters and importers, by ETM. In the trade literature, this metric is akin to the un-normalized Export (Import) Market Concentration Index that is usually calculated over value (UNCTAD 2018a, 2018b). However, we align ourselves with the existing ETM literature that we reviewed in the discussion on concentration indices, which uses production. The closest equivalent of production in our data is quantity of traded product.

The HHI is calculated by summing the square of the market share of each market player (Eq. 4.1).

$$HHI = \sum_{i}^{N} s_i^2 \qquad \textit{Eq. 4.1}$$

Where s_i is the market share of exporter i, and N is the number of exporters or importers.

It is desirable to be a major exporter of an ETM within a highly concentrated export market. This can be evidenced in the fluctuation of price-setting power by countries in the Organization of the Petroleum Exporting Countries (OPEC) over time (Fattouh and Mahadeva 2013). It is also evidenced in a variety of policy documents that consider the share of exports of a certain country in a certain product (UK Department of Business Innovation and Skills 2012). The same exporter prefers the opposite when it comes to the importer concentration of the same product.

Observe from Eq. 4.1 that the HHI depends partly on the number of exporters. This can make comparisons of the same product over time, or other products, difficult (Brown 2018). There are two ways to solve this. First, the researcher can cap the number of exporters included in the calculation. The U.S. Department of Justice tops it at 50. Second, they can calculate the difference between the HHI and the HHI minimum given the number of exporters for the given period, (1/ number of exporters).

At a large N, as is the case with trade, the minimum HHI is very small and there should not be much of a difference between the two options. However, so as not to lose any information, we opt for the latter. We, therefore, report the HHI score minus the minimum possible for the HHI (Eq. 4.2).

$$HHI = \sum_{i}^{N} s_i^2 - \frac{1}{N} \qquad \textit{Eq. 4.2}$$

Where s_i is the market share of exporter i, and N is the number of exporters.

We calculate both the importer and exporter concentration of products over the entire time period and dynamically. We consider how the products overall have shifted, what products are best positioned, and what products have had beneficial changes over the last two decades.

As explained in Brown (2018) the United States Department of Justice (2010) considers a score of more than 0.25 as high concentration, between 0.15 and 0.25 as moderate concentration, and lower than 0.15 as low concentration. For ease of interpretation, these are the cut-offs we adopt.

Nevertheless, they are necessary heuristics used to simplify analyses and they may be relatively arbitrary at the margins. For instance, the UK Competition and Market Authority (CMA) uses slightly different cutoffs. Ideally, the HHI is best discussed in a continuum and complemented with a market-by-market understanding of each of the 30 products (Brown 2018).As we contemplate further in the Discussion section, is not possible to study each product in such depth due to the breadth of the products studied in this chapter.

4.3.5 Major exporters

We identify and discuss the main exporters of our selected products. To do so, we rank exporters in descending order by value of exporters during the 20-year period, by product. We then choose either the top five, or those that cumulatively make up 90% of all the traded value for the particular product, whichever criterion occurs first. Like we did for concentration, we plot the number of goods each exporter was a top exporter in during the *entire period* (e.g., Brazil exported an average of three of the 30 products during the entire sample), and also the *changes over decade* in the number of products the exporters were major exporters (e.g. Brazil exported two products in Decade 1 and four in Decade 2).

For each major exporter, we also determine the percentage of the overall ETM products in each group within Classifications 1 and 2 (MC versus OC and CEMs versus TEMs). After doing so, we ask whether developing/developed countries are more likely to play a role as major exporters in some product groups, as expected based on the wider product space (Behrens et al. 2007). For instance, we expect that developing countries are more likely to be major exporters of OC (unrefined) and not MC (refined) products.

4.3.6 Summary of metrics

Following the literature, we assume that exporters prefer to face high growth rates and low volatility for their products, as well as a concentrated market (by supply) and a dispersed market (by demand). We also assume that exporters prefer a change over time towards higher growth, lower volatility, higher export concentration, and lower importer concentration. Table 4.7 lists each metric and summarizes key characteristics discussed in this Methods section.

Table 4.7. Summary of assumptions and metrics used in the analysis of this chapter.

Item	Metric	Exporters prefer	Measured over	Measured using	Time period	Measured over
1	Growth rates	High	Value	Average of annual growth rates in time sample	1999-2018 1999-2008 2009-2018	Product groups and products
2	Volatility	Low	Value	Standard deviation of annual growth rates in time sample	1999-2018 1999-2008 2009-2018	Product groups and products
3	Importer concentration	Low	Quantity	HHI	1999-2018 and changes over decade	Products (product groups in Appendix 4.5)
4	Exporter concentration	High	Quantity	HHI	1999-2018 and changes over decade	Products (product groups in Appendix 4.5)
5	Identification of major exporters	NA	Value	Top five exporters, or those cumulatively make up 90% of all value for a particular product	1999-2018 and changes over decade	Products (product groups in Appendix 4.6)

Source(s): Authors' elaboration based on the methods described in this chapter.

We identify and discuss implications for the major exporters behind these products (Item 5). The Discussion section synthesizes the static and dynamic trends (overall, by product group, and by individual product) and it reflects on how trends may affect exporters.

4.4 DATA

As described in the Methods section, UN Comtrade reports yearly bilateral flows of exporters, importers, value in thousand USD, and quantity in metric tons, by HS product code. Therefore, our dataset is composed of a panel of country exporters between 1995 and 2018. However, UN Comtrade reports some exporters in groups (Table 4.8). Additionally, we aggregate that the Economic and Monetary Union of the European Union as one exporter because the bloc acts as one for trade purposes.

Table 4.8. Country groups in the trade dataset.

Country group	Countries in groups
Southern African Customs Union	Botswana, Lesotho, Namibia, South Africa and Swaziland
Belgium (irrelevant due to EU aggregation, see below)	Belgium and Luxembourg
France (irrelevant due to EU aggregation, see below)	France and Monaco
Switzerland	Switzerland and Lichtenstein
Taiwan	Not recognized by China, referred to as 'Asia, not elsewhere specified' in UN Comtrade
Economic and Monetary Union of the European Union (as of 2019)	Austria, Belgium, Bulgaria, Croatia, Republic of Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, and United Kingdom

Sources: Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).

From now on, we simplify the product description in HS Comtrade in figures: (1) ores and concentrates are denoted by "[OC];" (2) oxides and hydroxides are denoted by "[OH]," (3) unwrought metals are denoted by "[UW];" and, (4) powders and flakes are denoted by "[PF]." Additionally, we denote REE compounds by REE1, and denote alloys by REE2 (Table 4.9).

Table 4.9. UN Comtrade description and simplified labels.

UN Comtrade description	Simplified label
Ores and concentrates	OC
Oxides and hydroxides	OH
Unwrought metals	UW
Powders and flakes	PF
REE compounds	REE1
REE alloys	REE2

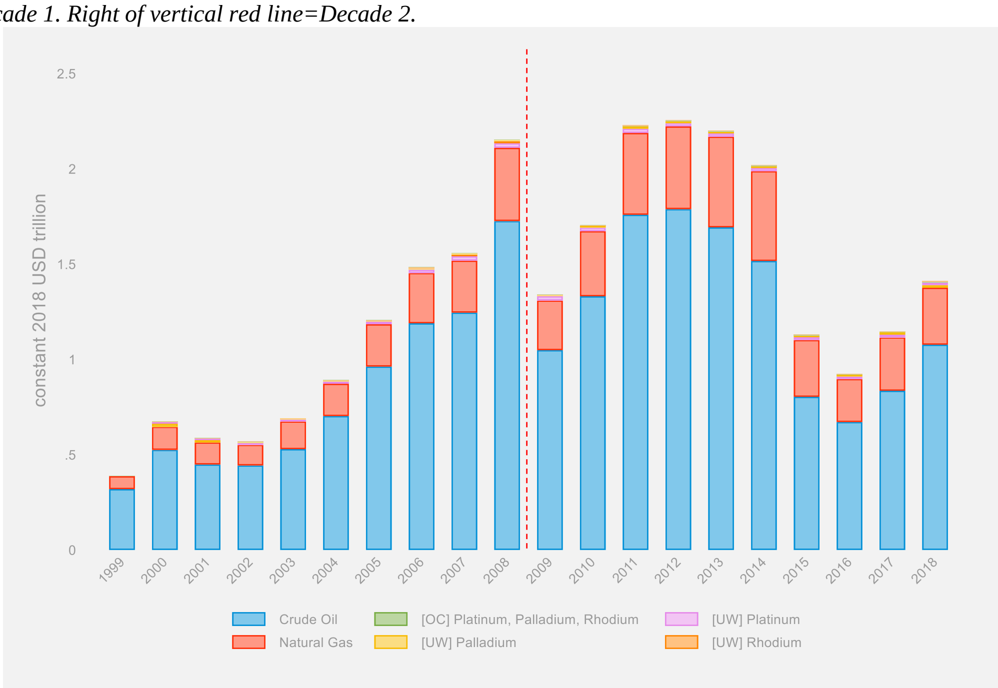
Sources: Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).

We deflate values to 2018 dollars using official US government statistics. The average trade value for the selected products is 120 million USD. The data for values has heavy tails and is highly positively skewed. In other words, the median is much lower than the average of 34 thousand USD, with a standard deviation of 1,460 million USD. The data for quantity displays the same pattern.

Figure 4.2 and Figure 4.3 show the value of TEMs and CEMs, respectively. Oil/gas dominate the aggregate trade value of our selected products and made up almost 90% of value in 2018.

World aggregate trade value for TEMs grew every year from 2001-2008, falling markedly after the 2008 financial crisis (Figure 4.2). From 2009-2012, TEMs experienced a period of growth and stabilization, reaching a 20-year peak in 2012. The aggregate values for TEMs decreased in the second half of 2014, hitting a nadir in 2016 due to the global collapse in commodity prices. A confluence of industry, macroeconomic, and financial conditions, including changing geopolitical risks and the U.S. dollar appreciation caused the commodity price collapse (World Bank 2015). Most recently, the aggregate value grew consistently from 2016-2018, approximating 2006 levels.

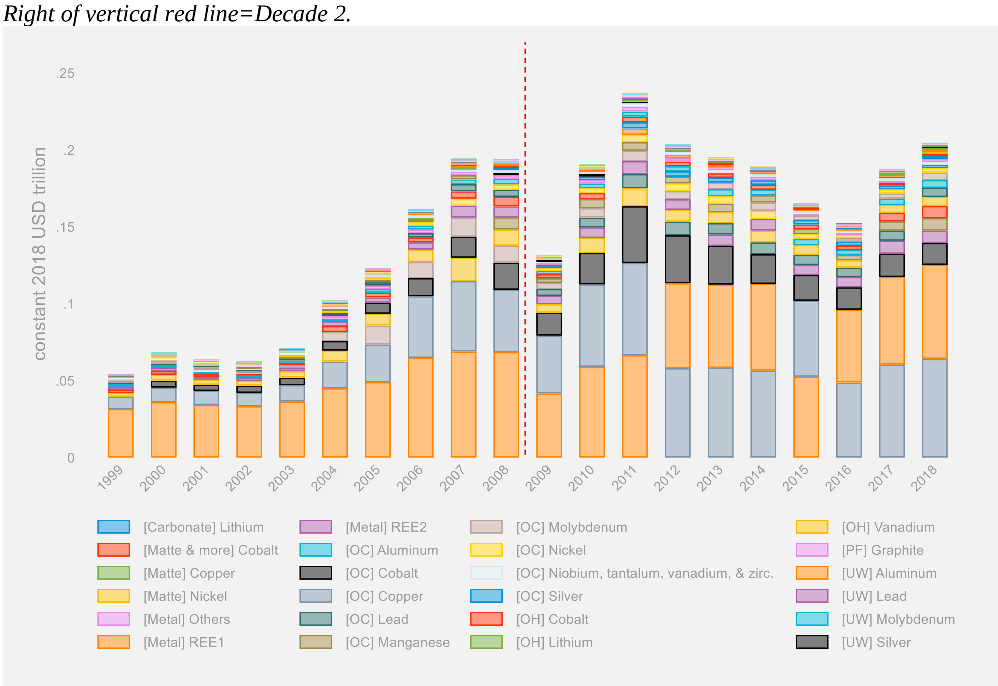
Figure 4.2. Traditional energy materials (TEMs), world trade value, 1999-2018, constant USD trillion. Left of vertical red line = Decade 1. Right of vertical red line=Decade 2.



Source: Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020)
Note: UW=Unwrought metals.

Trends over time are similar for CEMs, except that the group reached its 20-year peak in 2011 (Figure 4.3). Copper [OC] and aluminum [UW] make up the biggest share of this group but are small compared to TEMs because they correspond to 4.66% and 4.44% of oil/gas in 2018, respectively. In the interest of space, we do not repeat the figures by cutting the data into OCs and MCs.

Figure 4.3. Clean energy materials (CEM), world trade value, 1999-2018, constant USD trillion. Left of vertical red line = Decade 1. Right of vertical red line=Decade 2.



Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: REE= Rare Earth Elements; OC= Ores and concentrates; PF= powders and flakes; REE1=REE compounds; RE2=REE alloys; UW=Unwrought metals.

In both TEMs and CEMs, trade value mean and median grew over the decades of interest (Table 4.10). Volume decreased slightly in TEMs and increased in CEMs. The data is highly positively skewed, making a boxplot visualization of the metrics in Table 4.10 unwieldy. As an alternative, plotting logarithms and removing outliers yields very similar boxplots. Standard deviation (SD) increased in both groups over time. Appendix 4.1 contains the detailed statistics of the overall data, and summary statistics by product.

Table 4.10. Descriptive statistics, value (in constant USD million) and volume, by decade and groups.

TEMs	Decade	N	Mean	Std. Dev.	skewness	p5	Median	p95
Value	Decade 1	26,315	387.27	2,764.74	18.80	0.00	1.31	1,159.22
Volume		26,315	1,002,092.00	6,914,507.60	15.05	0.00	81.58	3,066,373.60
Value	Decade 2	32,469	502.88	3,384.97	17.32	0.00	1.64	1,468.71
Volume		32,469	953,914.31	8,816,579.20	54.21	0.00	41.18	2,829,437.30
CEMs	**Decade**	**N**	**Mean**	**Std.Dev.**	**skewness**	**p5**	**Median**	**p95**
Value	Decade 1	69,182	16.04	159.47	35.36	0.00	0.15	42.16
Volume		69,182	15,355.13	201,989.92	49.37	0.05	30.00	26,336.00
Value	Decade 2	85,274	22.21	191.21	27.23	0.00	0.19	65.09
Volume		85,274	26,890.01	594,645.36	58.02	0.03	31.08	28,578.41

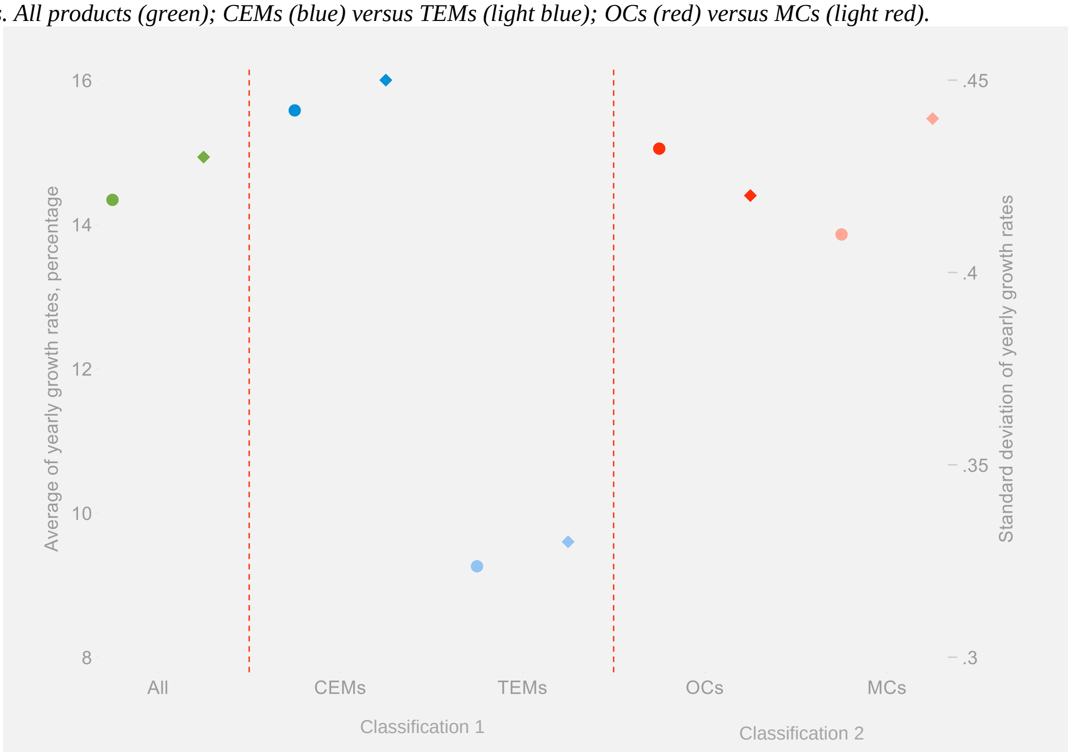
Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials.

4.5 RESULTS

4.5.1 Growth and volatility

Over the entire period of 1999-2018, the average growth rate for all products was 14.30%, and the standard deviation (or volatility) was 0.40. Figure 4.4 shows average growth rates in circles (left axis) and their volatility in diamonds (right axis). The average of yearly growth rates (which we call "average growth rates") were higher for CEMs (blue) than for TEMs (light blue) but CEMs were also more volatile. OCs (red) were best positioned than MCs (light red) in both metrics, with a higher average growth rate overall and a lower volatility. Appendix 4.2 contains the data at the product level.

Figure 4.4. Average of yearly growth rates (circles) and the volatility of yearly growth rates (diamonds, right axis), by product groups. All products (green); CEMs (blue) versus TEMs (light blue); OCs (red) versus MCs (light red).



Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals.

To compare whether the groups are statistically different from one another, we use the nonparametric equality-of-medians test and the Wilcoxon rank-sum test. We compare growth and volatility in the CEMs versus TEMs, and OCs versus MCs and use two tests for robustness. Using the conventional cut-off p-value of 0.05, we fail to reject the null hypothesis that the groups are the same as one another (Table 4.11) suggesting that the differences between groups seen in Table 4.11 may be due to chance.

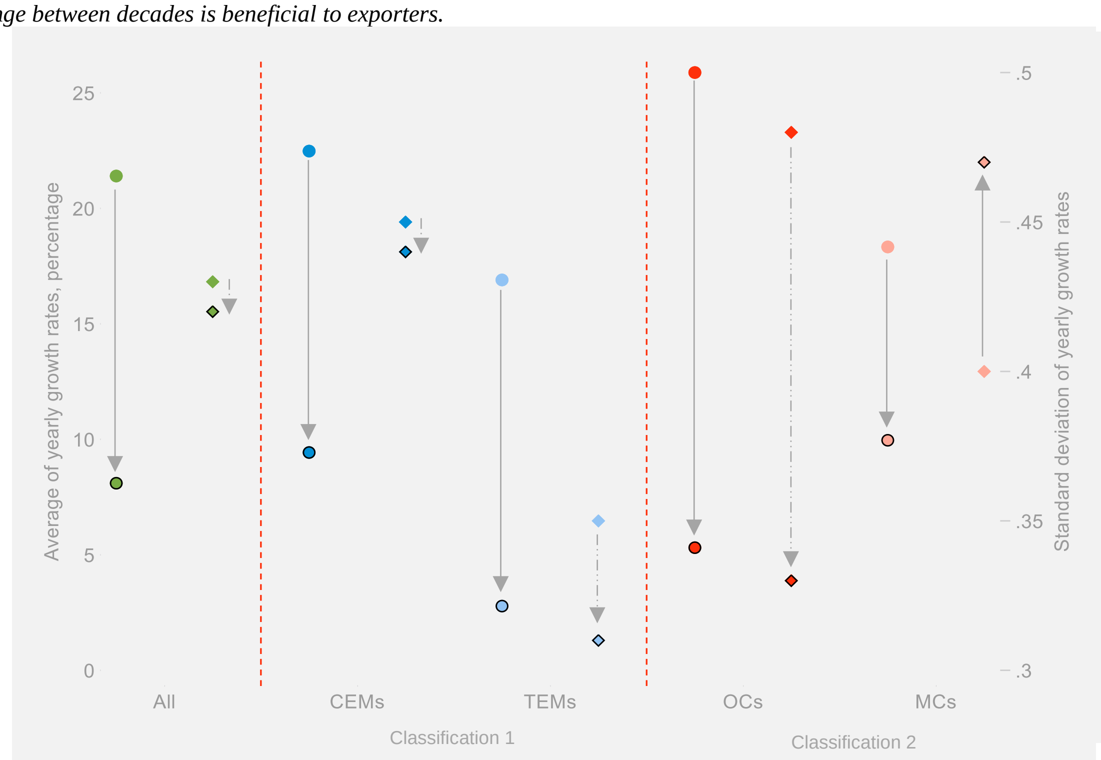
Table 4.11. P-values of nonparametric equality-of-medians test and Wilcoxon rank-sum test/Mann–Whitney two-sample statistic for the difference in growth rates and volatility of growth rates.

Group	Nonparametric equality-of-medians		Wilcoxon rank-sum test/Mann –Whitney two-sample statistic (exact p-value)	
	Growth	Volatility	Growth	Volatility
CEMs versus TEMs	0.539	0.648	0.442	0.210
OCs versus MCs	0.526	0.264	0.386	0.545

Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals.

We also compare the growth and volatility of each group over the two decades of our data. In Figure 4.5, Decade 2 is differentiated from Decade 1 with a black outline. Like before, circles represent average growth rates and diamonds (in the right axis) represent volatilities. Green represents all products, blues represent Classification 1, and reds represent Classification 2. Solid arrows depict a change over time that was detrimental to exporters, and dashed arrows depict a change over time that was beneficial to exporters. Appendix 4.3 contains the data behind the figure.

Figure 4.5. Average of yearly growth rates (circles) and volatility of yearly growth rates (diamonds, right axis), by product group and decade. All products (green); CEMs (blue) versus TEMs (light blue); OCs (red) versus MCs (light red). No outline= Decade 1. Black outline=Decade 2. Solid arrows = change between decades is detrimental to exporters. Dashed arrows = change between decades is beneficial to exporters.



Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals.

Within groups, all changes in the average growth changes over decade were detrimental to exporters. We run the same tests as above, which compared the average growth and volatility across groups, by decade. The results of unpaired tests within decades are the same as in Table 4.11. In other words, the differences in growth rates and volatility across groups are not statistically significantly different from one another in either decade (see Appendix 4.4).

We subject the detrimental changes over time to statistical analysis by comparing the average growth rates of Decade 1 with the same metric in Decade 2 (Table 4.12). A Shapiro-Wilk test shows the differences between paired averages by product are normally distributed, so we employ paired t-Tests. These t-Tests show that differences over time are statistically significant in all groups at a p-value of 0.10, and all groups except TEMs at a p-value of 0.05. In other words, in Decade 2 the products experience less growth than Decade 1, and this change is unlikely to be due to chance.

Table 4.12. Paired t-Tests comparing Decades 1 and 2.

Indicator	Overall	CEMs	TEMs	OCs	MCs
Average of growth rates	0.000	0.000	0.0973	0.000	0.031
SD of growth rates	0.818	0.718	0.257	0.128	0.240

Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals.

Admittedly, paired tests (comparing same item over time) are more powerful than unpaired tests (comparing different groups) (StataCorp 2021). Therefore, the difference in the statistical significance of the results of Table 4.11 and Table 4.12 could reflect the power of the tests themselves. We attempted to mitigate this by employing two tests for robustness when working with unpaired data.

The result of statistically lower growth in Decade 2 is visually supported in Figure 4.6, which displays all underlying data points. In Figure 4.6, CEMs are in green, TEMs are in red. OCs are marked in crosses, and MCs are marked in x's. Figure 4.6 shows that in Decade 2, no selected products surpass an average growth rate of 30%. It also shows that there is a positive relationship between growth rates and volatility. Therefore, products with high growth and low volatility would be positive anomalies for exporters.

Figure 4.6. Average yearly growth (x axis), volatility of average yearly growth rates (y axis), Decade 1 (left); Decade 2 (right) Red = TEMs, Green=CEMS; + markers = OCs; X markers=MCs.

Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals; OC= Ores and concentrates; PF= powders and flakes; REE1=REE compounds; RE2=REE alloys; UW=Unwrought metals.

Table 4.13 lists the top 20% products in terms of growth and volatility, by decade, which can be visually verified in Figure 4.6. Note that there is no overlap between the top growers in Decades 1 and 2. All the top growers within Decade 1 lose their position to REE2 [Metal], vanadium [OH], cobalt [OH], lithium [OH], lithium [carbonate] and REE1 [Metal]. This change coincides with the adoption of smartphones (and the materials found in the lithium-ion battery found therein) in developed countries in 2007-08 (Gündüç 2019). Additionally, while in Decade 1, all high-growth products except for nickel [OC] were also highly volatile (Figure 4.6, left), lithium products stand out as top growers that are not in the top 20% by volatility in Decade 2.

Observe also that in Decade 2, TEMs played a smaller role as high-growth products (overall and by decade) than they do in the overall sample (0 versus 20%). OCs played a larger role within high-growth products than within the product sample in Decade 1 (66.67 versus 40%), but this fell to zero in Decade 2. Within high-growth products, CEMs and MCs are the winners of Decade 2.

This result suggests that there has been a measurable change in trends of top growing materials traded over the past decades, and energy decarbonization may play a role. Given the direction of change in energy technologies and the materials used in them, energy decarbonization may reinforce these trends in the coming years. Additionally, if our upcoming exporter analysis supports the literature in that developing countries tend to export more TEMs and OCs, then this first result may help strengthen the rationale for targeted policy consideration to help balance industry towards CEMs and MCs.

Table 4.13. Top growth (green check) and top volatility (red X) products, in Decades 1 and 2. Ordered by growth in each decade. CEMs are blue, TEMs are dark blue; OCs are red, MCs are light red.

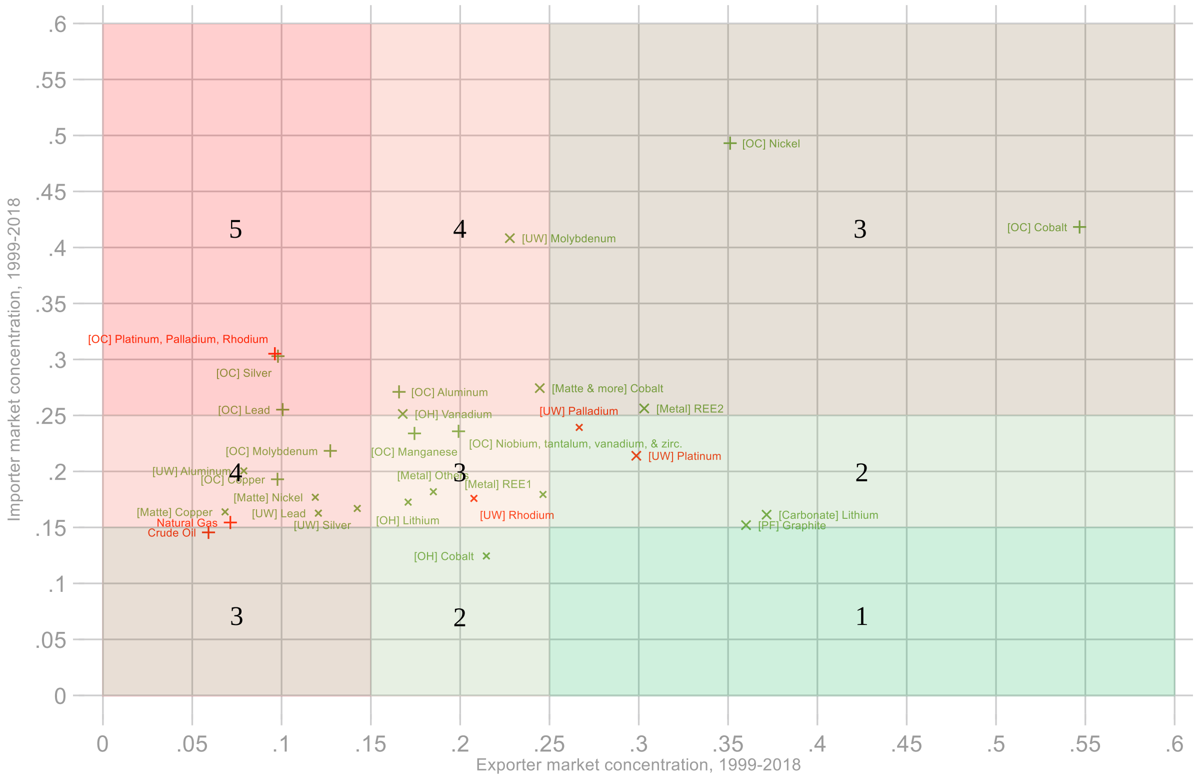
				Decade 1		Decade 2	
		Classification 1	Classification 2	High growth	High volatility	High growth	High volatility
1	Molybdenum [OC]	CEM	OC	✓	X		
2	Cobalt [OC]	CEM	OC	✓	X		
3	Molybdenum [UW]	CEM	MC	✓	X		
4	Manganese [OC]	CEM	OC	✓	X		
5	Copper [Matte]	CEM	MC	✓	X		
6	Nickel [OC]	CEM	OC	✓			
7	REE2 [Metal]	CEM	MC			✓	X
8	Vanadium [OH]	CEM	MC			✓	X
9	Lithium [OH]	CEM	MC			✓	
10	Cobalt [OH]	CEM	MC			✓	X
11	Lithium [Carbonate]	CEM	MC			✓	
12	REE1 [Metal]	CEM	MC			✓	X
13	Rhodium [UW]	CEM	MC		X		X

Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals; UW=Unwrought metals.

4.5.2 Importer and exporter concentration

Figure 4.7 shows the results of the import and exporter HHI metrics. Area 1, in green, contains the most favorable metrics for exporters because it represents high exporter market concentration and low importer market concentration. Higher numbers indicate worsening conditions for exporters with area 5, in red, being the most unfavorable.

Figure 4.7. Exporter and importer concentration (HHI), by product, 1999-2018; Red = TEMs, Green=CEMS; + markers = OCs; X markers=MCs.



Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals; OC= Ores and concentrates; PF= powders and flakes; REE1=REE compounds; RE2=REE alloys; UW=Unwrought metals.

Figure 4.7 shows that exporter HHI is more spread out than importer HHI, and that importer HHI is relatively more concentrated, opposite to the interests of exporters. In fact, 28 products are either concentrated or highly concentrated by importers, compared to 18 by exporters (see the Methods section for a discussion on the cutoffs for concentration that we chose. Additionally, there are no products in the first-best combination (Area 1) for exporters, and there are products in the worst possible combination for exporters (Area 5).

The products in Area 2 (the second-best section) are palladium [UW], platinum [UW], lithium [carbonate], graphite [PF], and cobalt [OH]. Of these, lithium [carbonate] and cobalt [OH] were within the top 20% growers in Decade 2 of the growth and volatility analysis. Appendix 4.5 contains the results by groups.

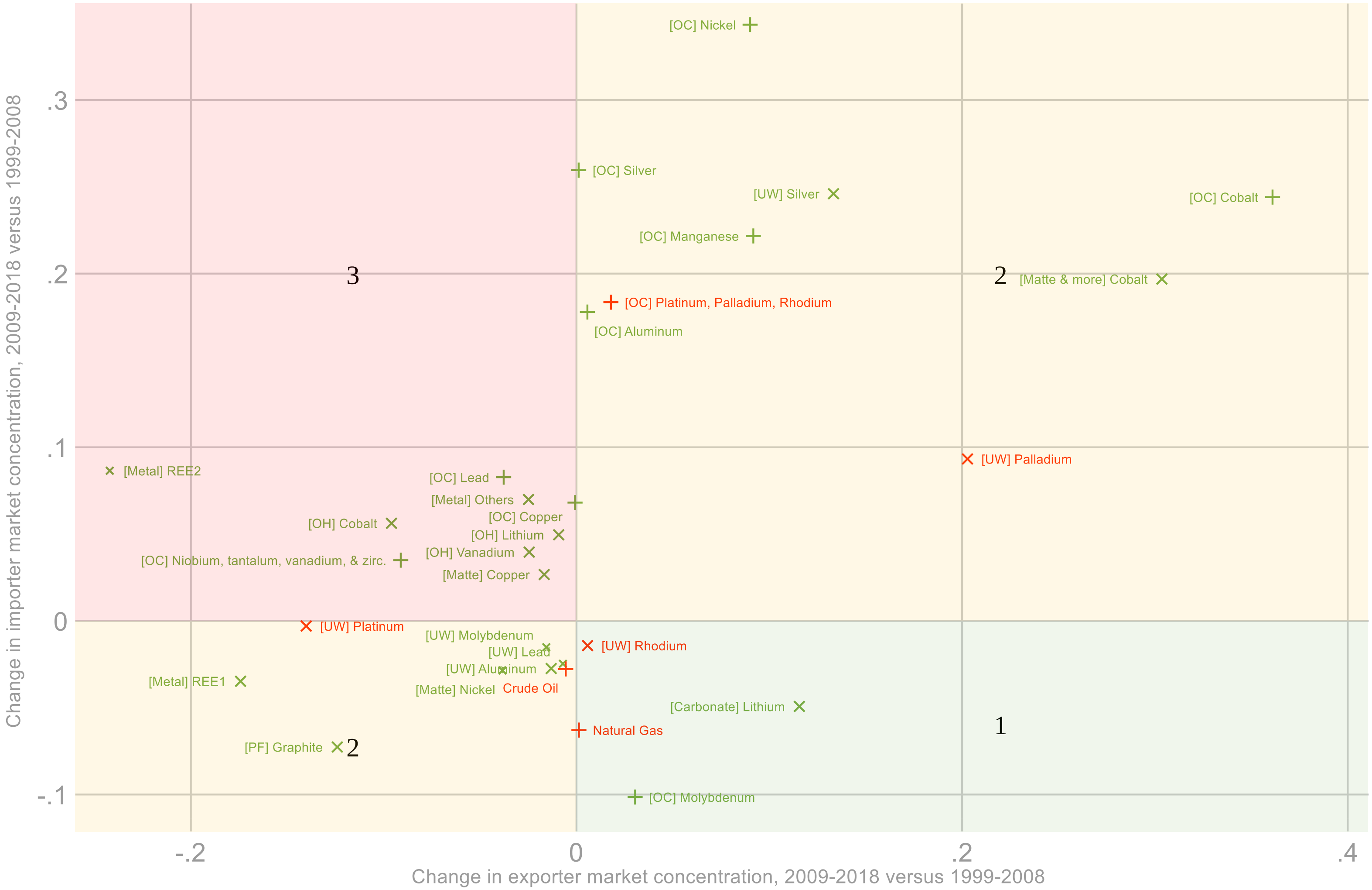
We turn to a dynamic analysis of changes in the HHI in quantity traded between Decades 1 and 2 in Figure 4.7. The horizontal axis of Figure 4.8 shows the change in exporter concentration, Decade 2 minus Decade 1. A positive value on the x-axis means that exporter concentration in the second decade grew in comparison to the first decade. Likewise, the vertical axis shows the change in importer concentration. Hence, a positive value on the y-axis means that importer concentration in the second decade is higher than in the first decade.

Like before, colors help us understand the results. Favorable conditions for exporters are found in Area 1 (green), representing increasing exporter market concentration and decreasing importer market concentration. The opposite is true for products in the top left quadrant (red, Area 3).

The products are disproportionately found to the left of the y-axis (17 versus 13), suggesting an overall decrease in exporter concentration, which is detrimental to exporters. Products are also disproportionately found on the top quadrants (18 versus 12), suggesting an increase in importer concentration, also detrimental to exporters. The top quadrants each share 9 products, more than each of the bottom two quadrants.

On top of being highly concentrated by exporters, and relatively unconcentrated by importers in the static analysis, the changes in concentration over the last two decades have been beneficial to exporters of lithium [carbonate]. Molybdenum [OC], natural gas, and rhodium [UW] have also benefited from changes in importer and exporter concentration in these decades.

Figure 4.8. Change in market concentration by exporter (x-axis), importer (y-axis), Decade 2 minus Decade 1. CEMs are in green, TEMs are in red. OC markers are crosses, and MC markers are x's. The colors of quadrants represent the preference for exporters. Green indicates an increase in the export concentration and a decrease in the import concentration. The opposite happens on the red quadrant.



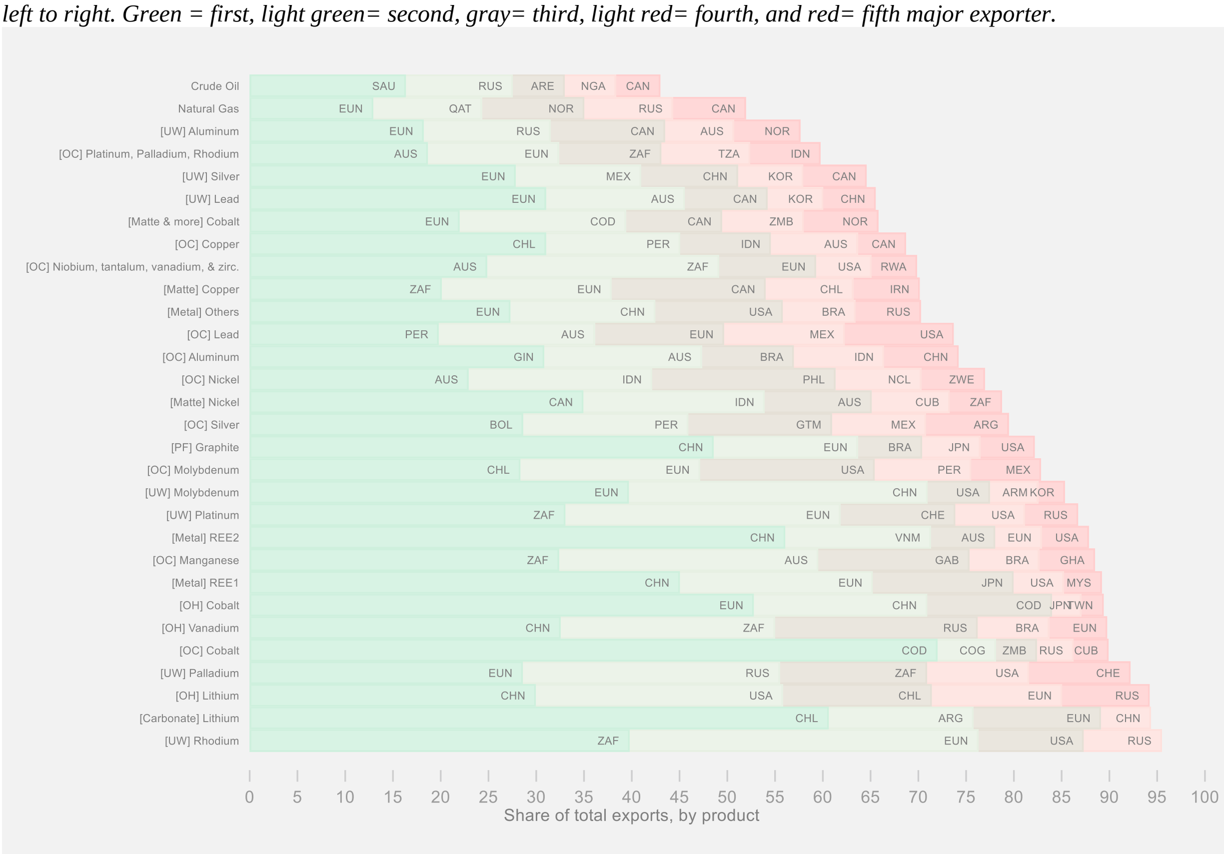
Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals; OC= Ores and concentrates; PF= powders and flakes; REE1=REE compounds; RE2=REE alloys; UW=Unwrought metals.

4.5.3 Major exporters over time and over product groups

To pinpoint major exporters of each product, we rank exporters in descending order by export value during the 20-year period, by product. We then choose the top five, or those that cumulatively make up 90% of all value for the particular product, whichever criterion occurs first. Figure 4.9 summarizes the top exporters per product, and individual market shares.

There are 40 major exporters for the 30 selected products. It is worth noting that some developing countries have a big share of exports in several products, for instance, note the Republic of the Congo and the Democratic Republic of the Congo's position in cobalt [OC], Bolivia's position in lead [OC] and silver [OC], or Guinea's position in aluminum [OC]. In all products except crude oil, the top five exporters made up more than 50% of the total world traded value for the product. Although we do not employ it for this purpose in this paper, Figure 4.9 could also be used as an alternative to the HHI as a measure of concentration because it is the equivalent of the Concentration Ratio recommended in Brown (2018) that we discussed in the Literature Review.

Figure 4.9. Major exporters by product 1999-2018. Exporters are ordered in descending order of exporter size in the market, left to right. Green = first, light green= second, gray= third, light red= fourth, and red= fifth major exporter.



Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: ARE, United Arab Emirates; ARG, Argentina; ARM, Armenia; AUS, Australia; BOL, Bolivia; BRA, Brazil; CAN, Canada; CHE, Switzerland; CHL, Chile; CHN, China; COD, Democratic Republic of the Congo; COG, Republic of the Congo; CUB, Cuba; EUN, European Union; GAB, Gabon; GHA, Ghana; GIN, Guinea; GTM, Guatemala; IDN, Indonesia; IRN, Iran; JPN, Japan; KOR, Korea; MEX, Mexico; MYS, Malaysia; NCL, New Caledonia; NGA, Nigeria; NOR, Norway; PER, Peru; PHL, Philippines; QAT, Qatar; RUS, Russia; RWA, Rwanda; SAU, Saudi Arabia; TWN, Taiwan; TZA, Tanzania; USA, United States; VNM, Vietnam; ZAF, Southern Africa Customs Union; ZMB, Zambia; ZWE, Zimbabwe.

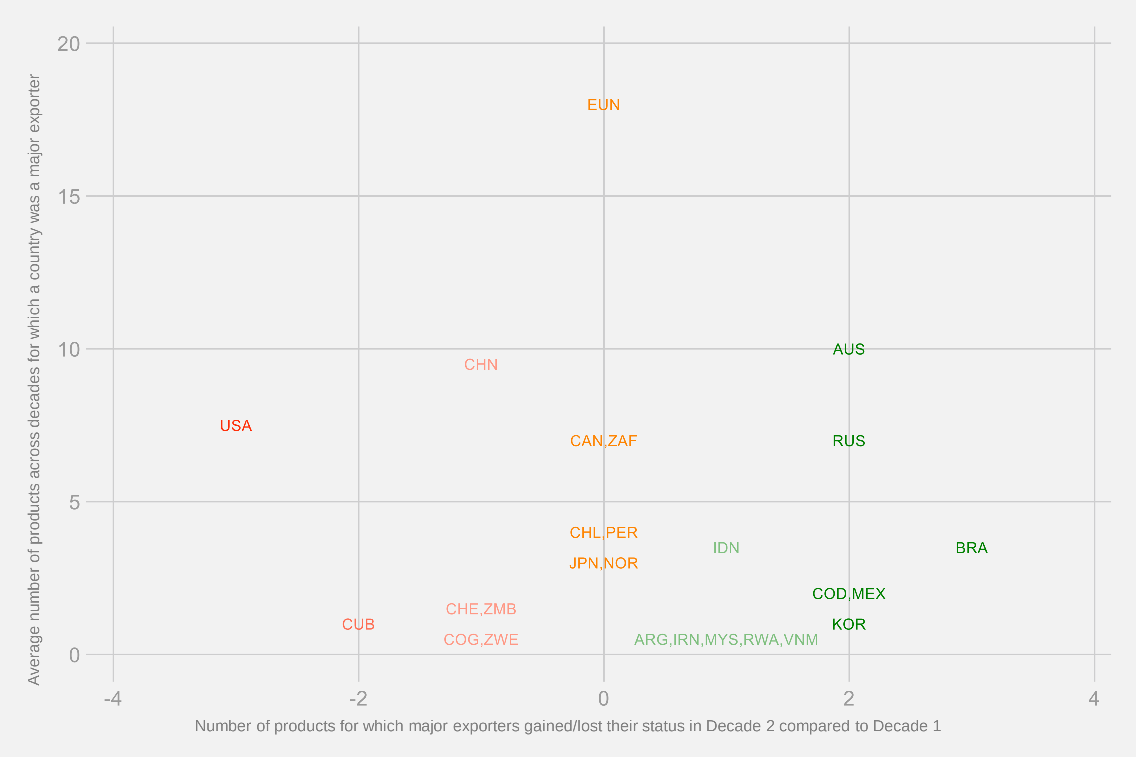
Looking at the composition of major exporters by product, we find that developed countries tend to have a lower representation of OCs as part of their exports, as opposed to processed MCs (see Appendix 4.6 for a visualization of this). This finding is in line with the relatively higher level of industrialization in developed countries and it supports existing literature (Behrens et al. 2007). The one exception is Australia, a global mining hub.

Appendix 4.6 also shows that major oil and gas exporters that are not in the OECD (Saudi Arabia, Nigeria, United Arab Emirates, and Qatar, as opposed to Canada, Europe, Norway) tend to have less diversification of goods and are 100% made up of TEMs. The only OECD country that is 100% made up of TEMs is Switzerland, which is a major exporter of unwrought palladium and platinum. These are refined products that may also become CEMs over time however, as discussed in the Methods section.

Last, we perform a dynamic analysis of major exporters. The vertical axis of Figure 4.10 shows the average number of goods for which a country was a major exporter by value during the two decades included in our analysis. We find that most countries are major exporters of fewer than five goods. There are seven countries that export more than five goods, however. These countries are: Australia, Canada, China, the European Union, Russia, the Southern African Customs Union, and the United States. The European Union outperforms all countries.

The horizontal axis of Figure 4.10 shows the change in the number of products for which the country saw a status change (turning into or stopped been a major exporter) over the decades of interest. Red labels indicate that an exporter lost products; orange indicate no change; green labels indicate that a country gained products over time. Most countries gained or lost their position as a major exporter in at most one good. However, the United States stands out as a top major exporter that lost major exporter status in three goods over the decades of interest. This result may help support the motivation behind the blossoming criticality literature.

Figure 4.10. Number of products for which major exporters gained/lost major exporter status, Decade 2 minus Decade 1 (x-axis) and average number of products across decades for which each country was a major exporter (y-axis). Red labels=country lost products; orange=no change; green labels=country gained products.



Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: ARE, BOL,GAB,GIN,GTM,NCL,NGA,PHL,QAT,SAU,TZA are missing from the graph because they are major exporters in one product, and have not seen a change in that over the decades.
ARE, United Arab Emirates; ARG, Argentina; ARM, Armenia; AUS, Australia; BOL, Bolivia; BRA, Brazil; CAN, Canada; CHE, Switzerland; CHL, Chile; CHN, China; COD, the Democratic Republic of the Congo; COG, Republic of the Congo; CUB, Cuba; EUN, European Union; GAB, Gabon; GHA, Ghana; GIN, Guinea; GTM, Guatemala; IDN, Indonesia; IRN, Iran; JPN, Japan; KOR, Korea; MEX, Mexico; MYS, Malaysia; NCL, New Caledonia; NGA, Nigeria; NOR, Norway; PER, Peru; PHL, Philippines; QAT, Qatar; RUS, Russia; RWA, Rwanda; SAU, Saudi Arabia; TWN, Taiwan; TZA, Tanzania; USA, United States; VNM, Vietnam; ZAF, Southern Africa Customs Union; ZMB, Zambia; ZWE, Zimbabwe.

4.6 Discussion

Energy decarbonization is a crucial objective but it cannot be pursued in isolation from other priorities. It interacts with other areas, including economic competitiveness and development, in which trade plays a central role. The energy transition will bring about a change in trade patterns in the materials that are used in energy but current literature on the materials for energy decarbonization has focused on other issues.

Our study advances the literature by using trade data to interpret changes in the value and volume of traded products and product groups along ETM supply chains across developed and developing countries with a unique exporter perspective. We consider products are either traditional or clean energy materials (CEMs or TEMs). We also distinguish between unrefined (OCs, ores and concentrates) and refined products (MCs, metals and chemicals). We engage with the following questions: How have the characteristics of growth, volatility, and importer and exporter concentration in trade value and volume evolved for the products in the two decades between 1999-2018? What are the products (and product groups) that exhibit characteristics that are more beneficial to exporters?

We find that changes over time do not benefit the exporters of the selected ETM products. Growth rates were generally lower in Decade 2, and the changes are statistically significant. This is likely to be the result of the deep crisis in commodities during 2014, seen in the Data section. At the same time, the results point to an overall change towards exporter dispersal and importer concentration.

The movements in both metrics are exactly the opposite of what would benefit major exporters. They also seem to be in direct contradiction to the premise and findings of the criticality literature, in which importing countries will suffer from demand jumps and supply bottlenecks in materials for clean energy technologies (Ali et al. 2017). The contradiction may be explained by differences in methods (estimation of historical metrics instead of forecasting), data (trade instead of reserves and production), perspective (exporters instead of importers), and material coverage (narrow [i.e., minerals for clean energy technologies] instead of broad [i.e. refined and unrefined materials for clean and traditional energy technologies]).

Table 4.14 helps synthesize some of our main results for the purposes of discussion. In the most recent decade, CEMs appear disproportionately represented in the products with higher growth rates (Table 4.14, column 2). This result is an indication that the transition to decarbonized energy may already be affecting the trade of materials. Viewed in conjunction with the analysis of exporters, developing country exporters of TEMs must continue to strive towards capturing enriching the opportunities around TEMs, such as services and knowledge, if not export diversification, as discussed in Renner and Wellmer (2019).

The rest of Table 4.14 summarizes the sub-sample of top-performing "notable" products across the analyses of the Results section. Of the 30 products, lithium [carbonate] exhibits the most beneficial trade patterns, putting its major exporters (Chile, Argentina, the European Union, and China) in a position to benefit the most from current trade trends as energy decarbonization continues.

Making up 10 of the 12 products, MCs are more highly represented in Table 4.14 than in the overall product sample. MCs are also disproportionately represented in the group of top growth products in Decade 2 (column two). These patterns reinforce the importance of thorough planning for developing countries, which are more likely to be exporters of OCs. We found this result is not borne out in the existing literature, but this may be because, to the best of our knowledge, we are the first to divide ETMs between unrefined and refined products while the existing literature concentrates on minerals, or unrefined materials.

Table 4.14. Notable products that stand out in the static and dynamic analyses.

	High growth, Decade 2[1]	High growth and not high volatility, Dec 2[2]	Favorable concentration[3]	Favorable concentration changes[4]	Technologies	2050 growth %[5]	CEMs/ TEMs	OCs/ MCs
Graphite [PF]			✓		1	494	CEM	MC
Lithium [OH]	✓	✓			1	488	CEM	MC
Lithium [Carbonate]	✓	✓	✓	✓	1	488	CEM	MC
Cobalt [OH]	✓		✓		1	460	CEM	MC
Vanadium [OH]	✓				3	189	CEM	MC
REE1 [Metal]	✓				1	37	CEM	MC
REE2 [Metal]	✓				1	37	CEM	MC
Molybdenum [OC]				✓	8	11	CEM	OC
Palladium [UW]			✓		1		TEM	MC
Platinum [UW]			✓		1		TEM	MC
Rhodium [UW]				✓	1		TEM	MC
Natural gas				✓	1		TEM	OC

Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals. [1] Table 4.13 [2] Table 4.13 [3] Area 2 in Figure 4.7. [4] Area 1 in Figure 4.8. [5] See description of Table 4.2.

Table 4.15 further summarizes the results by showing the countries that stand to benefit the most from the trends in these specific notable products. The results are ordered by the number of notable products for which a country is a major exporter.

The European Union is a major exporter of all notable products, although this finding was expected due to the size of the trading bloc and analysis of major exporters. Also expectedly, China and the United States come next. Certainly, it is unreasonable to compare these countries with the other major exporters without considering the sizes of their economies. However, observe two additional points. China holds the highest average market share rank compared to all countries that export any of the notable products (column 3). And, on top of coming second to the European Union, the United States plays a higher role in the notable products than in the overall sample (75% versus 25%). These two points show that these two countries are not only large exporters generally (which is expected) but also that they are relatively well-positioned for changes in ETM trade. To its benefit, the Southern African Customs Union closely follows China in column 3 due to its role in the platinum group metals. This is an exceptional position to be in, as we discussed that those products may shift from TEMs to CEMs.

Table 4.15. Major exporter market share rank, by notable product. Count of notable products for which each main exporter is a main exporter, and average rank across notable products. Green = first, light green= second, gray= third, light red= fourth, and red= fifth major exporter.

Exporter	Count	Average rank	Graphite [PF]	Lithium [OH]	Lithium [Carbonate]	Cobalt [OH]	Vanadium [OH]	REE1	REE2	Molybdenum [OR]	Palladium [UW]	Platinum [UW]	Rhodium [UW]	Natural gas
EUN	12	2.4												
USA	8	3.8												
CHN	7	1.6												
RUS	6	3.8												
ZAF	4	1.8												
CHL	3	1.7												
JPN	3	3.7												
BRA	2	3.5												
CHE	2	4.0												
ARG	1	2.0												
VNM	1	2.0												
QAT	1	2.0												
COD	1	3.0												
NOR	1	3.0												
AUS	1	3.0												
PER	1	4.0												
TWN	1	5.0												
MEX	1	5.0												
CAN	1	5.0												
MYS	1	5.0												

Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: ARG, Argentina; AUS, Australia; BRA, Brazil; CAN, Canada; CHE, Switzerland; CHL, Chile; CHN, China; COD, the Democratic Republic of the Congo; EUN, European Union; MEX, Mexico; MYS, Malaysia; NOR, Norway; PER, Peru; QAT, Qatar; RUS, Russia; TWN, Taiwan; TZA, United States; VNM, Vietnam; ZAF, Southern Africa Customs Union.

It behooves developing countries to consider strengthening policy towards CEMs and MCs export capabilities. However, comparable policy advice has proven difficult to materialize in the past (Renner and Wellmer 2019). If the trends found in this chapter have any bearing on the future, then the chances of success may become even slimmer, especially for TEMs exporters because TEMs have historically been a potential long-term and growing source of state assets that could be used to invest, direct, and develop industrial capabilities.

We consider three limitations to our work, mostly related to the tradeoffs between broad and detailed analyses. First, as mentioned in the Methods section, the level of detail with which we can study ETMs in a wide range of countries over several decades using trade data depends on the product differentiation provided by trade product classifications. This means that there may be products that we cannot isolate as well as other ETM studies (for example, those that differentiate some REE).

Simplifications do not only come from the structure of our primary dataset. As we explained in the Methods, the breadth of the data leads us to create predetermined rules to translate continuous data into discrete data for analysis (e.g., HHI into low, medium, and high concentration products or average product growth into top-performers and the rest). However, while the definitions we created may affect some of the top-performer and notable products that may lie on the margin, they do not affect the overall results of the discussion.

Second, UN Comtrade data provides information on the quantity and value of traded products at the equilibrium between supply and demand, and we do not attempt to identify and isolate demand or supply sources of change. For instance, the high volatility in cobalt [OC] could be related to the fact that it is a byproduct of copper (Nassar, Graedel, and Harper 2015).

Third, cross-comparisons of equilibrium value and volume are challenging in absence of a detailed discussion of each market and substitution between ETMs under current technological conditions, which is not possible when covering 30 products over two decades. We discuss future avenues for research that address this in the Conclusion.

4.7 CONCLUSION

According to our analysis of historical ETM trade data, we find that CEMs and MCs hold relatively larger promise than TEMs and OCs for exporters as energy decarbonization advances. However, in accordance with existing literature and our own data, these are markets in which developing countries are generally underrepresented. While some developing countries may still benefit from trade trends in individual OC and TEM products, it is imperative to further consider and evaluate policy that strengthens trade capabilities in refined and clean energy materials.

Future research could narrow the scope of analysis of trade patterns in greater granularity. For instance, it could use the same data to analyze and compare countries in specific regions (e.g., Sub-Saharan Africa) and specific technologies (including a detailed consideration of possible substitutions between different ETMs by technology). It could otherwise veer closer towards focused topics in resource economics and macroeconomic policy. In this case, it could engage with considerations on fiscal resources and terms of trade in a given country and ETM market, and be accompanied by a discussion on the extent, direction, and results of existing export, industrialization, and innovation policies.

APPENDIX 4.1. DATA, ADDITIONAL STATISTICS

Table 4.16. Detailed statistics, value (constant 2018 USD mil) and quantity, 1995-2018, all selected products.

	value, USD mil	quantity, metric tons		value, USD mil	quantity, metric tons
N	213,240	213,240	iqr	4	1,184
Mean	120	284,646	1st Perc.	0	0
Std. Dev.	1,460	4,251,106	p5	0	0
range	129,345	838,800,000	p10	0	0
min	0	0	p25	0	1
max	129,345	838,800,000	Median	0	34
variance	2,131,649	18,070,000,000,000	p75	4	1,185
cv	12	15	p90	56	44,161
skewness	35	82	p95	213	278,607
kurtosis	1,854	13,321	p99	2,336	4,899,092

Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).

Table 4.17. Summary trade statistics v (value, in constant 2018 USD million) and q (quantity), 1995-2018, by product.

Product	HS		Mean	SD	Median
Graphite [powders/flakes]	2504	v	0.762	4.79	0.026
		q	1372.44	10353.161	22.5
Manganese [ore/concentrate]	2602	v	10.2	61.057	0.148
		q	68943.35	467951.87	458.239
Copper [ore/concentrate]	2603	v	102.353	411.604	1.331
		q	56853.04	220256.85	1301.478
Nickel [ore/concentrate]	2604	v	19.053	86.964	0.085
		q	276674.25	2443238.3	56.777
Cobalt [ore/concentrate]	2605	v	6.888	46.291	0.1
		q	3115.311	19142.672	28.344
Aluminum [ores/concentrates]	2606	v	8.412	54.619	0.15
		q	206533.78	1614446.8	320.212
Lead [ore/concentrate]	2607	v	20.293	65.348	0.36
		q	14374.702	41253.776	537.157
Molybdenum [ore/concentrate]	2613	v	23.766	106.335	0.731
		q	1489.077	4980.633	83.96
Niobium tantalum vanadium zirconium [ore/concentrate]	2615	v	3.11	14.199	0.196
		q	3043.089	17675.03	84.15
Silver [ore/concentrate]	261610	v	15.018	45.82	0.436
		q	2716.031	11222.395	20.336
PGM [ore/concentrate]	261690	v	13.112	47.324	0.149
		q	3448.922	16752.099	3.447
Crude oil	2709	v	1220.069	5038.755	72.284
		q	2841234.2	10754529	173312
Natural gas	2711	v	188.431	1540.974	0.783
		q	630825.72	8985540	1269.115
Earth-metals, rare and scandium and yttrium, whether or not intermixed or interalloyed	280530	v	1.95	15.937	0.037
		q	145.595	1436.489	1.741
Cobalt chemical [oxide/hydroxide]	2822	v	2.752	20.069	0.062
		q	152.763	1299.757	3.555
Lithium chemicals [oxide/hydroxide]	282520	v	0.911	6.087	0.05
		q	124.042	669.026	7.75
Vanadium chemical [oxide/hydroxide]	282530	v	2.778	12.357	0.083
		q	257.26	909.721	8
Lithium chemicals [carbonate]	283691	v	2.018	12.389	0.028
		q	339.758	1601.662	4.635

Product	HS		Mean	SD	Median
Compounds, inorganic or organic, of rare-earth metals, of yttrium or of scandium, or of mixtures of these metals [unwrought, powder, waste/scrap]	2846	v	2.87	20.185	0.036
		q	259	1556.228	2.688
Silver [unwrought]	710691	v	28.005	177.77	0.274
		q	147.813	3772.52	0.77
Platinum [unwrought, powder, semi-manufactured]	711011	v	28.535	127.973	0.366
		q	2.499	46.908	0.029
Palladium [unwrought, powder, semi-manufactured]	711021	v	20.507	91.247	0.268
		q	3.844	72.106	0.036
Rhodium [unwrought, powder, semi-manufactured]	711031	v	15.094	68.022	0.236
		q	0.696	4.583	0.023
Copper [matte]	7401	v	3.577	18.382	0.052
		q	1351.567	5159.475	23.637
Nickel [matte]	7501	v	37.321	163.291	0.089
		q	4028.672	14754.092	13.187
Aluminum [unwrought]	7601	v	37.392	296.009	0.576
		q	18514.265	134500.4	267.8
Lead [unwrought]	7801	v	6.645	55.221	0.312
		q	4025.006	28643.756	200.584
Molybdenum [unwrought]	810291	v	1.826	8.874	0.067
		q	71.298	323.231	3.51
Cobalt mattes and other intermediate products of cobalt metallurgy [unwrought, powders, waste/scrap]	8105	v	5.953	46.975	0.114
		q	314.716	4412.124	3.425
Beryllium, chromium, germanium, vanadium, gallium, hafnium, indium, niobium (columbium), rhenium and thallium [metals]	8112	v	2.8	14.6	0.053
		q	209.873	2106.129	2.821

Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).

APPENDIX 4.2. GROWTH AND VOLATILITY RESULTS, BY PRODUCT

Table 4.18. Average yearly growth and average yearly growth standard deviation, 1999-2018, Decade 1, and Decade 2.

HS code	Product	Avg growth			Avg growth standard deviation			TEMs (1) CEMs (2)	OCs (1) MC (2)
		1999-2018	Decade 1	Decade 2	1999-2018	Decade 1	Decade 2		
2709	Crude Oil	10.55	22.76	-0.44	0.28	0.24	0.29	1	0
2711	Natural Gas	11.43	23.66	0.42	0.28	0.27	0.24	1	0
283691	[Carbonate] Lithium	17.92	15.99	19.65	0.28	0.13	0.37	0	0
8105	[Matte & more] Cobalt	14.58	19.28	10.35	0.44	0.45	0.44	0	0
7401	[Matte] Copper	23.21	35.59	12.07	0.60	0.81	0.31	0	0
7501	[Matte] Nickel	10.78	23.19	-0.40	0.39	0.40	0.35	0	0
2846	[Metal compounds/mixtures] REE	13.75	8.10	18.27	0.58	0.15	0.79	0	0
280530	[Metals, incl intermixed/alloyed] REE	20.14	14.85	24.91	0.67	0.42	0.86	0	0
8112	[Metals, incl. waste/scrap] Others	8.86	15.69	2.72	0.32	0.31	0.34	0	0
2606	[Ore/concentrate] Aluminum	8.44	10.18	6.88	0.22	0.16	0.26	0	1
2605	[Ore/concentrate] Cobalt	25.69	42.93	10.17	0.87	1.09	0.64	0	1
2603	[Ore/concentrate] Copper	13.75	22.64	5.75	0.24	0.28	0.16	0	1
2607	[Ore/concentrate] Lead	12.78	21.87	4.59	0.25	0.26	0.22	0	1
2602	[Ore/concentrate] Manganese	23.49	38.06	10.38	0.58	0.66	0.49	0	1
2613	[Ore/concentrate] Molybdenum	22.02	45.62	0.78	0.63	0.76	0.41	0	1
2604	[Ore/concentrate] Nickel	18.50	34.99	3.67	0.43	0.46	0.36	0	1
2615	[Ore/concentrate] Niobium, tantalum, vanadium, & zirc.	9.91	12.54	7.55	0.29	0.19	0.37	0	1
261690	[Ore/concentrate] Platinum, Palladium, Rhodium	9.22	11.79	6.90	0.18	0.19	0.17	0	1
261610	[Ore/concentrate] Silver	14.82	23.51	7.00	0.30	0.33	0.27	0	1
2822	[Oxide/hydroxide] Cobalt	19.51	18.26	20.63	0.65	0.44	0.82	0	0
282520	[Oxide/hydroxide] Lithium	16.99	12.51	21.02	0.23	0.21	0.25	0	0
282530	[Oxide/hydroxide] Vanadium	24.05	25.25	22.97	0.58	0.47	0.69	0	0
2504	[Powders/flakes] Graphite	6.76	8.52	5.18	0.21	0.17	0.26	0	0
7601	[Unwrought] Aluminum	5.15	9.62	1.13	0.18	0.12	0.22	0	0
7801	[Unwrought] Lead	9.59	17.12	2.82	0.24	0.28	0.18	0	0
810291	[Unwrought] Molybdenum	23.09	41.40	6.61	0.60	0.66	0.51	0	0
711021	[Unwrought] Palladium	5.02	-3.85	12.12	0.35	0.37	0.35	1	0
711011	[Unwrought] Platinum	3.18	13.85	-5.34	0.15	0.13	0.10	1	0
711031	[Unwrought] Rhodium	15.99	32.24	2.98	0.60	0.66	0.54	1	0
710691	[Unwrought] Silver	9.72	19.91	1.56	0.29	0.22	0.33	0	0
	Mean	14.30	21.27	8.10	0.40	0.38	0.39		

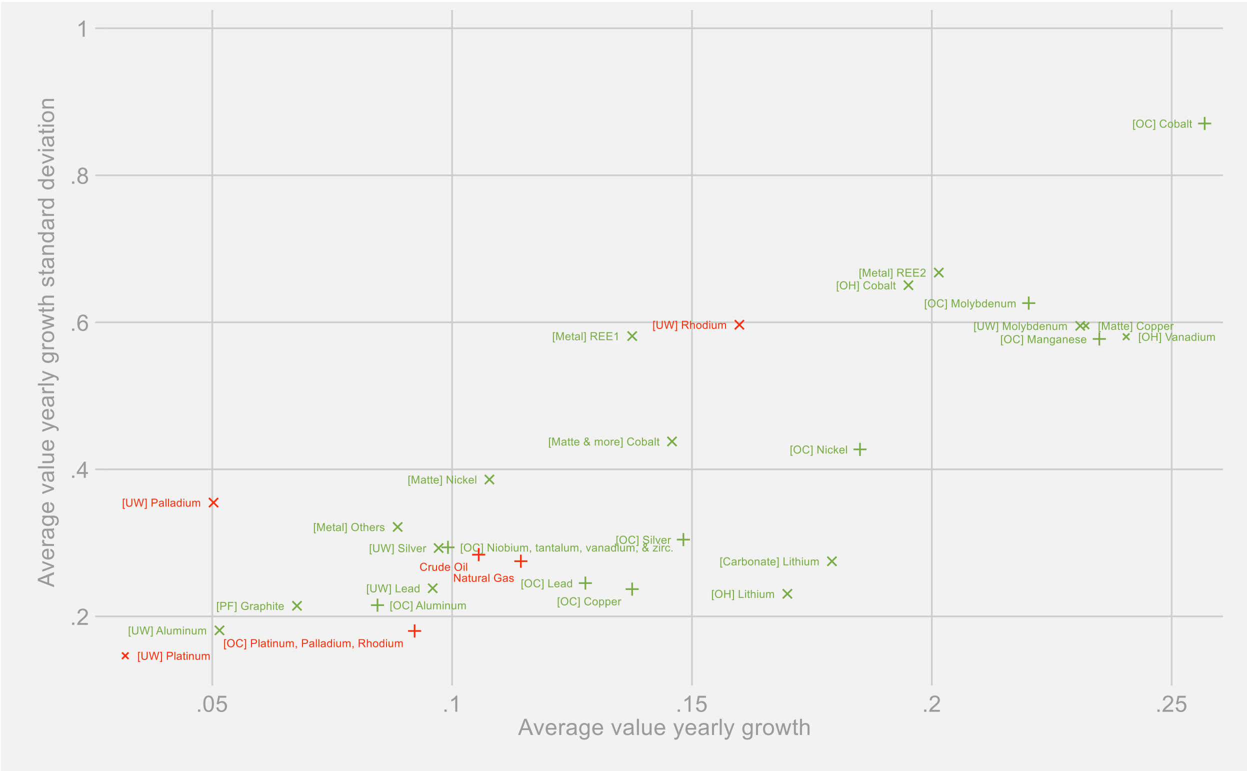
Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: REE= Rare earth elements; TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals.

APPENDIX 4.3. GROWTH AND VOLATILITY, ADDITIONAL VISUALIZATION

Figure 4.11 disaggregates the data of Figure 4.11 into products. Products are plotted along a horizontal axis representing average growth rates, and the vertical axis representing volatility. CEMs are in green, TEMs are in red. OCs are marked in crosses, and MCs are marked in x's.

Those in the top 20% by growth overall are: cobalt [OC], vanadium [OH], manganese [OC], copper [matte], molybdenum [UW] and molybdenum [OC]. Half of these, vanadium [OH], manganese [OC], and molybdenum [UW] were not among the top 20% by volatility.

Figure 4.11. Average yearly growth (x axis), average yearly growth standard deviation (y axis), 1999-2018; Red = TEMs, Green=CEMS; + markers = OCs; X markers=MCs.



Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals; OC= Ores and concentrates; PF= powders and flakes; REE1=REE compounds; RE2=REE alloys; UW=Unwrought metals.

APPENDIX 4.4. GROWTH AND VOLATILITY, ADDITIONAL STATISTICS AND TESTS

Table 4.19. Average growth rates and volatility by groups, 1999-2018.

	Average of growth rates	Volatility
All	14.34	0.43
TEMs	9.26	0.33
CEMs	15.58	0.45
OCs	15.05	0.42
MCs	13.86	0.44

Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals.

Table 4.20. Average growth rates and volatility by groups and decade.

	Average of yearly growth rates			SD of yearly growth rates		
	Decade 1	Decade 2	Dec2-Dec1	Decade 1	Decade 2	Dec2-Dec1
All	21.4	8.1	-13.31	0.43	0.42	-0.01
TEMs	16.9	2.78	-14.12	0.35	0.31	-0.04
CEMs	22.48	9.43	-13.05	0.45	0.44	-0.01
Difference	-5.58	-6.65		-0.1	-0.14	-
OCs	25.88	5.31	-20.57	0.48	0.33	-0.14
MCs	18.33	9.96	-8.37	0.4	0.47	0.07
Difference	7.55	-4.65	-	0.08	-0.13	-

Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals.

Table 4.21. Differences in growth rates and volatility of growth rates, P-values of nonparametric equality-of-medians test and Wilcoxon rank-sum test/ Mann –Whitney two-sample statistic.

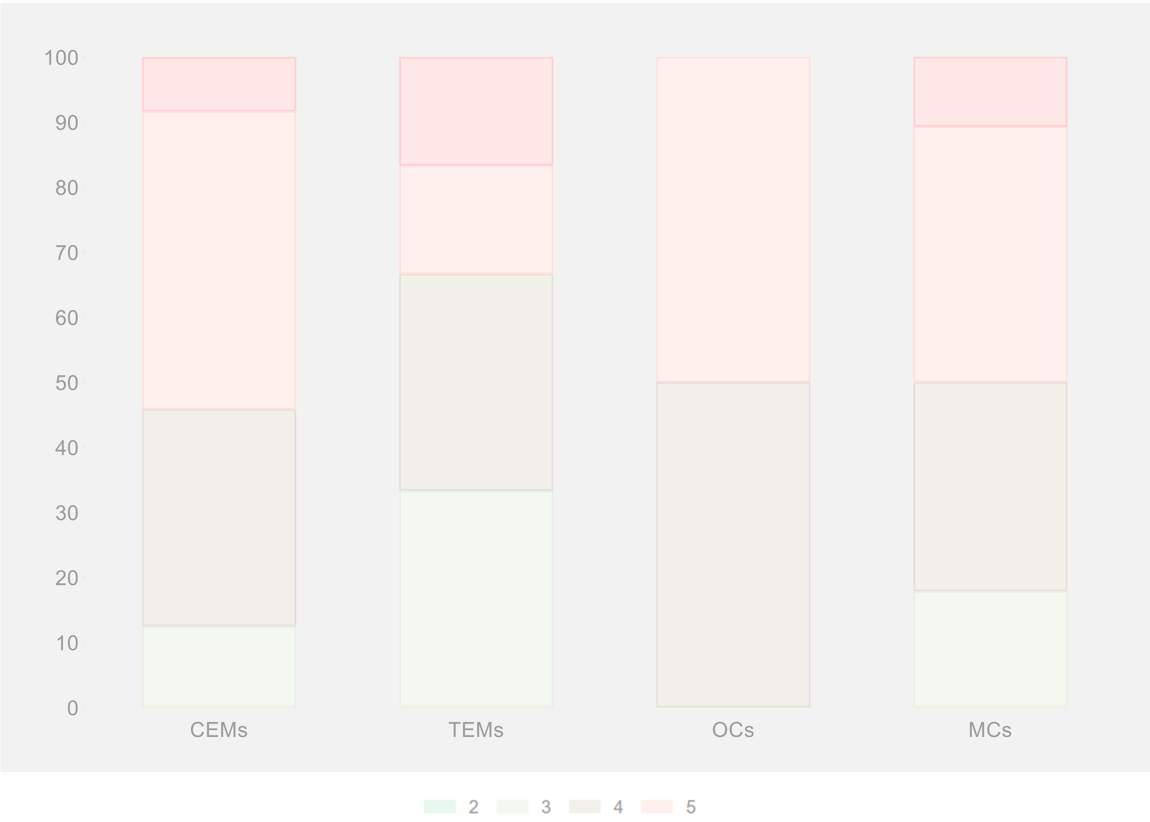
		Nonparametric equality-of-medians		Wilcoxon rank-sum test/ Mann –Whitney two-sample statistic (exact p-value)	
		Decade 1	Decade 2	Decade 1	Decade 2
Growth	CEMs versus TEMs	0.976	0.665	0.818	0.563
	OCs versus MCs	0.240	0.906	0.203	0.964
Volatility	CEMs versus TEMs	0.648	0.648	0.494	0.143
	OCs versus MCs	0.709	0.709	0.755	0.249

Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals.

APPENDIX 4.5. IMPORTER AND EXPORTER CONCENTRATION, GROUP COMPARISONS

Figure 4.12 shows the percentages of products within each group that are in each area of Figure 4.7. The colors of the stacks in the bars are the same as the colors in the areas of Figure 4.7. The results are nuanced. Observe that TEMs have more than double the percentage of products than CEMs in Area 2 (the second-best overall). However, as can be seen in Figure 4.7, this pattern is likely led by the platinum group metals (which may become CEMs over time, see the Methods section). Additionally, CEMs have a smaller fraction of materials in Area 5. Relatedly, neither OCs nor MCs are better positioned. MCs have a wider range of exporter and importer HHI combinations, whereas OCs are evenly split between the extremes.

Figure 4.12. Export and import concentration by CEMs and TEMs and OCs versus MCs, using the same Area colors as Figure 4.7.



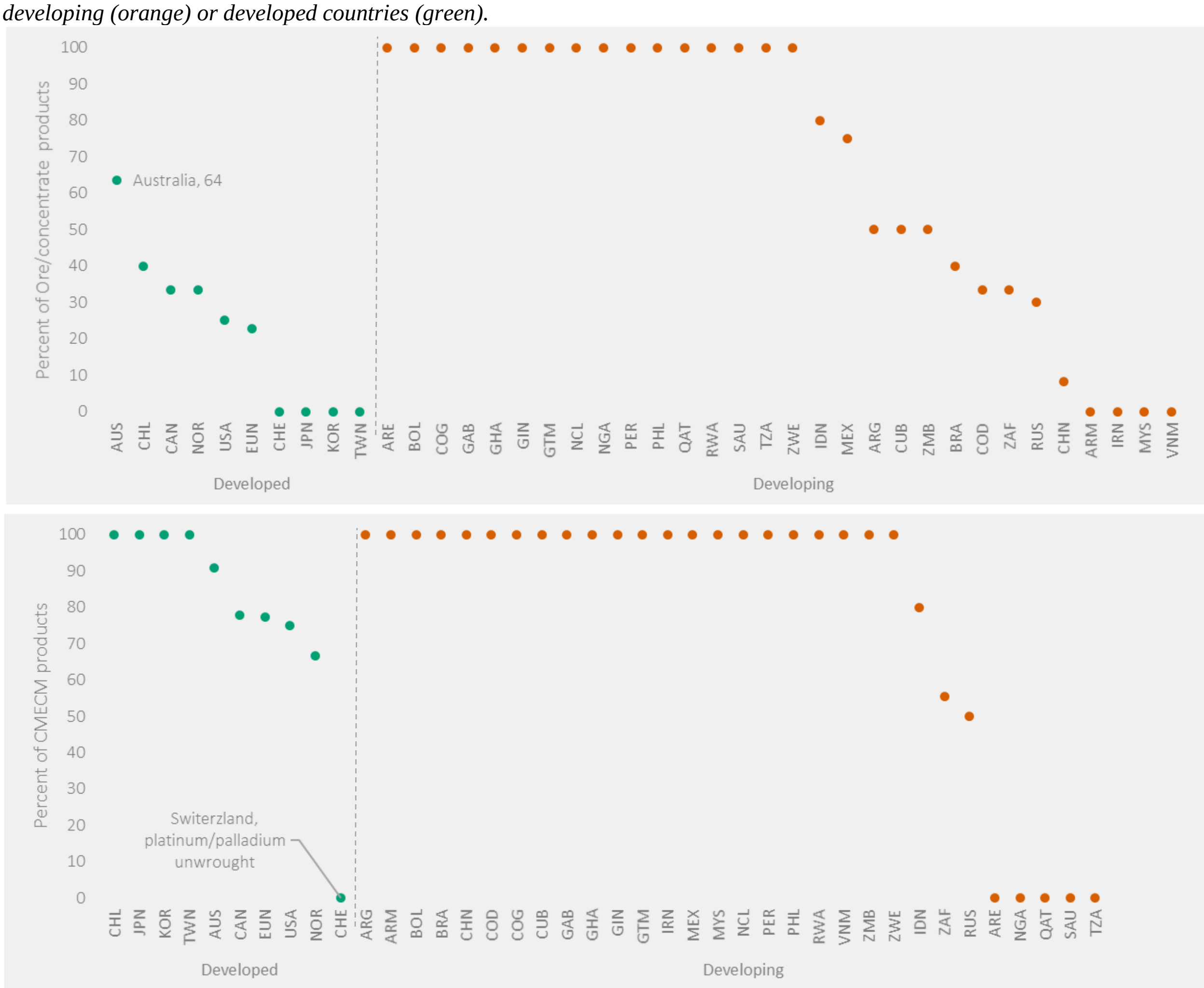
Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals.

We also discuss the products by Classifications 1 and 2 based on Figure 4.7. Exporter and importer concentration (HHI), by product, 1999-2018; Red = TEMs, Green=CEMS; + markers = OCs; X markers=MCs30% of CEMs are in Area 3, which is opposite to the interests of major exporters. Yet no TEMs are found here. Instead, 33% of TEMs are in Area 1 (the first-best option), compared to about 7% of CEMs. We alternatively cut the data by Classification 2. OCs are less likely to lie in Area 3 (25% versus 33.33%), and they are more represented in Area 1 (17% versus 11%).

APPENDIX 4.6. EXPORTER ANALYSIS, ADDITIONAL VISUALIZATIONS

Figure 4.13 summarizes the percentage of a country's products that belong to each product group within the 30 products selected in the Methods section of this chapter. As discussed in the text, CEMs versus TEMs and OCs versus MCs make up different proportions of exporters' product portfolios, and generally run along developed/developing country lines.

Figure 4.13. Percentage of a country's export made up of OCs versus MCs (top) and TEMs versus CEMs (bottom), by developing (orange) or developed countries (green).



Source(s): Author's elaboration based on the methods described in this chapter and UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).
Note: TEMs=traditional energy materials; CEMs=clean energy materials; OCs=ores and concentrates; MCs=metals and chemicals.

CHAPTER 5: A NOVEL ESTIMATION OF STRUCTURAL TRADE ELASTICITIES AND AN APPLICATION TO ENERGY TECHNOLOGY MATERIALS

Abstract

Elasticities of demand and supply are a core concept in economics with far-reaching applications. For the first time, and in the context of trade and energy decarbonization, we ask: what are the price elasticities of import demand (or the change in trade demand due to a change in price, simplified as "trade demand elasticity"), for each energy technology material (ETM)-and-exporter pair (e.g. gas from Russia or lithium from Argentina)? Additionally, is there a difference between developed and developing exporters in these ETM elasticities?

Despite their importance in economics, calculating trade elasticities is frequently an elusive task because of the difficulty of identifying supply and demand curves from existing data. To answer the research questions, we propose modifications to current structural trade demand and supply price elasticities building on the methods developed by Broda and Weinstein (2006), based on Feenstra (1994). With a mean trade demand elasticity of 3.94, our trade demand elasticities are broadly in line with the methods on which ours is based.

Our main result is to present the trade elasticities over two decades for 29 products and 22 exporters, which can be used by researchers and policymakers in a variety of settings, including IAMs. Additionally, we find that developed countries have weakly statistically significantly lower ETM trade demand elasticities than developing countries, which we discuss in context of the *portfolio* of ETM products exported by the two groups.

Nevertheless, there are indications of a convergence of ETM elasticities between developed and developing countries over time. This convergence is at least partially explained by the characteristics of the exporters–- i.e., a change how the importer perceives the quality differential between exports from developing and developed countries–- rather than a change in the *portfolio* of exports of the two exporting country groups. The convergence implies that developed country exporters may have lost competitive edge over time. Continued surveillance with more trade data over time is necessary.

5.1 INTRODUCTION

Elasticity is an important concept in economics. It measures the percentage change of one economic variable in response to a change in another. A common elasticity is the "price elasticity of demand," which refers to how much demand changes for a given change in price. It can be understood as the slope of the demand curve on a quantity (horizontal) and price (vertical) graphical representation of the market. The lower the elasticity of demand, the less change in demand with a given change in price.

Knowing the price elasticity of demand has both specific and general applications. However, despite their importance in economics, calculating price elasticities of demand and supply is an often complex and frequently elusive task. This is because existing data only tells you where the curves meet (the market equilibrium), and nothing about the slopes of the curves. In other words, it is difficult to "identify" the demand and supply curves.

Given the importance of trade for growth, and the potential impacts of energy decarbonization on trade, we ask: What are the price elasticities of import demand, the change in trade demand due to a change in price, for each ETM-and-exporter pair (example gas from Russia or lithium from Argentina)? Is there a difference between developed and developing exporters in ETM trade demand elasticities?

These questions lead us to make an analytical contribution to empirical trade analysis by proposing modifications to structural trade demand and supply price elasticities building on theory and identification strategies developed by Broda and Weinstein (2006) and Soderbery (2015), as well as Feenstra (1994), Krugman (1979), Leamer (1981), Armington (1969), and more. The method behind the elasticities in the literature we engage and contribute to is based on the idea that the trade elasticity of products is related to the physical product characteristics, but that the origin also matters for importers (e.g., wine from France is not the same as wine from Sweden).

As we will see in the Literature Review, the elasticities in question were originally conceived to study questions on gains from trade and their conclusions largely support economic theory on the economic benefits of trade. While such conclusions may seem tangential to our research questions, we argue that they offer added support to the motivation behind our research questions on ETM trade, due to the importance of trade to competing policy priorities such as sustainable growth.

To adjust the model to our aims, we adapt the interpretation of the underlying Constant Elasticity of Substitution (CES) utility function in a way that allows us to interpret the result of our model as the price elasticity of import demand (simplified as "trade demand elasticity") an *exporter* faces when supplying *towards the rest of the world*, instead of the trade demand elasticity of an *importer* for a given product *from the rest of the world*.

To give a concrete example, this means that we study how world trade demand for oil from Norway reacts to prices, instead of how the U.S. demand for oil from anywhere in the world reacts to prices. (We shall see that the most literal interpretation of our results is the *trade elasticity of substitution for the demand of a certain product from a certain exporter, between importers*. However, we show that we can interpret the estimates as the trade elasticity of demand for a product from a certain exporter when calculated over many countries.) In other words, we estimate the trade demand elasticity of the world for a given ETM-exporter pair. To our knowledge, we are the first to modify them in this way, and also to ask the question in the context of ETMs.

We apply Soderbery's (2015) limited information maximum likelihood (LIML) estimation strategy for the identification of the supply and demand curves. We use an open-access Stata code he provided with the paper. In doing so, we catch a small error that may have affected the elasticities in Soderbery (2015).

Although our contribution can be used for any traded product, we limit the application of our methods to ETMs for the purposes of our research questions. We use UN Comtrade and apply the ETM code list produced by our research in the previous chapter. The length and nature of available trade data also allow us to look at changes over time.

As reflected in the broader literature, several ETMs suffer price fluctuations (Renner and Wellmer (2019), and "uncertainty about the export earnings accruing to a country (sometimes referred to as export instability) is an important source of macroeconomic uncertainty" (Ghosh and Ostry 1994). Our discussion, therefore, assumes that exporters prefer a low trade demand elasticity because, by definition, a low trade demand elasticity has a low impact on the quantity demanded.

The stability in demand granted by a low trade demand elasticity in ETMs allows, ceteris paribus, for a range of actors (from government officials to investors and project developers) to efficiently allocate policy, assets, and efforts for production over the long term, and this facilitates meeting interrelated policy goals. Indeed, energy decarbonization is a long-term project requiring policy coordination (Surana and Anadón 2015) and large capital investments over decades (Yeo 2019). Therefore, a low trade demand elasticity means that assets surrounding ETM exports are relatively less likely to be stranded and investments are more likely to have expected returns, making decarbonization efforts work for development, and for decarbonization itself.

Our first finding is the ETM trade demand elasticities themselves. We find that our method results in elasticities that are broadly in line with the papers with which we engage, and the final sample that we analyze spans two decades, 29 ETMs, and 22 major exporters. The individual results that we present could be used by subsequent researchers to help answer a range of ETM or country-specific research questions. They could, for instance, be used in integrated assessment models (IAMs) to determine economic indicators for different countries under a range of climate scenarios that necessitate different amounts of ETMs (World Bank 2017).

Our second question revolves around differences between developed or developing country exporters. We hypothesize that, if differences exist, they can be due to at least two factors (or their interaction): (1) differences in the *portfolio* of ETMs exported by developed and developing countries (e.g., Bolivia exports copper and silver and Switzerland exports the platinum group metals); and, (2) differences in the *characteristics* of the same ETMs perceived by importers (e.g. natural gas from Norway versus natural gas from Russia).

The results indicate that developed countries have weakly statistically significantly lower ETM elasticities, which is expected. However, there are indications of a convergence in ETM elasticities between developed and developing countries over time, and that that this convergence is at least partially due to the characteristics of the exporters, not the portfolio of ETMs.

Importantly, the elasticities are applicable only to trade, and disregard internal markets, which may be large in some countries. Nevertheless, we show that a major strength of the method is that it addresses identification issues in trade data. This is important because trade data is an accessible source of information for small or developing countries that export ETMs in an otherwise poor-data environment.

While we discuss several shortcomings to the method, the most glaring unresolved issue is the time length of available trade data. As we shall see, this is the reason for several missing elasticities by decade, ETM, and main exporters, which makes definitive comparisons and conclusions limited. However, over time, longer trade data may help to solidify the method.

Section 2 of this chapter reviews the relevant trade elasticities literature and explains how we fit in it; Sections 3 and 4 describe our methods and data, respectively; Section 5 presents our data; Section 6 discusses the results, and Section 7 concludes, suggesting avenues for future research.

5.2 LITERATURE REVIEW

The three parts of this Literature Review focus on trade theory that directly underpins our empirical strategy on supply and demand substitution elasticities at the product level.

We first introduce the idea of "varieties," a concept that allows us to estimate elasticities over product and country. We then discuss Krugman's love-of-variety monopolistic competition trade framework, a theory that underpins our methods, and Feenstra (1994), which found a way to empirically test Krugman's theoretical contributions.

More recently, Broda and Weinstein (2006) seminally improved on Feenstra (1994)'s empirical strategy, making it possible for researchers to use trade data to easily compute trade elasticities in a low-data environment for many countries and products at once. Their methods allow us to "structurally" (i.e., from first-principles) identify supply and demand functions from trade data without needing to study specific markets and countries individually. We fully discuss the robustness and applicability of Broda and Weinstein (2006), especially to "commodity" products, a category in which many of our products fall. We also show that the perspective that previous research has taken is not suitable for our analysis of the exporters of ETMs. Last, we discuss how Soderbery (2010, 2015) improved Broda and Weinstein (2006)'s estimation, and explain why we use his estimation method for our elasticities.

We summarize the review in [Table 1] at the end of the section. Importantly, most contributions we cite below are motivated by broad macroeconomic questions. We are interested in elasticities in the context of energy decarbonization. In the review, we focus on the methodological questions of the literature, although the results of the literature on gains from trade helps to show the importance of studying ETM trade for an economically sustainable transition to decarbonized energy.

5.2.1 Varieties

In the traditional comparative advantage framework dating at least as far back as David Ricardo in the 18^{th} century, consumers are indifferent to the origin of a good and are sensitive only to price. However, Armington (1969) posited a trade model where the same goods are differentiated by country of origin. He suggests French and Japanese machinery are considered dissimilar goods for a given importer, and they are thus imperfect substitutes, different "varieties." The idea of "variety" underpins most international computable general equilibrium models of trade today, our research question, and the rest of this review.

Employing a Constant Elasticity of Substitution (CES) utility function (used in all studies mentioned here and widely in the literature for its tractability) to model bilateral trade, Armington (1969) develops the "Armington elasticity," which is a measure of the substitutability between home and foreign goods. However, our research question does not intend to find the "Armington elasticity;" instead, we are interested in how demand changes with price, for a certain ETM and exporter. Armington (1969)'s relevant contribution is the idea of variety, and the use of a CES utility function, which are common to all the papers discussed below.

5.2.2 The love-of-variety monopolistic competition trade framework

In a Ricardian comparative advantage framework, consumers substitute goods from different countries according to price. As a result, the elasticity of demand substitution between varieties, defined as a country origin, is infinite and gains from trade for importers occur only with price decreases.

In Krugman (1979) and (1980), contributions for which he was awarded the 2008 Nobel Memorial Prize in Economic Sciences, Krugman proposes a "love-of-variety" monopolistic competition trade framework. (The definition of variety used in different models is of crucial importance and Krugman (1980) refers specifically to firm-level imports.) The relevant contribution of his research is that monopolistic competition leads to new varieties, and consumers like variety. Contrary to the Ricardian model, Krugman's framework proposes a small elasticity of demand substitution. His theory also implies that welfare can increase without price decreases. For instance, welfare can improve either through decreasing trade costs or through the growth of a foreign country and their subsequent export of more varieties. Albeit framed around macroeconomic questions, the love-of-variety monopolistic competition trade framework is the basis for the most relevant empirical work related to our research question on trade elasticities, by ETMs-and-exporter pairs.

5.2.3 Feenstra (1994)'s empirical application

Feenstra (1994) bridges the gap between Krugman's theory and empirical work. His model calculates the elasticities of new varieties, defined as exporters (e.g., for the United States, importing the same product from France or the United Kingdom constitute different 'varieties'), for six manufactured products. His use for these elasticity estimates is to create a CES aggregate of import price and quantity indices. These indices are then used to analyze gains from varieties in trade.

In favor of the monopolistic competition trade framework proposed by Krugman, Feenstra (1994) finds that the failure to account for new varieties of products that were otherwise treated as identical, "seriously overestimated" the income elasticity of demand for imports in the USA.

What makes Feenstra (1994) relevant to our analysis is the development of a method to consistently and structurally quantify the elasticity of substitution between varieties of a traded product, e.g., lithium carbonate, with only trade data as an input. Refer to Koopmans (1949) for a discussion on structural versus reduced-form modeling.

Given that most countries report import and export data and the data is posted publicly, it is possible to systematically estimate trade elasticities over varieties for thousands of products for many instances in which there is otherwise missing data. All the papers discussed in the rest of this review refine Feenstra (1994)'s empirical strategy.

Feenstra (1994)'s method for calculating trade elasticities is based on comparing deviations in prices and quantities with respect to the dominant "reference" exporter for each good. For this, he builds upon Leamer (1981)'s supply and demand curve identification strategy. Leamer (1981) had shown that, assuming upward and downward sloping supply and demand curves, respectively, with independent errors between them, price and quantity data can be used to define the bounds of a hyperbola in which the true values of supply and demand elasticities lie. However, using time-series data, this method can only yield information on either the supply or the demand curve, and not both.

Feenstra (1994) addresses Leamer (1981)'s limitation by exploiting the panel nature of the product-level trade data. He plots the hyperbola of each variety for a given importer and product pair. When doing so, there are as many hyperbolae as there are varieties for a given importer and product pair. Because of the CES assumption first used in Armington (1969), each variety is part of the same underlying supply and demand elasticities for a specific importer, and has a common elasticity of supply.

Ideally, the estimates of multiple hyperbolae made possible through trade data would all intersect, and do so at exactly one point, which would precisely indicate the demand or supply elasticity. In reality, the hyperbolae may intersect various times, or never. In that case, Feenstra (1994) proposes choosing the elasticity estimates that minimize the sum of weighted least squares of residuals of the line of best fit between the hyperbolae.

To do so, he applies a two-stage least squares (2SLS) instrumental variables estimation, where exporters are the instrumental variable. The aim of the 2SLS procedure is atypical. It is simply to convert the hyperbolae into data points. To account for the possible measurement error in the unit value, which is computed by dividing the quantity by value and is used as a proxy to price in trade literature, Feenstra (1994) uses shares of trade value from each exporter instead of quantity and price data.

Despite its important contribution, a major impediment of Feenstra (1994) is the creation of infeasible estimates when theoretical assumptions of declining and increasing supply and demand curves, respectively, are violated. Broda and Weinstein (2006) seminally, and Soderbery (2015), further improve upon Feenstra (1994)'s empirical approach, and are what we apply in our model.

5.2.4 Improvements on Feenstra (1994)'s empirical specifications

Broda and Weinstein (2006)

Between 2006-2008, Broda and Weinstein coauthored three separate but related papers that are relevant to our analysis, including the seminal "Globalization and the Gains from Variety." Harking back to Krugman (1980), the goal of their 2006 paper is to quantify the impact that new varieties have had on national welfare between 1972-2001 in the USA, as measured by their effect on GDP.

Broda and Weinstein (2006)'s most relevant contribution was to address the creation of infeasible estimates in Feenstra (1994)'s 2SLS method, which occurs in about 40% of products (Soderbery 2015). To address this, Broda and Weinstein (2006) impose a constrained optimization grid search within a feasible region of 1.05 to 80, over increments of 0.05, for the demand substitution elasticity of the products that created infeasible estimates. This means that they find the point of smallest distance between hyperbolae in a space where imports, e.g., unrefined molybdenum, decrease by 1.05% - 80% when its price changes by 1%.

There are several economic theories against which researchers have assessed the robustness of the elasticities estimated using Broda and Weinstein (2006)'s method. One way is by comparing the elasticities of different types of products against the way that economic theory would predict their elasticities to behave.

Economic theory postulates that, despite differentiation by country of origin, the lower the degree of differentiation between goods, the higher the degree of substitutability between them. Rauch (1999) proposes a popular typology that helps define goods: (1) Goods, or commodities, sold in organized exchanges (like the London Metals Exchange), (2) goods that have a reference price in the US; and, (3) all other goods.

Although our research questions focus on groups of exporters and not types of products, Rauch's classification of good is relevant to our analysis because several ETMs are sold in organized exchanges (e.g., oil and refined cobalt metal) and if the methods are shown to work for them, our results are likely to reflect reality. The next section of this Literature Review evaluates the estimates published in Broda and Weinstein (2006) in the context of our ETMs.

Robustness checks and applicability of Broda and Weinstein (2006) to our ETMs

Broda, Greenfield, and Weinstein (2006) and Broda, Limao, and Weinstein (2008) apply and evaluate the elasticity estimation methods in Broda and Weinstein (2006). Their robustness checks help us gauge the reasonableness and usability of the methods. Both papers find the elasticity estimates behave as expected when they separate product estimates into Rauch (1999)'s product groups.

Broda, Greenfield, and Weinstein (2006) apply the elasticity methodology of Broda and Weinstein (2006) to 73 countries from 1994-2003 for all available products in UN Comtrade. They attempt to reconcile detailed micro and macro evidence for the benefits of trade of new varieties on growth across countries and their results suggest that 15 percent of total factor productivity growth stems from new imported varieties on average, with larger effects on developing versus developed countries, at 20 and 5 percent, respectively. To assess the elasticities, they include a comparison of their descriptive statistics by Rauch (1999) product groups. When subject to this analysis, Broda, Greenfield, and Weinstein (2006) strongly reject the null hypothesis that the median or mean for commodities, where many of our ETMs would be categorized into, are lower than in the other groups, with an average elasticity of 12.1 and 7.2, respectively.

Amongst other questions, they also ask whether elasticities remain in the expected range for their Rauch product groups over time. To study this, they calculate elasticities over two decades (as we do) and regress the logs of the latter decade on the first, including good fixed-effects. They find that differentiated goods in one period are also differentiated in the second, robust to several specifications. In their words, "we conclude that our elasticity estimates are reasonable by a number of criteria."

Broda, Limao, and Weinstein (2008) extends the application of Broda and Weinstein (2006). Unlike us, they publish supply (and not demand) elasticities, but because both our elasticities stem from the same methods and because they assess the behavior of the elasticity estimates against economic rationale, the paper is relevant to us.

Broda, Limao, and Weinstein (2008) evaluate the relationship between the supply elasticity (interpreted as the inverse of importer market power) and the consequent import tariffs set by importing countries. According to them, higher market power should translate to higher import tariffs. Amongst several findings, they posit that tariffs by WTO non-members are 9 percentage points higher on inelastically supplied imports. Specifically, Broda, Limao, and Weinstein (2008) expect importers to have lower market power in commodities because it is relatively easier to substitute across varieties of commodities than other products. Again following Rauch (1999), Broda, Limao, and Weinstein (2008) find that the descriptive statistics over the three different groups follow the theory. The inverse supply elasticity for commodities is 0.5 and 2.4 for differentiated products.

Soderbery (2010, 2015): Limitations and improvements on Broda and Weinstein (2006)

Soderbery (2010) and Soderbery (2015) show that 2SLS used in Broda and Weinstein (2006) and Feenstra (1994) suffers from small sample bias as a result of the small number of years inherent to trade data. This problem is directly relevant to the UN Comtrade database we are using, which is only available as of 1995 for most countries. The small number of years in the trade data leads to the generation of outlier hyperbolae and weak instruments, which trigger infeasible estimates and the grid search first presented in Broda and Weinstein (2006).

To avoid triggering a grid search in the first place, Soderbery (2015) suggests using limited information maximum likelihood (LIML) estimation instead of 2SLS. LIML is a form of instrumental variable estimation that predates but is similar to 2SLS based on Anderson and Rubin (1949). While asymptotically equivalent to 2SLS, LIML has been shown to perform better with weak instruments, thereby helping to mitigate the small time sample of trade data (Hahn and Inoue 2002). The difference lies in that 2SLS weighs all hyperbolae equally, while LIML weighs them by the estimated residuals. At t=15, LIML triggers a grid search 20% of the time versus 70% for 2SLS.

It is inevitable that LIML still yields some infeasible estimates. Here, Soderbery (2015) proposes triggering a nonlinear LIML search instead of the grid search in Broda and Weinstein (2006). According to Monte Carlo experiments on simulated data, the second stage grid search bias ranges from 15-40%, depending on *t*, the time length of the sample, due to weak identification of the supply elasticity and the coarseness of the grid. However, the bias is about 5% using the nonlinear LIML search.

The resulting 'hybrid estimators' (HE), by Soderbery (2015) for US trade data at the 8-digit level between 1993-2007 have a 35% lower median demand elasticity than the Broda and Weinstein (2006) 'standard estimators' (SE). Our study uses the HE.

Some limitations to HE remain. Theory based on Feenstra (1994) assumes that the supply and demand errors are uncorrelated. In reality, they often are. But, according to Soderbery (2015), this does not stop HE from overperforming compared to the SE.

For instance, when errors are negatively correlated, Soderbery (2015) shows that the demand elasticity from the SE is upward biased by 50-125%, while the HE is only moderately biased. When errors are negatively correlated, we can interpret the existence of hidden varieties due to the nature of the aggregation of trade data. In this case, consumers appear to be more responsive to price changes than they are (Hallak and Schott 2008).

When errors are positively correlated, Soderbery (2015) shows that both SE and HE exhibit a moderate bias of 10-15%. When supply and demand errors are positively correlated, we can interpret the group of goods as possessing a hidden quality (Feenstra 1994). In this case, consumers would appear to be less responsive to price changes than they really are (Hallak and Schott 2008).

5.2.5 Summary

While it is possible to calculate trade demand elasticities bilaterally while attempting to control for various characteristics of individual markets (an example is Anderson (1979)), it is not easily done over various countries and ETMs, and so does not align with our research question. Additionally, a bilateral approach quickly runs into simultaneity and identification issues, which our method resolves by applying Leamer (1981).

Trade elasticities by Broda and Weinstein (2006) have helped trade economists subject theory to empirical analysis and deepen their understanding of gains from trade and varieties. Table 5.1 summarizes the papers that led or are directly related to the methods we use. These methods make it possible for researchers to circumvent low-data environments for many countries and products at once and allow them to calculate elasticities without needing to specify methods for each market and country individually. We contribute to the literature by presenting a useful adaptation of the Broda and Weinstein (2006) model to calculate trade demand elasticities for products and main exporters. We also demonstrate an application of the methods Broda and Weinstein (2006) to the discussion of ETMs.

Table 5.1. Key publications that advanced trade theory and methods relevant to this paper, and their main takeaways.

Paper(s)	Goal	Data used	Definition of variety	Relevance to this chapter	Result
Armington (1969), "A Theory of Demand for Products Distinguished by Place of Production"	To posit a trade model where the same goods are differentiated by country of origin based on CES preferences	None	A product from a particular country. Not explicitly referred to as variety.	Provides theoretical rationale for the differentiation of goods by origin.	A theory of demand for products distinguished by good and place of production
Krugman (1979) and Krugman (1980), "Increasing returns, monopolistic competition, and international trade" and "Scale Economies, Product Differentiation, and the Pattern of Trade"	To develop a general equilibrium model of non-comparative advantage trade, and to incorporate several the elements of: 1) economies of scale, 2) product differentiation, and 3) imperfect competition into a cohesive trade model.	None	A product category from a particular firm	Introduced the love-of-variety trade framework, supporting the idea of monopolistic competition and varieties in trade.	Showed that, contrary to comparative advantage trade framework, gains from trade can occur without price decreases.
Leamer (1981), "Is it a Demand Curve, or is it a Supply Curve? Partial Identification through Inequality Constraints"	To describe the "sets of maximum likelihood estimates of parameters in two-equation under-identified simultaneous equation systems".	None	Not applicable	Showed how hyperbolae can help identify either the supply and demand curve, but not both.	If demand and supply have an independent error structure, maximum likelihood estimates of the demand and supply elasticities lie

Paper(s)	Goal	Data used	Definition of variety	Relevance to this chapter	Result
					on a hyperbola defined by the second moments of the data.
Feenstra (1994), "New product varieties and the measurement of international prices"	To bridge the gap between theoretical trade models with product differentiation and empirical analysis	*Data used*: 6 products 1969-1987, 7-digit Tariff System of the USA; *Output:* demand substitution elasticity	An HS product category from a particular country	Used panel data at 2SLS to estimate both supply and demand elasticities from Leamer's (1981) hyperbolae.	The failure to account for new varieties seriously overestimated the income elasticity of demand for imports in the USA.
Broda and Weinstein (2006), "Globalization and Gains from Variety"	To quantify the impact that new varieties have had on national welfare in the USA	*Data used*: 7-digit Tariff System of the USA (1972-1988) and 10-digit, COMTRADE, 1990-2001 for USA; *Output*: demand substitution elasticity 1972-2001 for USA	An TSUSA/HS product category from a particular country	Showed how a grid search could estimate supply and demand elasticities when Feenstra (1994) yielded infeasible estimates.	Value of new varieties to USA consumers is 2.6 percent of GDP between 1997-2001
Broda, Greenfield, and Weinstein (2006), "From Groundnuts to Globalization: A Structural Estimate of Trade and Growth"	To estimate the impact that trade in new and better varieties has had on growth around the world	*Data used*: 6 digit, COMTRADE, 1994-2003, 73 countries; *Output*: 4-digit demand substitution elasticities	An HS product category from a particular country	Review of reasonableness of Broda and Weinstein (2006) methods	Average of 15 percent of TFP growth stemming from new imported varieties
Broda, Limao, and Weinstein (2008), "Optimal Tariffs and Market Power: The Evidence"	To quantify the importance of the market power (inverse elasticity of supply, or terms-of trade) motive in trade policy	*Data used:* 6 digit, COMTRADE, 1994-2003, 15 non WTO members; *Output:* 4-digit demand substitution and supply elasticities	An HS product category from a particular country	Review of reasonableness of Broda and Weinstein (2006) methods	Strong evidence that importers with market power set higher tariffs
Soderbery (2010), "Investigating the Asymptotic Properties of Import Elasticity Estimates"	To establish the presence of weak instruments in trade data, and that the instruments appear to drive significant small sample biases in the estimator.	*Data used:* Simulated data based on underlying elasticity estimates, drawing heteroskedastic variances from a Uniform	A product category from a particular country	Identifies problems with and improves Broda and Weinstein (2006) estimation strategy	There are weak instruments in trade data. These instruments appear to drive significant small sample biases in the estimator.

Paper(s)	Goal	Data used	Definition of variety	Relevance to this chapter	Result
		distribution and imposing random missing values; *Output:* none			
Soderbery (2015), "Estimating Import Supply and Demand Elasticities: Analysis and Implications"	To analyze and improves the technique to provide a unified estimator of import supply and demand elasticities.	*Data used*: 8 and 10 digit, COMTRADE, 1993-2007, USA *Output:* Standard and hybrid demand substitution and supply elasticities for USA	An HS product category from a particular country	Improves Broda and Weinstein (2006) estimation strategy; review of reasonableness of estimates	Estimation strategy yields a 35% lower median demand elasticity than Broda and Weinstein (2006)

Sources: In the table.

5.3 MODEL AND METHODS

In this methods section, we explain why we must conceive an alternative interpretation of "variety" and introduce the demand and supply curves behind our model. Importantly, we also explain how the new interpretation of the variety alters the meanings of the curves. Second, we review the theory linking the demand and supply curves to the estimating equation. Last, we summarize the estimating strategy.

Note that the model composed of demand, supply, and estimating equations builds on theory published in Feenstra (1994) and Broda and Weinstein (2006). We follow the model and the notation used in Soderbery (2015) because our estimation adapts code by Soderbery (2015), but it is the same model proposed in works before that (Feenstra (1994) and Broda and Weinstein (2006)). We simplify Feenstra (1994)'s econometric contribution in the estimating equation.

5.3.1 Demand

A representative consumer faces nested CES preferences over goods, g, and set of varieties, v, denoted by $I_{gt} \in \{1, \ldots, v \ldots, V\}$. The elasticity of substitution between varieties is $\sigma_g > 1$. b_{gvt} represents a good and time variety-specific taste shock, and the aggregate quantity consumed of a certain variety at time t is x_{gvt}. The demand for a certain variety of a good at time t, x_{gvt}, is a function of its price, p_{gvt}, taste for that variety, b_{gvt}, and a good-specific price index, $\phi_{gt}(b_{gt})$.

The good price index frames the variety within all available varieties of that good, and is defined as:

$$\phi_{gt}(b_{gt}) \equiv \sum_{v \in I_{gt}} (b_{gvt}\, p_{gvt}{}^{1-\sigma_g})^{\frac{1}{1-\sigma_g}} \qquad \text{Eq. 5.1}$$

Total demand for the variety is:

$$x_{gvt} = p_{gvt}^{-\sigma_g} b_{gvt} \left(\phi_{gt}(b_{gt})\right)^{\sigma_g - 1} \quad \textit{Eq. 5.2}$$

The utility derived from consumption of good *g* is:

$$X_{gt} = \left(\sum_{v \in I_{gt}} b_{gvt}^{1/\sigma_g} x_{gvt}^{\sigma_g - 1/\sigma_g}\right)^{\frac{\sigma_g}{\sigma_g - 1}} \quad \textit{Eq. 5.3}$$

Where:

σ_g=good-specific constant elasticity of substitution
g= good
v = varieties (exporter for previous literature, importer for us)
t =time
x_{gt}= quantity consumed of good over all varieties
x_{gvt}= aggregate quantity of each variety consumed in period *t*
b_{gvt}= variety-specific taste shock

The original interpretation of σ_g is of an importer-and-good-specific elasticity of substitution of imports, over varieties of exporters. Concretely, how much an importer (e.g., USA) shifts their purchases of a good (e.g. oil) from one exporter (variety) to another, due to a price change (expressed through the price index $\phi_{gt}(b_{gt})$).

As is, despite being an applicable model for structural trade elasticities, it does not apply to our research questions because it gives us information on the demand substitution elasticity of a specific *importer*, over various exporters. Our aim instead is to understand how the demand for different traded ETMs differs amongst main *exporters*, and how it has evolved over the past decades.

To address this incompatibility, we propose a modification of the interpretation of varieties where the model and data may be adapted and used to analyze the demand for a good *from* a specific exporter instead of *to* a specific importer. In our modification, the utility function embodies the world aggregate utility as the sum of quantities of goods (e.g., oil) imported by all countries, from a specific exporter (e.g. Saudi Arabia). This implies that importers become the variety.

What is the impact of this change on the definition of σ_g? We propose that we interpret σ_g as a good-and-exporter specific world aggregate elasticity of substitution of imports over all importers (varieties). In other words, σ_g embodies how much demand is shifted among importers as price changes, for a certain good-exporter combination. It is a measure of the price sensitivity of an aggregate world importer to an exporter-good pair, or the elasticity.

In our running example, the estimated value of σ_g would quantify how much world importers shift their demand (between themselves) when there is an increase in the price of oil from Saudi Arabia. Krugman

(1979) showed that at a large number of varieties, v, σ_g can be considered a measure of the demand elasticity. In this case, the estimate can thus be considered the world demand elasticity of a good from a specific exporter.

5.3.2 Supply

We define supply through price, p_{gvt}, with an inverse export supply elasticity of $\omega_g \geq 0$, and a good-variety-time specific technology factor, η_{gvt}:

$$p_{gvt} = \left(\frac{\sigma_g}{\sigma_g - 1}\right) \exp(\eta_{gvt})\, (x_{gvt})^{\omega_g} \qquad \textit{Eq. 5.4}$$

Where:
ω_g= good-specific inverse export supply elasticity
g= good
v = varieties (exporter)
t =time
p_{gvt} =price of variety at time t
x_{gt}= quantity consumed of good over all varieties
x_{gvt}= quantity consumed of varieties at time t
η_{gvt}= random technology factor

The interpretation of ω_g is of a good-and-importer-specific inverse export supply elasticity. As discussed in the Literature Review, it is analyzed extensively in Broda, Limão, and Weinstein (2006). ω_g can be considered the importer market power, as it captures how changes in the quantity demanded by one importer affects prices of that variety.

Our discussion focuses only on the estimation of σ_g; however, it is useful to note that when the variety represents importers, ω_g becomes the good-and-exporter-specific inverse export supply elasticity of each variety (importer). It can be thought of as the market power of the exporter (a parameter that influences how quantity exported, x_{gvt}, by one country affects prices of goods it exports).

5.3.3 Estimating equation

As explained in the Literature Review, Feenstra (1994) converts the demand for a product by one country in a particular year into shares. This is done to mitigate the measurement error caused by utilizing unit values (trade quantities divided by trade values) as a proxy for prices because shares of expenditure should be uncorrelated with the measurement error of the unit value.

In this section, we continue to use the notation of (Soderbery 2015). The market share of a variety, s_{gvt}, it is a function of the taste parameter, b_{gvt}, and the relation of its price, p_{gvt} to the price index $\phi_{gt}(b_{gt})$:

$$s_{gvt} \equiv \frac{(p_{gvt}x_{gvt})}{\sum_{v \in I_{gt}}(p_{gvt}x_{gvt})} = \left(\frac{p_{gvt}}{\phi_{gt}(b_{gt})}\right)^{1-\sigma_g} \cdot b_{gvt} \qquad \textit{Eq. 5.5}$$

Like we did with demand, we also convert supply into shares:

$$p_{gvt} = \left(\sum_{v \in I_{gt}} exp\left(\frac{-\eta_{gvt}}{\omega_g}\right) p_{gvt}^{\frac{1+\omega_g}{\omega_g}}\right)^{\frac{\omega_g}{1+\omega_g}} exp\left(\frac{\eta_{gvt}}{1+\omega_g}\right) s_{gvt}^{\frac{\omega_g}{1+\omega_g}} \qquad \textit{Eq. 5.6}$$

To make the equations more workable, Feenstra (1994) first-differences, takes logs, and generates an error term. Shares (demand) become:

$$\Delta ln(s_{gvt}) = \varphi_{gt} - (\sigma_g - 1)\Delta ln(p_{gvt}) + \varepsilon_{gvt} \qquad \textit{Eq. 5.7}$$

Where $\varphi_{gt} \equiv (\sigma_g - 1)\Delta \ln\left(\phi_{gt}(b_{gt})\right)$, is a random shock specific to time and product based on taste parameter, b_{gt}. In contrast, the random shock $\varepsilon_{gvt} = \Delta \ln(b_{gvt})$, is variety-specific taste shock.

Eliminating good-specific unobservables from the price (supply) in natural logs, we are left with:

$$\Delta lnp_{gvt} = \psi_{gt} + \left(\frac{\omega_g}{1+\omega_g}\right)\Delta^k \ln(s_{gvt}) + \delta_{gvt} \qquad \textit{Eq. 5.8}$$

Where $\psi_{gt} = \frac{\omega_g}{1+\omega_g}\Delta ln\left(\sum_{v \in I_{gt}} exp\left(\frac{-\eta_{gvt}}{\omega_g}\right) p_{gvt}^{\frac{1+\omega_g}{\omega_g}}\right)$ are time-product specific shocks to production. On the other hand, $\delta_{gvt} = \left(\frac{\eta_{gvt}}{1} + \omega_g\right)$ are random technology shocks to the production of each variety.

Leamer (1981)'s contribution to the identification of supply and demand curves was to show that, given independent error structures in the demand and supply equations, a hyperbola of the second moments of the data would contain the set of possible maximum likelihood estimates. Building upon Leamer (1981), Feenstra (1994) eliminates the time-product shock, φ_{gt}, by differencing over reference country, k, resulting in the following structural demand curve where demand shock $\varepsilon_{gvt}^k = \Delta^k \ln(b_{gvt})$:

$$\Delta^k lns_{gvt} \equiv \Delta lns_{gvt} - \Delta lns_{gkt} = (\sigma_g - 1)\Delta^k \ln(p_{gvt}) + \varepsilon_{gvt}^k \qquad \textit{Eq. 5.9}$$

The same is done for the supply curve. We eliminate the time-product shock, ψ_{gt} by differencing over reference country, k, where supply shock $\delta_{gvt}^k = \Delta^k \ln\left(\frac{\eta_{gvt}}{1+\omega_g}\right)$.

$$\Delta^k lnp_{gvt} \equiv \Delta lnp_{gvt} - \Delta lnp_{gkt} = \left(\frac{\omega_g}{1+\omega_g}\right)\Delta^k \ln(s_{gvt}) + \delta_{gvt}^k \qquad \textit{Eq. 5.10}$$

As discussed in the review, the reference country plays a central role in Feenstra (1994)'s elasticities. In fact, to be able to compare elasticities of a good by exporter (importer in the original model), both estimates must be based on the same reference importer (exporter in the original model). For instance, if we are comparing the trade elasticity of demand for oil from Saudi Arabia and the same estimate from Qatar, we must make sure that the reference importer is the same in both estimates. This is built into the method and automated in our code.

The method for choosing the reference country itself is ultimately up to the implementing researcher. For computational purposes, it must be a variety sold every year. Yet, if there are several such varieties, Mohler (2009) suggests that the variety with the largest value yields the most stable elasticities.

In principle Feenstra (1994), Broda and Weinstein (2006), Soderbery (2015) all choose the variety with the largest market share as the reference. However, upon close inspection, modification, and implementation of Soderbery (2015)'s code that we use as the basis for our estimates, the original code fails to consistently choose the variety with the largest market share as the reference when there are multiple varieties sold every year. We amend this, and the change is reflected in our final estimates.

Estimating strategy
Following Feenstra (1994), we now transform the above into a single equation. We abridge Feenstra (1994)'s (econometric) contribution in the interest of space. Multiplying the demand and supply shocks, we generate a combined shock:

$u_{gvt} = \frac{\varepsilon_{gvt}^k \delta_{gvt}^k}{(1-\rho_g)}$, where *Eq. 5.11*

$\rho_g \equiv \frac{\omega_g(\sigma_g-1)}{1+\omega_g\sigma_g}$ for $\in \left[0, \frac{\sigma_g-1}{\sigma_g}\right]$ *Eq. 5.12*

Further scaling by $\frac{1}{(1-\rho_g)}$, and rearranging , we arrive at Feenstra (1994)'s estimating equation:

$$Y_{gvt} = \theta_1 X_{1gvt} + \theta_2 X_{2gvt} + u_{gvt} \qquad \textit{Eq. 5.13}$$

Coefficients θ_1 and θ_2 are functions of σ_g and ρ_g:

$\theta_1 \equiv \frac{\rho_g}{(\sigma_g-1)^2(1-\rho_g)}$ and *Eq. 5.14*

$\theta_2 \equiv \frac{2\rho_g-1}{(\sigma_g-1)(1-\rho_g)}$ *Eq. 5.15*

And, $Y_{gvt} \equiv (\Delta^k lnp_{gvt})^2$; $X_{1gvt} \equiv (\Delta^k lns_{gvt})^2$ and $X_{2gvt} \equiv (\Delta^k lnp_{gvt})(\Delta^k lns_{gvt})$.

Most conservatively, we can interpret the model output as an elasticity of substitution for the demand of a certain product from a certain exporter, between varieties of importers. More broadly, we could interpret that, in a large group of *n* countries, our estimates become the trade elasticity of demand for a product from a certain exporter (Krugman 1979). Therefore, even at the broadest level, our output is strictly an elasticity of demand for the *trade* of a certain product from a certain exporter, not an elasticity of demand by product and country of production.

Because the trade demand elasticities are applicable only to trade, they may have a relatively narrow application for countries that have large internal demand for the ETMs. It is still useful for countries that have negligible internal demand, or for the export sectors of economies with large internal demand.

Appendix 1 explains how we input the data into the empirical model so that it respects the theoretical interpretation we propose. Our work breaks the second assumption of the model that states that supply and demand elasticities are identical across varieties (i.e., exporting countries) within goods. However, in running a Kolmogorov-Smirnov test on his data, Soderbery (2015) finds this is not the case for export supply elasticities and writes Soderbery (2018) on it. The code was implemented in Stata 15.0. It is available upon request.

5.4 DATA

We use 30 ETMs products in UN Comtrade that were systematically identified in the methods of Chapter 4. In the interest of space, we refrain from describing the dataset, but we note that this is an example of an application of the contributions that chapter. In this section, we discuss characteristics of the dataset that are relevant only to the questions and methods unique to this chapter.

As discussed in the Literature Review, the elasticities are best calculated in a data-rich environment, so we consider only major exporters, defined as either within the top five in total value for a certain good during the 20 years, or those included in the cumulative top 90% of exporters, whichever comes first.

Additionally, Broda, Limão, and Weinstein (2006) maintain that the more varieties (importers for us) available, the more precise the elasticities (though this is called into question in (Soderbery 2010)). As you may recall: (1) HS nomenclature is standardized internationally up to six digits; (2) the more disaggregated the HS codes (e.g., six- instead of four-digit HS codes), the fewer the number of varieties per ETM; and, (3) the greater the aggregation used (four- instead of six-digit HS codes), the more data the researcher has.

Broda and Weinstein (2006) and subsequent papers that discussed their methods empirically tested behaviors predicted by trade theory over all products. As a result, they chose products according to only one level of aggregation, say 6-digit products, for their analysis. The research questions of this chapter relate to a specific subset of all available traded products, so we actively consider the level of aggregation needed to isolate each ETM. For instance, HS 2616 refers to ores and concentrates of all precious metals, including silver (HS 261610), gold, and the platinum group metals (HS 261690). However, crude oil is sufficiently differentiated at the four-digit HS level (HS 2709). We, therefore, choose the adequate level of aggregation, between four- and six-digit HS codes, according to each ETM.

Remember that in our data, varieties are given by both the ETM and the importer. In our case and over all decades, ETMs face an average of 104 importers, with a minimum of 31 (cobalt [OC]) and a maximum of 165 (aluminum [UW]) (Table 5.2). However, the sample is somewhat smaller when we slice the data by decade, with an average of 87 importers in Decade 1 and of 91 in Decade 2.

Table 5.2. Varieties, by ETM and decade. Ordered by highest to lowest, overall.

Energy technology material	HS	Overall	Decade 1	Decade 2	Growth by decades
Aluminum [UW]	7601	168	145	154	9
Natural gas	2711	165	156	158	2
Beryllium, chromium, germanium, vanadium, gallium, hafnium, indium, niobium (columbium), rhenium and thallium [metals]	8112	158	138	148	10
Graphite [PF]	2504	153	135	138	3
Lead [UW]	7801	149	137	132	-5
Cobalt mattes and other intermediate products of cobalt metallurgy [UW, powders, waste/scrap]	8105	143	133	128	-5
Compounds, inorganic or organic, of rare-earth metals, of yttrium or of scandium, or of mixtures of these metals [UW]	2846	137	115	127	12
Platinum [UW]	711011	133	115	119	4
Crude oil	2709	127	104	106	2
Niobium tantalum vanadium zirconium [OC]	2615	122	107	103	-4
Silver [UW]	710691	118	100	109	9
Cobalt chemical [OH]	2822	115	95	100	5
Lithium chemicals [OH]	282520	113	94	96	2
Earth-metals, rare and scandium and yttrium, whether or not intermixed or interalloyed	280530	108	85	86	1
Lithium chemicals [carbonate]	283691	108	86	98	12
Palladium [UW]	711021	108	96	92	-4
Copper [matte]	7401	104	93	84	-9
Lead [OC]	2607	96	76	75	-1
Aluminum [OC]	2606	88	74	78	4
Molybdenum [OC]	2613	87	70	68	-2
Rhodium [UW]	711031	84	66	66	0
Manganese [OC]	2602	83	67	72	5
PGM [OC]	261690	77	55	70	15
Vanadium chemical [OH]	282530	77	68	65	-3
Molybdenum [UW]	810291	67	48	61	13
Copper [OC]	2603	64	45	55	10
Nickel [matte]	7501	58	48	39	-9
Nickel [OC]	2604	40	20	38	18
Silver [OC]	261610	32	20	27	7
Cobalt [OC]	2605	31	28	25	-3
Mean		103.77	87.3	90.57	3.27

Sources: Author's elaboration based on UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).

There are 40 major exporters of the products (Table 5.3). On average, major exporters face about 51 importers. As with ETMs, the number of importers drops when slicing the data by decade, with an average of 42 and 43 varieties per exporter. Over the 20 years, the European Union stands with the highest number of importers (173), which is not surprising. In contrast, Armenia and Guatemala stand out as having the lowest number of importers, with 4 varieties in both cases.

Table 5.3. Varieties, by major exporter and decade.

Major exporter	Major exporter (ISO code)	Overall	Decade 1	Decade 2	Change over decades
European Union	EUN	173	169	165	-4
USA, Puerto Rico and US Virgin Islands	USA	149	133	135	2
China	CHN	140	118	134	16
Canada	CAN	124	94	108	14
Australia	AUS	111	83	94	11
Russian Federation	RUS	109	83	105	22
Southern African Customs Union	ZAF	93	78	80	2
Norway, Svalbard and Jan Mayen	NOR	86	69	78	9
Chile	CHL	75	63	61	-2
Brazil	BRA	71	56	68	12
Republic of Korea	KOR	66	51	51	0
Nigeria	NGA	65	43	54	11
United Arab Emirates	ARE	63	50	52	2
Switzerland, Liechtenstein	CHE	59	49	52	3
Japan	JPN	58	45	52	7
Qatar	QAT	48	34	44	10
Saudi Arabia	SAU	45	37	35	-2
Mexico	MEX	40	33	34	1
Peru	PER	40	29	35	6
Gabon	GAB	39	31	24	-7
Zambia	ZMB	37	33	27	-6
Indonesia	IDN	35	26	31	5
Taiwan (Other Asia, not elsewhere specified)	TWN	30	24	22	-2
Argentina	ARG	28	18	26	8
Malaysia	MYS	25	18	19	1
Guinea	GIN	24	18	15	-3
Rwanda	RWA	24	20	20	0
Plurinational State of Bolivia	BOL	23	17	20	3
Philippines	PHL	23	7	22	15
Ghana	GHA	20	19	8	-11
United Republic of Tanzania	TZA	19	14	14	0
Cuba	CUB	17	17	3	-14
Democratic Republic of the Congo	COD	16	15	14	-1
Congo	COG	12	12	5	-7
New Caledonia	NCL	12	10	7	-3
Viet Nam	VNM	9		9	
Iran	IRN	8	5	4	-1
Zimbabwe	ZWE	7	3	6	3
Armenia	ARM	4	3	3	0
Guatemala	GTM	4	3	3	0
Mean		50.78	41.8	43.48	2.56

Sources: Author's elaboration based on UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020).

5.5 RESULTS

5.5.1 Descriptive statistics of the calculated elasticities

In the second column of Table 5.4, we present the summary statistics of trade demand elasticity estimates output by our model. By design, Broda, Limao, and Weinstein (2008) limit sigma at 131.05, and Soderbery (2015) does so as well to compare his proposed estimation method with the original. When we impose the limit, the mean trade demand elasticity, or the average percentage decline of demand for a one percent change in price, is 5.70, just above Soderbery (2015)'s mean, at 5.26 (third column of Table 5.4). Soderbery includes all available products, but as we discussed in the Literature Review, commodities (which are highly represented in our study) tend to have slightly higher elasticities, both theoretically and empirically, so our results are broadly in line with what is expected. To keep the discussion manageable, we exclude outlier estimates, over the 95th percentile (fourth column of Table 5.4) from our analysis.

Within that sample, some product-exporter pairs have trade demand elasticity values for only one decade. Keeping them in our output would allow for a greater representation of the trade demand elasticities by product. However, including product-exporter pairs that have trade demand elasticities in only one decade would bias the analysis. Therefore, we restrict the sample to ETM-exporter pairs for which there is output for both Decade 1 and Decade 2, understanding that the statistics below are representative of the restricted sample only (last column of Table 5.4.).

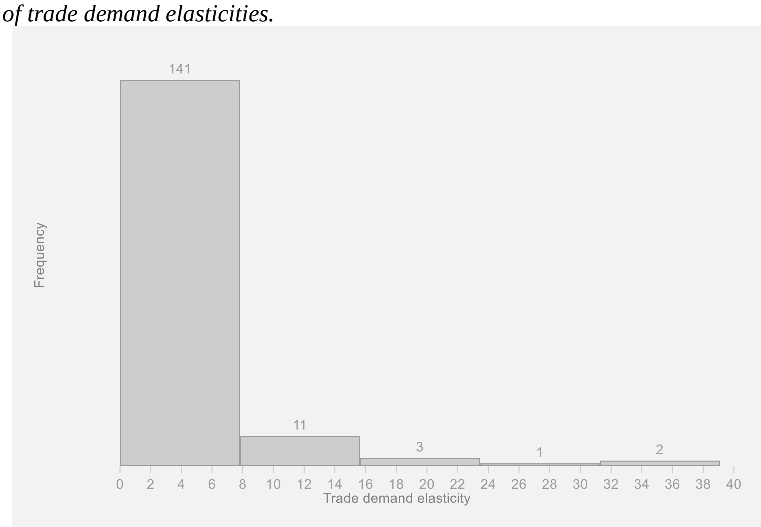
This yields trade demand elasticities over two decades for 29 of the initial 30 products (crude oil did not output two decades for any exporter), with a mean trade demand elasticity of 3.94, a standard deviation of 5.40, and positive skewness visually evidenced (last column of Table 5.4 and Figure 5.1). Additionally, the final trade demand elasticity sample contains 22 of the 40 major exporters (we consider the results from this perspective in detail in subsequent sections and the discussion). The analysis in the subsequent section uses this sample.

Table 5.4. Trade demand elasticities summary statistics, by sample.

	Raw data	All except sigma ≥131.5	All except ≥p95	All except ≥p95 and exporter contains both decades
N	229	221	217	158
Mean	216.64	5.703	4.332	3.937
Std. Dev.	2479.599	11.983	6.178	5.403
skewness	14.45	5.238	3.711	4.055
iqr	4.129	2.608	2.441	1.978
p5	1.143	1.143	1.134	1.134
Median	2.229	2.175	2.121	1.984
p95	61.833	21.272	18.019	14.303

Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.

Figure 5.1 Frequency of trade demand elasticities.



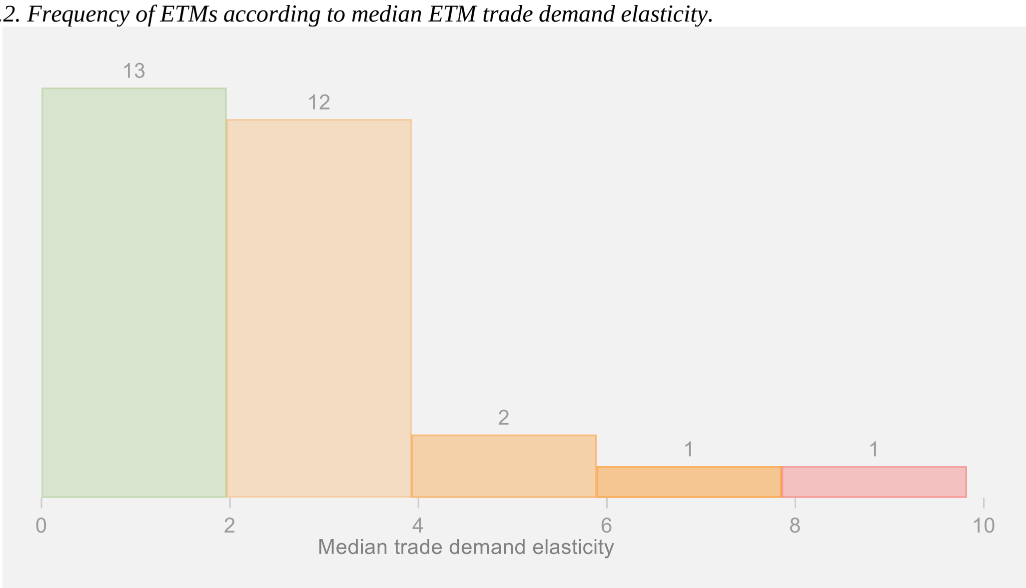
Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.

The appendixes provide more information and analysis. Appendix 5.2 contains detailed statistics of each of the columns in Table 5.4, additional analysis by product, and over time. Appendix 5.3 compares all possible exporter and product combinations in the primary dataset with the results of our model and code.

5.5.2 Product-exporter pairs

Our first research question was to estimate the trade demand price elasticities for each product-and-main-exporter pair of ETMs. To visualize the elasticities by product-exporter pair, we first divide the dataset into a five-bin histogram based on each ETM's median value. We denominate the bins into low, low-medium, medium, high, very-high trade demand elasticity ETM groups from green, to orange, to red in Figure 5.2.

Figure 5.2. Frequency of ETMs according to median ETM trade demand elasticity.



Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.

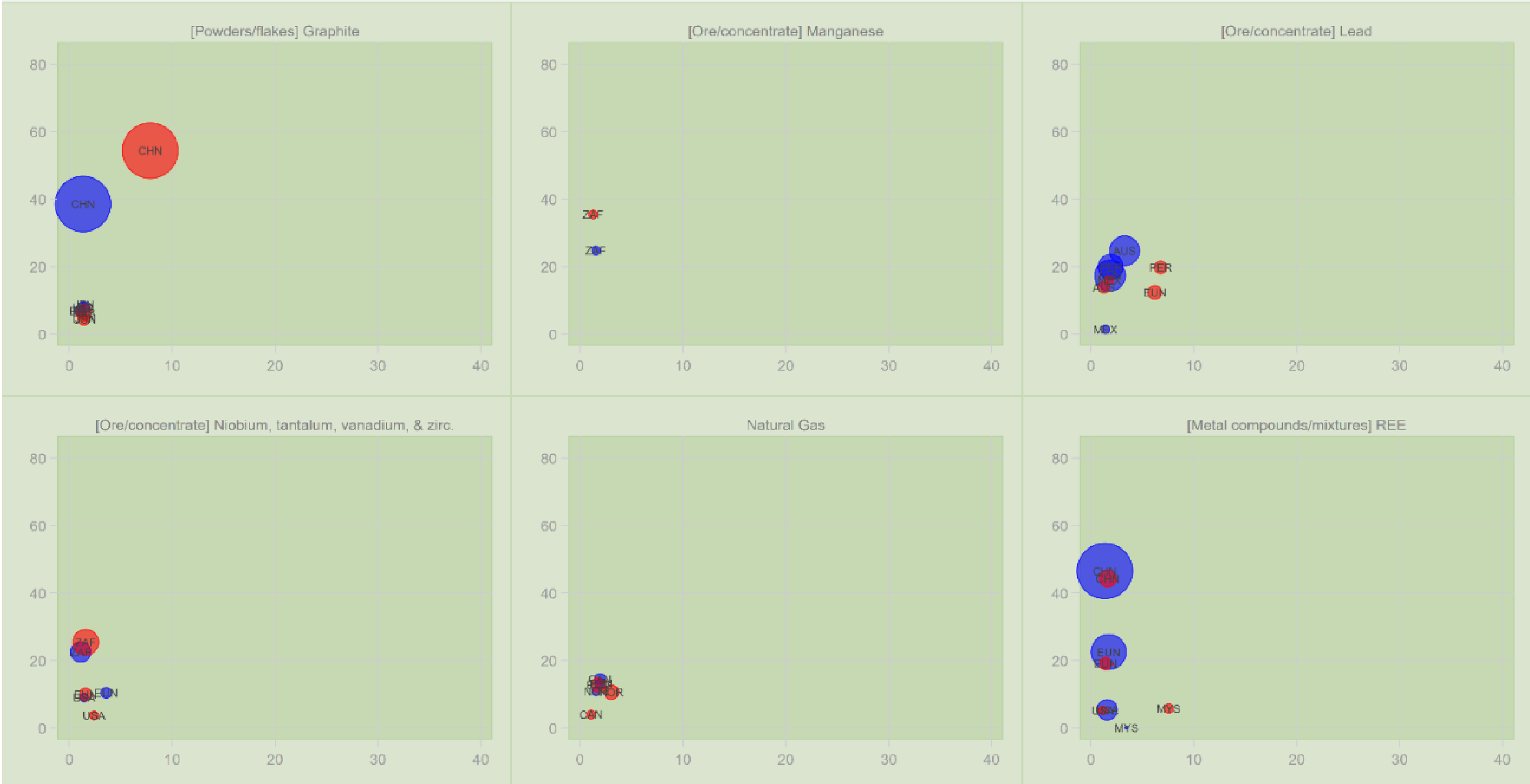
Figure 5.3 allows us to compare trade demand elasticities by exporter, ETM, and decade. The colors of the backgrounds follow the bins in Figure 5.2. The x-axis contains the trade demand elasticity value. The y-axis indicates the market share of the exporter by value, and the bubble size is the market share of the exporter by quantity. The color of the bubble denotes the decade; red is Decade 1, and blue is Decade 2.

As an example of how to read the figure, we look at lithium carbonate, which is used in lithium-ion batteries with wide applications and is expected to grow 488% in quantity produced by 2050 in comparison to 2018 (World Bank 2020b). In descending order, its major exporters between 1999-2018 have been Chile, Argentina, the European Union, and China. We have trade demand elasticities in this product for all except the European Union (Figure 5.3). The background color of the figure indicates that its median trade demand elasticity across countries is in the low-medium group.

As per Mohler (2009), researchers investigating individual elasticities instead of broad macroeconomic questions should compare relative differences in elasticities instead of the exact number. Chile, the country with the highest market share by value, has experienced an increase in trade demand elasticity over time. However, the opposite occurred in Argentina and China. The interpretation of this result is that, if the trends of the last decade continue, Argentina and China will suffer less from volatility in prices lithium [carbonate] than Chile.

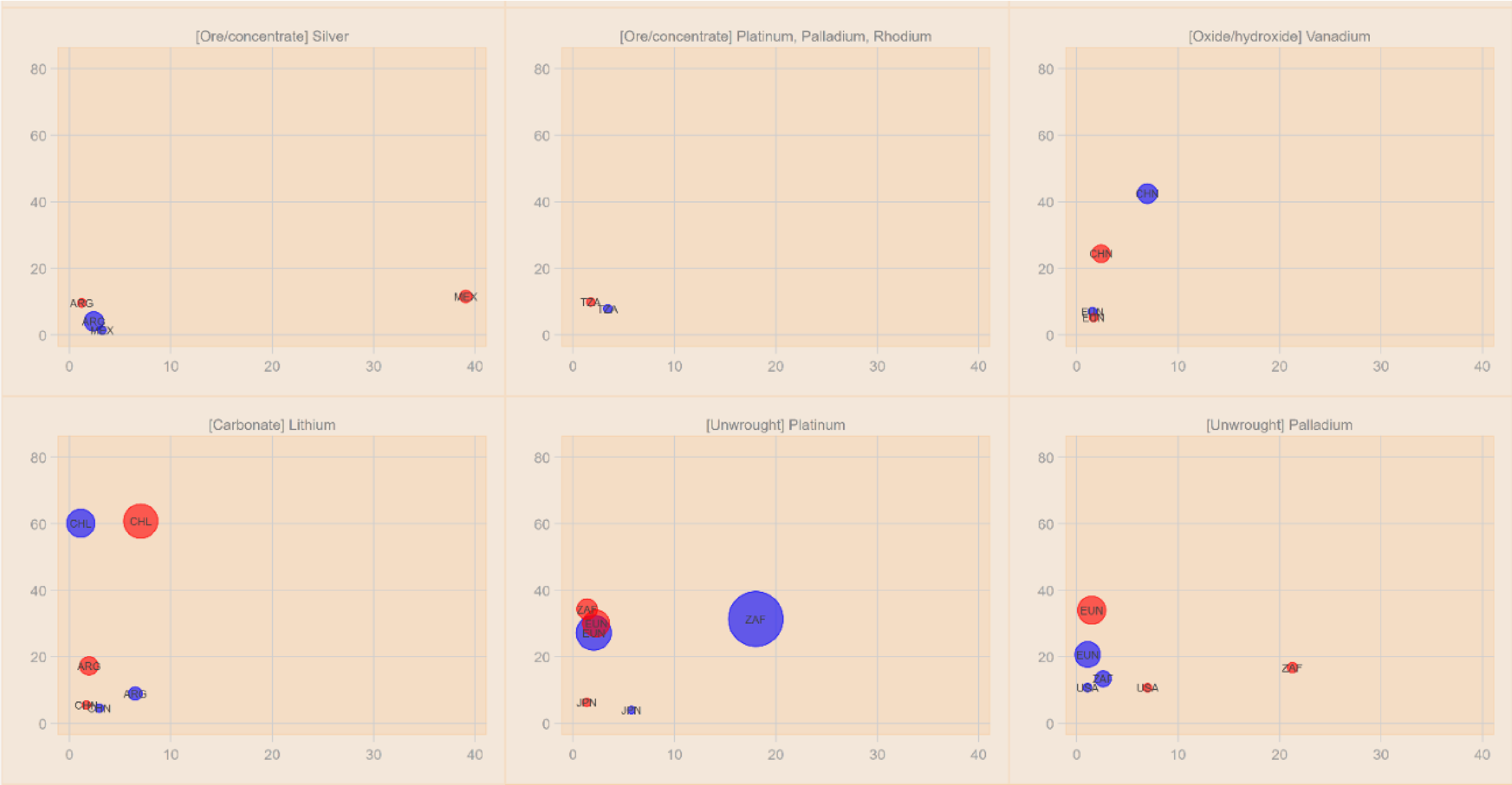
Despite our efforts, it is still difficult to visually differentiate all the elasticities by exporters in the graphs. We provide the results in table format in Appendix 5.4.

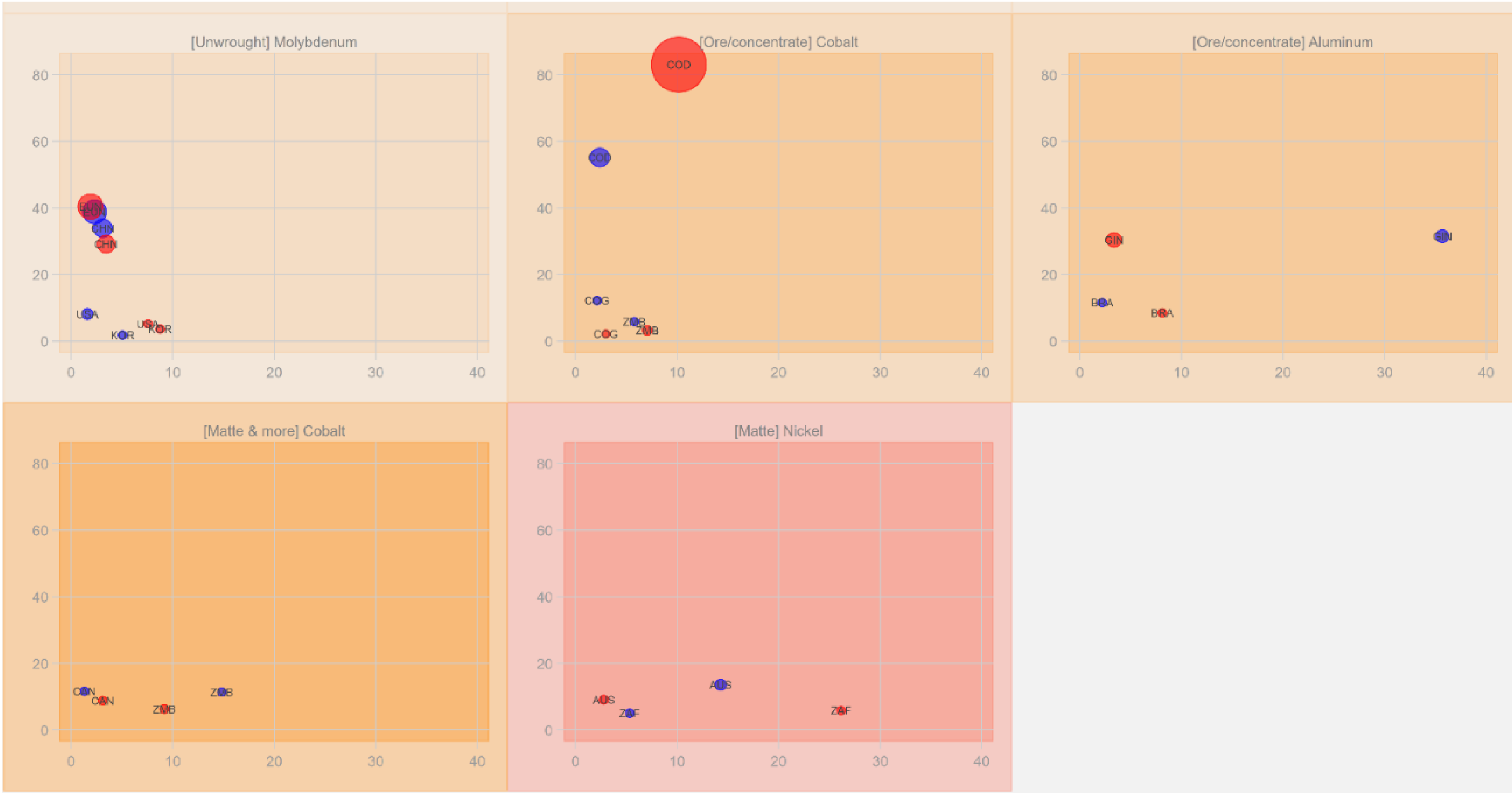
Figure 5.3. Trade demand elasticity (x-axis), market share by value, % (y-axis), market share by volume (bubble size); Decade 1 (blue); Decade 2 (red) for all available countries output by the model; background colors correspond to bins from Figure 5.2.



[Matte] Copper
[Unwrought] Aluminum
[Metals, incl. waste/scrap] Others
[Metals, incl intermixed/alloyed] REE
[Oxide/hydroxide] Lithium
[Unwrought] Silver
EUN
CHN
USA
0
10
20
30
40
60
80


[Unwrought] Rhodium
[Ore/concentrate] Copper
[Ore/concentrate] Nickel
[Ore/concentrate] Molybdenum
[Oxide/hydroxide] Cobalt
[Unwrought] Lead
0
10
20
30
40
60
80
CHL
PHL
AUS
CHN
JPN
EUN
KOR


[Ore/concentrate] Silver
[Ore/concentrate] Platinum, Palladium, Rhodium
[Oxide/hydroxide] Vanadium
[Carbonate] Lithium
[Unwrought] Platinum
[Unwrought] Palladium
ARG
MEX
CHN
CHL
ZAF
EUN
JPN
USA



Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.

5.5.3 Exporters

Our second objective is to compare the position of developing and developed exporters in ETM elasticities. Table 5.5 summarizes the elasticities by exporter. Seven of these only have data for one product. The exporters for which we have trade demand elasticity data for the most quantity of products are: China, Europe, and the United States, with 10, 15, and 9 products, respectively. This result is expected as they are major exporters of many products over the entire product space.

Observing the difference between the number of products for some exporters (e.g., China has 10 and Tanzania only one), we consider whether there may be a relationship between the mean trade demand elasticity and the number of products (observations) by exporter. If such a relationship exists, there would be a bias in our results. We subject this to statistical testing by using a Pearson correlation between the mean and the number of products that each mean represents. The results suggest that there is a negative correlation between the size of the sample and the mean of the products, but that it cannot be distinguished from zero at a p-value of 5% (correlation of -0.25 and a p-value of 0.26).

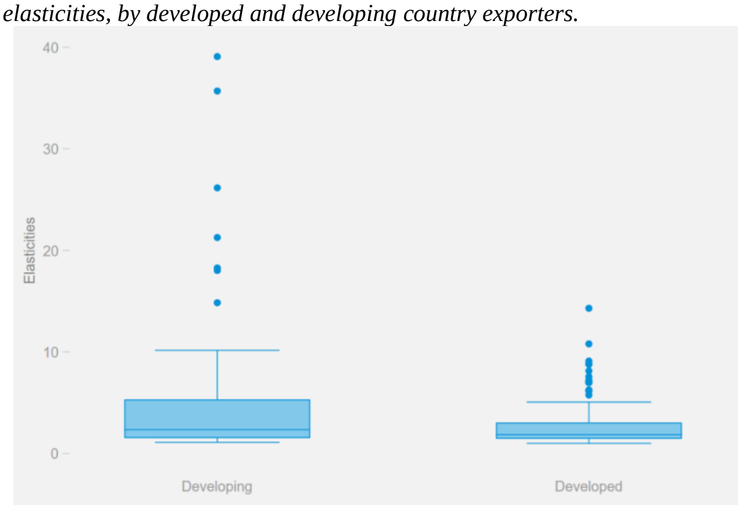
Table 5.5. Summary statistics, by exporter.

ISO code	Products	Mean	SD	Country group
EUN	15	2.32	1.37	Developed
CHN	10	2.67	2.00	Developing
USA	9	2.51	2.10	Developed
ZAF	6	7.12	9.12	Developing
AUS	6	4.19	3.87	Developed
CAN	4	1.89	0.68	Developed
CHL	4	5.13	4.22	Developed
BRA	3	2.63	2.73	Developing
JPN	3	2.54	1.69	Developed
ARG	2	3.02	2.37	Developing
MEX	2	11.38	18.48	Developing
PER	2	3.21	2.41	Developing
ZMB	2	9.23	4.00	Developing
KOR	2	8.66	6.90	Developed
NOR	2	1.85	0.80	Developed
COD	1	6.28	5.49	Developing
COG	1	2.57	0.62	Developing
GIN	1	19.53	22.85	Developing
IDN	1	2.06	1.00	Developing
MYS	1	5.52	2.88	Developing
PHL	1	2.27	0.05	Developing
TZA	1	2.59	1.18	Developing

Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.

Table 5.5 shows that the highest mean trade demand elasticity by country is 19.53 (Guinea) and the lowest is 1.85 (Norway). The average for developing countries is 5.92 and the average for developed countries is 3.64. The data therefore naturally leads to our research question, pointing towards developed countries having lower elasticities, visually depicted in the boxplots of Figure 5.4.

Figure 5.4. Boxplots of elasticities, by developed and developing country exporters.



Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.

We subject the question of whether developing countries have higher elasticities than developed countries to statistical tests. A t-test is not applicable to our data because (as shown in the histogram of Figure 5.1) it is not normally distributed. We, therefore, apply a non-parametric test of medians called the Wilcoxon rank-sum test (or the Mann–Whitney two-sample statistic) and the nonparametric k-sample test on the equality of medians. The first tests whether the distribution of the groups are the same, and we reject the null hypothesis when p-values are low. The second tests the null hypothesis that the *k* samples were drawn from populations with the same median, and we reject the null hypothesis when p-values are low. Note that, as can be intuited from the boxplots of Figure 5.4 visually displaying summary statistics, in the case of this data, a test of medians will be less likely to show statistical differences between the two groups than a t-test of means.

The result of the Wilcoxon test is on the cusp of being significant at a p-value of 10% (Table 5.6). This means that the distribution of the groups are weakly different from one another. As hypothesized, the ETM trade demand elasticity patterns over developed and developing countries could be due to at least two separate factors or their interaction: (1) the ETM make-up of the portfolios of the exporters[1]; and, (2) the characteristics of the products from the point of view of importers, when developing and developed countries export the same ETM. We will take a closer look at these factors below.

For robustness, we check whether the finding holds when we remove the three trading giants of China, the European Union, and the United States. When we exclude China, the likelihood of the distributions being different increases, and the similarity between the medians (as per the Nonparametric k-sample test on the equality of medians) becomes statistically significant. Therefore, China may be a special

[1] We discussed in the Literature Review that Broda, Greenfield, and Weinstein (2006) show that commodities (goods sold on international exchanges) tend to have higher elasticities. In previous analyses outside of this chapter, we showed that developing countries portfolios were more heavily made up of unrefined products. Note that while "unrefined products" and "commodities" have similarities, they are not equal. For instance, metal powders are refined products, which are sold on exchanges.

type of developing country, which is closer to its developed counterparts. When we exclude the European Union or US, the likelihood of the distributions being different decreases, which shows that they partly drive the differences between the two country groups.

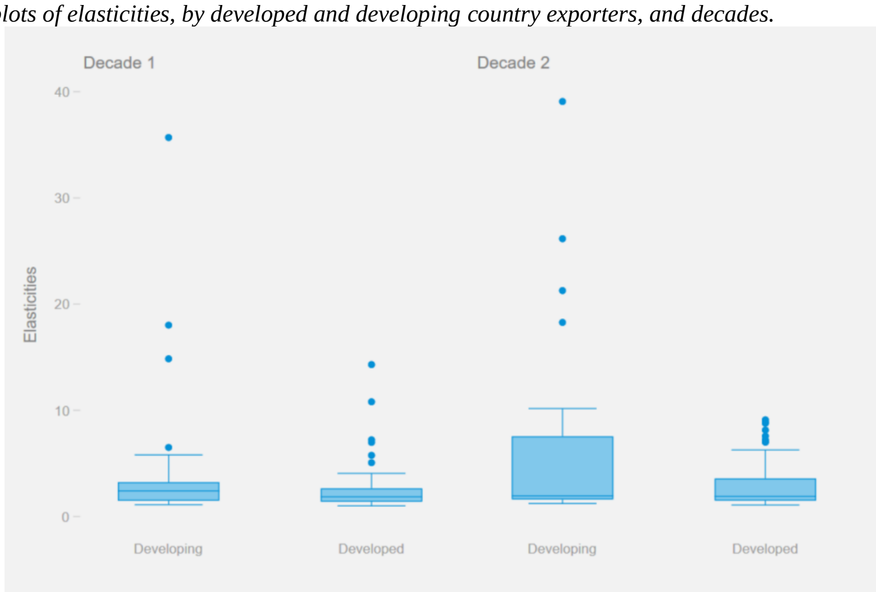
Table 5.6. P-values of statistical tests comparing the ETM trade demand elasticities, developing versus developed country exporters.

Wilcoxon rank-sum test/ Mann–Whitney two-sample statistic (exact p-value)	Nonparametric equality-of-medians	Sample
0.1077	0.259 (nc 0.197)	All
0.0132	0.021 (nc 0.013)	All minus China
0.1802	0.377 (nc 0.289)	All minus EU
0.2796	0.236 (nc 0.176)	All minus US

Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.
Note: nc= not continuity corrected.

We turn back to the question of whether the differences in the distributions of the groups are due to the ETM make-up of the exporters' portfolios, or the characteristics of the products or exporters from the point of view of importers. Recall that the sample is balanced so that each product-exporter combination exists in both decades. When we cut the data into decades to look at changes, this allows us to rule out the first option and allows us to consider the second. Changes over decades are represented in the boxplots in Figure 5.5.

Figure 5.5. Boxplots of elasticities, by developed and developing country exporters, and decades.



Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.

We repeat the tests by decade (Table 5.7). Over the whole sample, the changes in significance point towards a *convergence* in the distribution of the elasticities and medians between the two groups. This is because in Decade 1, the difference was more statistically significant than in Decade 2 in both tests. This means that, given the same ETMs on either side of each decade (within each country group), their elasticities converged.

Table 5.7. P-values of statistical tests comparing the ETM trade demand elasticities, developing versus developed country exporters, by decade.

Wilcoxon rank-sum test/ Mann–Whitney two-sample statistic (exact p-value)	Nonparametric equality-of-medians	Decade	Sample
0.1460	0.055 (nc 0.032)	1	All
0.3008	0.924 (nc 0.746)	2	
0.0394	0.009 (nc 0.004)	1	All minus China
0.1036	0.554 (nc 0.400)	2	
0.2082	0.133 (nc 0.080)	1	All minus EU
0.4959	1.000 (nc 0.802)	2	
0.3928	0.338 (nc 0.231)	1	All minus US
0.3863	1.000 (nc 0.811)	2	

Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.
Note: nc= not continuity corrected.

Removing China reinforces the convergence, suggesting that China's pattern is different from its group. Removing the United States or the European Union again decreases the likelihood of the distributions being different, with a marked decrease in Decade 2 for the European Union, suggesting that the European Union has comparatively lower elasticities than its group, and that they went down further over time. In the next section, we discuss how further research may continue to investigate this topic.

5.6 Discussion

Elasticity is an important concept in economics and has a variety of uses. This paper aimed to calculate the trade demand price elasticities (the change in trade demand due to a change in price) for product-and-main-exporter pairs of ETMs. This means that our proposed metric can help a country understand the sensitivity of demand to its exports for a given change in price. A low trade demand elasticity is beneficial to exporters because it leads to more stable returns on investments, fiscal resources, and more. Amongst other applications, calculating trade elasticities across all ETMs and major exporters is a springboard from which exporters can compare their performance with others and identify points of opportunity or improvement.

We set out to find the trade demand price elasticities, or the change in trade demand due to a change in price, for each product-and-main-exporter pair of ETMs (example cobalt ore and concentrate from the Democratic Republic of the Congo or platinum group metals from South Africa). For this, we modify and calculate existing elasticity methods based on a series of methodological and theoretical improvements including Armington (1969), Leamer (1981), Feenstra (1994); Krugman (1979), Broda and Weinstein (2006), Soderbery (2015), and more. Because we aimed to calculate these elasticities over a large group of countries and products, we modified existing structural models to our needs. A major strength of structural methods such as this one is it only requires trade data and deals with identification issues. This is crucial when estimating elasticities for country exporters that have limited data, and because using disaggregated data limits the scope of other analyses.

We find that our modification of the elasticities yields results that are broadly in line with papers published before ours. Our final sample of ETM trade demand elasticities covers two decades over 29 products and 22 major exporters, with a mean trade demand elasticity of 3.94. The trade giants of the European Union, China, and the United States are most represented in our final elasticities sample. This was expected and is simply a reflection of the number of products in which they were major exporters.

The results of each product and exporter pair are available for researchers to use as inputs in a variety of product or country-specific research questions. We also asked whether developed or developing country exporters demonstrate different elasticities patterns. Developed countries have weakly statistically significantly lower mean ETM elasticities. We expected this result either as a reflection of their ETM portfolio (biased towards differentiated goods), or the perceived or concrete quality of the same ETM products (which may have "irreplaceable" differentiating qualities stemming from superior industrial power and capabilities).

However, we also find indications of a convergence of the distribution and means of ETM elasticities between developed and developing countries over time, which was unexpected. We put forth the hypothesis that the *changes* are at least partly due to characteristics of the products and exporter countries, as perceived by importers, and not due to the *portfolio* of ETMs exported by each group. This is because the results are based on a sample of goods for which we have data over both decades. In other words, within each country group, we are comparing over the same basket of goods.

The convergence implies there may have been a leveling of the playing field in the stability of ETM export demand between the two groups of countries, making the issue of trade demand elasticities relevant across the board for competitiveness and other considerations. More years of trade data may help future researchers confirm or deepen our understanding of this finding. Additionally, by focusing on China, the United States, and the European Union, we show that specific countries may be affected differently.

We acknowledge the related issue of missing trade demand elasticities by decade, product, and exporters, which we explore in the first section of the Results. As introduced in the Literature Review, Soderbery (2010) establishes the presence of weak instruments in trade data through Monte Carlo simulations. He shows that short length (as opposed to the number of varieties) appears to drive significant small sample biases in the estimator. Therefore, while we are limited by the lack of available data before 1995, future researchers with more years of data will likely have increasingly robust results.

We used various simplifying assumptions in our estimations that also limit the scope of our results, starting from rational agents that exhibit a downward (upward) sloping demand (supply) function based on neoclassical economic theory. When the data yields theoretically unsound results (for instance, upward-facing demand), our estimation strategy is to force the relationship between price, demand, and supply using a grid search over a restricted area. Additionally, agents maximize their utility based on CES preferences, a utility function chosen for its theoretical tractability and ease of estimation when faced with identification issues (Broda, Limão, and Weinstein 2006). A possible criticism is that, for the types of goods we select, there may not be price competition between exporters. Yet, by definition in the CES utility function, agents "care about varieties" (Broda, Limão, and Weinstein 2006).

For ETMs, this theory can be backed up by real-world events. For instance, Tesla has announced intent to no longer use cobalt in its batteries because of the implications of relying on supply based in the Democratic Republic of the Congo, with associated human and environmental concerns (Forbes 2020). Another example of importers concerned about the source of ETMs is the very existence of literature on criticality, spawning from developed countries (like the United States, the European Union, Japan, and Australia) (Bazilian 2018). These countries have launched technology initiatives to substitute away from some products entirely and/or secure their supply internally. Last, despite general similarity across crudes, the preference for oil from one exporter over another is reflected in the rich literature on energy security and geopolitics of oil (Kharrazi and Fath 2016).

Additional criticisms to our model are likely to stem from the use of a CES supply function. On the one hand, Leontief production functions may be better suited for brownfield mines over greenfield products, and overall supply may be very slow to react (securing investment, environmental and social impact assessment, land tenure, exploration, and project development, etc.). On the other hand, supply will be very different for main or co- or by-product production. We also acknowledge that co- or by-product supply is limited by the production of the main product (Nassar, Graedel, and Harper 2015), a salient example being cobalt, which is a co-product of nickel and copper mining. By their nature, the elasticity of supply for these products can be both very high within a certain range because producers can make small changes to recover the by-product of their main mining activity, and low because there is little ability to increase production beyond the amount available from the main mining activity.

While these supply-side and ETM-specific attributes are better suited for more focused analysis, it is limitations related to these attributes that motivate our emphasis on interpreting the results as *trade* elasticities, not demand and supply elasticities. They also motivate our decision to analyze the demand elasticities instead of the supply elasticities that were also output by the model.

5.7 CONCLUSION

Our final sample of trade demand elasticities covers two decades over 29 ETMs and 22 major exporters, with a mean trade demand elasticity of 3.94. We encourage researchers to use the results of each ETM and exporter pair as inputs to a variety of ETM or country-specific research questions, including IAMs.

A low trade elasticity of demand is beneficial to exporters because it is related to stability that has impacts on a range of economic indicators. Developed countries have weakly statistically significantly lower ETM elasticities overall (as expected) but there are also indications of a convergence of ETM elasticities between developed and developing over the last two decades (not expected). We hypothesize and show why the changes are likely to be at least partly due to country characteristics, not the portfolio of ETMs exported by each group. The results imply that ETM trade demand elasticities and their changes are relevant across the board of countries, not only developing countries.

More years of trade data or complementary analysis across other datasets may help clarify the issue. New data sources may be able another avenue that can complement and provide additional insights on the research questions of this study. For instance, geographical Information Systems (GIS) is providing some new avenues for data collection on international trade. A dataset entitled OILX provides real-time data on shipments and inventory of oil, and DBX is evolving to do the same for dry bulk commodities, which includes coal and metals. Once fully available, this data could provide new and relatively timely answers to related research questions. While UN Comtrade is slower to be updated, it would still provide a wider product and time coverage and includes landlocked countries like the Democratic Republic of the Congo, which would be unavailable with shipping data.

APPENDIX 1. AMENDING TRADE DATA TO FIT THE MODEL AND EXISTING CODE

Despite the change in theoretical interpretation, we continue to use a large part of Soderbery (2015)'s estimation code by amending the structure of the data we input in to it. Table 5.8 shows the variables and structure of the panel data used in previous papers. Each code loop estimates the trade elasticities σ_g (demand) and ω_g (supply) for an importer-good pair (e.g., oil entering the US). In each loop, the importer is constant (third column) and the exporter changes (first column).

Table 5.8. Original layout of the input data layout.

Exporter	Year	Importer	Product	Value	Quant
SAU	t=1	US	Oil	V, t=1	Q, t=1
SAU	…t=20	US	Oil	V, t=20	Q, t=20
ARE	t=1	US	Oil	V, t=1	Q, t=1
ARE	…t=20	US	Oil	V, t=20	Q, t=20
KWT	t=1	US	Oil	V, t=1	Q, t=1
KWT	…t=20	US	Oil	V, t=20	Q, t=20

Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.
Note: ARE=United Arab Emirates; KWT= Kuwait; SAU=Saudi Arabia.

As we explain in the methods in this chapter, we want to estimate calculate σ_g (demand) and ω_g (supply) elasticities for each exporter and product (e.g., oil leaving Saudi Arabia). It is possible to do so without inventing a new code to Soderbery (2015), but we must iterate loops of data by exporters instead of importers, for a given product. An immediate limitation to this is that the observations in the exporter variable (first column) must be unique in each loop iteration, and the importer variable must constant be constant (just like Table 5.8).

To do this, we make the following changes: (1) keep data for a certain exporter-product pair; and, (2) amend the data layout. In the first column of Table 5.9, the exporter is constant (Saudi Arabia), but the code runs because each observation is "unique" and labelled by exporter-importer pair (e.g. Saudi Arabia-US, Saudi Arabia-China, etc.). The importer remains constant and is dubbed as one, the "world."

Table 5.9. Layout for the input data necessary to obtain the modified elasticities.

Exporter (exporter-importer pair)	Year	Imp	Product	Value	Quant
SAU-US	t=1	World	Oil	V, t=1	Q, t=1
SAU-US	…t=20	World	Oil	V, t=20	Q, t=20
SAU-CHN	t=1	World	Oil	V, t=1	Q, t=1
SAU-CHN	…t=20	World	Oil	V, t=20	Q, t=20
SAU-UK	t=1	World	Oil	V, t=1	Q, t=1
SAU-UK	…t=20	World	Oil	V, t=20	Q, t=20

Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.
Note: CHN=China; SAU=Saudi Arabia; US=United States; UK=United Kingdom.

APPENDIX 2. DETAILED RESULTS AND FURTHER ANALYSIS

Table 5.10. Trade demand elasticities, detailed statistics.

	Raw data	All except sigma ≥131.5	All except ≥p95	All except ≥p95 and exporter contains both decades		Raw data	All except sigma ≥131.5	All except ≥p95	All except ≥p95 and exporter contains both decades
N	229	221	217	158	iqr	4.129	2.608	2.441	1.978
Mean	216.64	5.703	4.332	3.937	1st Perc.	1.063	1.063	1.063	1.077
Std. Dev.	2479.599	11.983	6.178	5.403	p5	1.143	1.143	1.134	1.134
range	37044.105	98.099	42.057	38.075	p10	1.249	1.249	1.23	1.31
min	1.002	1.002	1.002	1.002	p25	1.492	1.486	1.484	1.489
max	37045.107	99.101	43.06	39.078	Median	2.229	2.175	2.121	1.984
variance	6148410.4	143.59	38.169	29.196	p75	5.622	4.094	3.924	3.467
cv	11.446	2.101	1.426	1.373	p90	18.019	10.168	8.882	8.131
skewness	14.45	5.238	3.711	4.055	p95	61.833	21.272	18.019	14.303
kurtosis	214.475	34.121	18.736	22.519	p99	2537.613	73.160	35.69021	26.156

Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.

Table 5.11 offers further insight and statistics by product. The greatest number of available country comparisons for any one product is five (lead [UW]). We investigate whether there may be an inherent bias over products between the mean and the number of observations. The Pearson correlation yields a value of -0.12 and p-value of 0.53). This result points towards no statistically significant inherent bias to the results of the mean trade demand elasticity by ETM and the number of datapoints that we have.

Table 5.11. Trade demand elasticity summary statistics for ETMs for which there are two decades, by ETM.

Product	HS code	Exporters	Mean	SD
[UW] Lead	7801	5	5.026	5.34
[UW] Molybdenum	810291	4	4.234	2.676
[OC] Copper	2603	4	3.377	3.08
[OC] Lead	2607	4	3.069	2.201
[Metal compounds/mixtures] REE	2846	4	2.495	2.166
[PF] Graphite	2504	4	2.204	2.3
[UW] Palladium	711021	3	5.755	7.925
[UW] Platinum	711011	3	5.148	6.514
[OC] Cobalt	2605	3	5.097	3.181
[OC] Molybdenum	2613	3	3.669	2.713
[Carbonate] Lithium	283691	3	3.544	2.578
[UW] Aluminum	7601	3	2.603	2.3
[Metals, incl. waste/scrap] Others	8112	3	2.267	1.97
[OC] Niobium, tantalum, vanadium, & zirc.	2615	3	1.967	0.908
Natural Gas	2711	3	1.903	0.651
[Metals, incl intermixed/alloyed] REE	280530	3	1.547	0.311
[OC] Aluminum	2606	2	12.351	15.769
[Matte] Nickel	7501	2	12.149	10.562
[OC] Silver	261610	2	11.487	18.412
[Matte & more] Cobalt	8105	2	7.118	6.156
[OH] Lithium	282520	2	3.197	3.943
[OH] Vanadium	282530	2	3.156	2.575
[OH] Cobalt	2822	2	2.332	0.688
[OC] Nickel	2604	2	2.18	0.287
[Matte] Copper	7401	2	2.136	1.014
[UW] Rhodium	711031	2	2.041	0.684
[UW] Silver	710691	2	1.779	0.633
[OC] Platinum, Palladium, Rhodium	261690	1	2.59	1.182
[OC] Manganese	2602	1	1.399	0.178

Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.

Having kept ETM product-exporter pairs with both decades, we also break down trade demand elasticities by decade. We find that between our decades of interest in our restricted sample, the mean trade demand elasticity for ETMs increased by 1.05, which is detrimental to exporters. Note that while the mean increased, the median decreased slightly -0.13, which can be explained by the changes in skewness (Table 5.12).

Table 5.12. Summary statistics, by decade and product groups.

Decade	1	2	Difference
N	79	79	-
mean	3.41	4.46	1.05
SD	4.79	5.94	1.16
skewness	4.69	3.62	-1.07
iqr	1.64	4.75	3.11
p5	1.11	1.27	0.16
Median	2.05	1.92	-0.13
p95	14.30	18.28	3.97

Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.

We determine whether the change over time was statistically significant, or whether there is a sufficiently large probability that it could be due to chance. We first obtain a p-value of less than 0.05 on a Shapiro-Wilk Test and we reject the null hypothesis that the differences of the paired trade demand elasticity observations over decades are normally distributed.

We therefore apply non-parametric paired t-Test alternatives. Specifically, we apply a non-parametric test that the median of differences between matched pairs is zero ("signtest" function in Stata) and obtain a p-value of 0.2604. For robustness, we repeat with the alternative Wilcoxon rank-sum test (also known as the Mann –Whitney two-sample statistic, "ranksum" function in Stata), which confirms our previous results (Table 5.13). In this case, we cannot reject the null hypothesis that the median and distributions of the difference between paired samples over Decades 1 and 2 are statistically the same. Therefore, it is possible that the changes are due to chance.

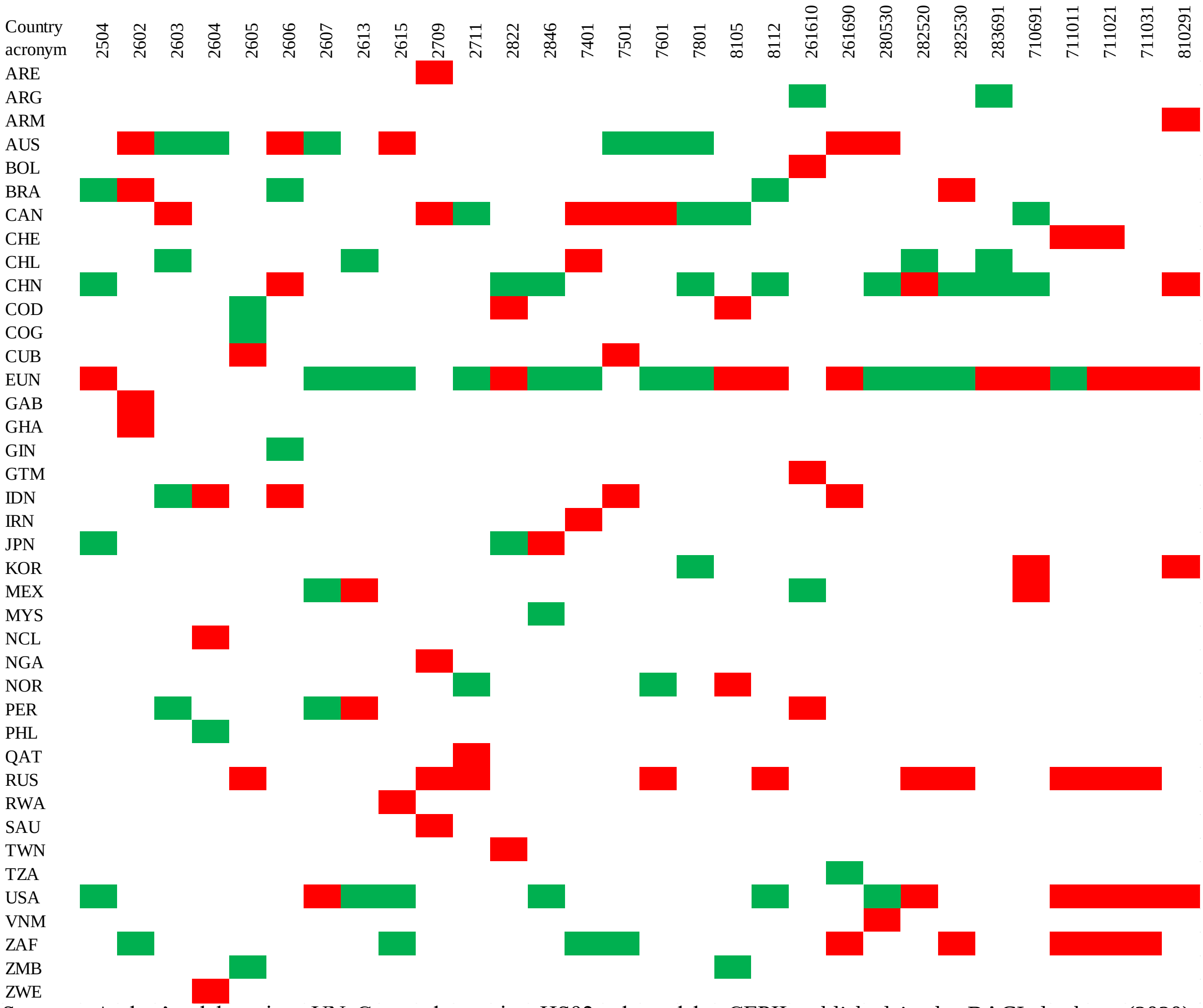
Table 5.13. P-values of nonparametric test that the median of differences between matched pairs is zero and the Wilcoxon matched-pairs signed-rank test.

	Test that the median of differences between matched pairs is zero	Wilcoxon matched-pairs signed-rank test
Overall	0.2604	0.2185

Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.

Appendix 3. Exporter-ETM combinations for which we have results in the final results sample

Table 5.14. ETM (columns) and exporter (rows) combinations, and whether trade demand elasticities are included in the final sample (green), not included or not output by the model (red), not applicable (blank).



Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.

APPENDIX 4. EXPORTER-ETM ELASTICITIES

Table 5.15. Elasticities by exporter-product pair and decade, calculated by the methods described in this chapter.

Group	Country	ISO code	Decade	Trade demand elasticity	HS code	ETM label
Developing	Argentina	ARG	1	2.41	261610	[Ore/concentrate] Silver
Developing	Argentina	ARG	1	6.50	283691	[Carbonate] Lithium
Developing	Argentina	ARG	2	1.22	261610	[Ore/concentrate] Silver
Developing	Argentina	ARG	2	1.94	283691	[Carbonate] Lithium
Developed	Australia	AUS	1	2.54	2603	[Ore/concentrate] Copper
Developed	Australia	AUS	1	2.41	2604	[Ore/concentrate] Nickel
Developed	Australia	AUS	1	3.28	2607	[Ore/concentrate] Lead
Developed	Australia	AUS	1	14.30	7501	[Matte] Nickel
Developed	Australia	AUS	1	7.22	7601	[Unwrought] Aluminum
Developed	Australia	AUS	1	1.41	7801	[Unwrought] Lead
Developed	Australia	AUS	2	3.58	2603	[Ore/concentrate] Copper
Developed	Australia	AUS	2	1.76	2604	[Ore/concentrate] Nickel
Developed	Australia	AUS	2	1.27	2607	[Ore/concentrate] Lead
Developed	Australia	AUS	2	2.80	7501	[Matte] Nickel
Developed	Australia	AUS	2	1.56	7601	[Unwrought] Aluminum
Developed	Australia	AUS	2	8.14	7801	[Unwrought] Lead
Developing	Brazil	BRA	1	1.11	2504	[Powders/flakes] Graphite
Developing	Brazil	BRA	1	2.21	2606	[Ore/concentrate] Aluminum
Developing	Brazil	BRA	1	1.14	8112	[Metals, incl. waste/scrap] Others
Developing	Brazil	BRA	2	1.42	2504	[Powders/flakes] Graphite
Developing	Brazil	BRA	2	8.13	2606	[Ore/concentrate] Aluminum
Developing	Brazil	BRA	2	1.78	8112	[Metals, incl. waste/scrap] Others
Developed	Canada	CAN	1	1.95	2711	Natural Gas
Developed	Canada	CAN	1	1.85	7801	[Unwrought] Lead
Developed	Canada	CAN	1	1.32	8105	[Matte & more] Cobalt
Developed	Canada	CAN	1	2.65	710691	[Unwrought] Silver
Developed	Canada	CAN	2	1.08	2711	Natural Gas
Developed	Canada	CAN	2	1.48	7801	[Unwrought] Lead
Developed	Canada	CAN	2	3.12	8105	[Matte & more] Cobalt
Developed	Canada	CAN	2	1.68	710691	[Unwrought] Silver
Developed	Chile	CHL	1	10.80	2603	[Ore/concentrate] Copper
Developed	Chile	CHL	1	1.20	2613	[Ore/concentrate] Molybdenum
Developed	Chile	CHL	1	1.00	282520	[Oxide/hydroxide] Lithium
Developed	Chile	CHL	1	1.13	283691	[Carbonate] Lithium
Developed	Chile	CHL	2	1.88	2603	[Ore/concentrate] Copper
Developed	Chile	CHL	2	8.88	2613	[Ore/concentrate] Molybdenum
Developed	Chile	CHL	2	9.10	282520	[Oxide/hydroxide] Lithium
Developed	Chile	CHL	2	7.05	283691	[Carbonate] Lithium
Developing	Congo, Dem. Rep.	COD	1	2.40	2605	[Ore/concentrate] Cobalt
Developing	Congo, Dem. Rep.	COD	2	10.17	2605	[Ore/concentrate] Cobalt
Developing	Congo, Rep.	COG	1	2.13	2605	[Ore/concentrate] Cobalt

Group	Country	ISO code	Decade	Trade demand elasticity	HS code	ETM label
Developing	Congo, Rep.	COG	2	3.00	2605	[Ore/concentrate] Cobalt
Developing	Guinea	GIN	1	35.69	2606	[Ore/concentrate] Aluminum
Developing	Guinea	GIN	2	3.37	2606	[Ore/concentrate] Aluminum
Developing	Indonesia	IDN	1	2.76	2603	[Ore/concentrate] Copper
Developing	Indonesia	IDN	2	1.35	2603	[Ore/concentrate] Copper
Developed	Japan	JPN	1	1.44	2504	[Powders/flakes] Graphite
Developed	Japan	JPN	1	3.06	2822	[Oxide/hydroxide] Cobalt
Developed	Japan	JPN	1	5.76	711011	[Unwrought] Platinum
Developed	Japan	JPN	2	1.61	2504	[Powders/flakes] Graphite
Developed	Japan	JPN	2	2.02	2822	[Oxide/hydroxide] Cobalt
Developed	Japan	JPN	2	1.36	711011	[Unwrought] Platinum
Developing	Korea, Rep.	KOR	1	2.54	7801	[Unwrought] Lead
Developed	Korea, Rep.	KOR	1	5.07	810291	[Unwrought] Molybdenum
Developing	Korea, Rep.	KOR	2	18.28	7801	[Unwrought] Lead
Developed	Korea, Rep.	KOR	2	8.77	810291	[Unwrought] Molybdenum
Developing	Malaysia	MYS	1	3.48	2846	[Metal compounds/mixtures] REE
Developing	Malaysia	MYS	2	7.55	2846	[Metal compounds/mixtures] REE
Developing	Mexico	MEX	1	1.44	2607	[Ore/concentrate] Lead
Developing	Mexico	MEX	1	3.24	261610	[Ore/concentrate] Silver
Developing	Mexico	MEX	2	1.78	2607	[Ore/concentrate] Lead
Developing	Mexico	MEX	2	39.08	261610	[Ore/concentrate] Silver
Developed	Norway	NOR	1	1.56	2711	Natural Gas
Developed	Norway	NOR	1	1.33	7601	[Unwrought] Aluminum
Developed	Norway	NOR	2	3.04	2711	Natural Gas
Developed	Norway	NOR	2	1.49	7601	[Unwrought] Aluminum
Developing	Peru	PER	1	2.49	2603	[Ore/concentrate] Copper
Developing	Peru	PER	1	1.93	2607	[Ore/concentrate] Lead
Developing	Peru	PER	2	1.63	2603	[Ore/concentrate] Copper
Developing	Peru	PER	2	6.77	2607	[Ore/concentrate] Lead
Developing	Philippines	PHL	1	2.31	2604	[Ore/concentrate] Nickel
Developing	Philippines	PHL	2	2.24	2604	[Ore/concentrate] Nickel
Developing	South Africa	ZAF	1	1.52	2602	[Ore/concentrate] Manganese
Developing	South Africa	ZAF	1	1.13	2615	[Ore/concentrate] Niobium, tantalum, vanadium, & zirc.
Developing	South Africa	ZAF	1	1.42	7401	[Matte] Copper
Developing	South Africa	ZAF	1	5.34	7501	[Matte] Nickel
Developing	South Africa	ZAF	1	18.02	711011	[Unwrought] Platinum
Developing	South Africa	ZAF	1	2.61	711021	[Unwrought] Palladium
Developing	South Africa	ZAF	2	1.27	2602	[Ore/concentrate] Manganese
Developing	South Africa	ZAF	2	1.61	2615	[Ore/concentrate] Niobium, tantalum, vanadium, & zirc.
Developing	South Africa	ZAF	2	3.64	7401	[Matte] Copper
Developing	South Africa	ZAF	2	26.16	7501	[Matte] Nickel
Developing	South Africa	ZAF	2	1.40	711011	[Unwrought] Platinum
Developing	South Africa	ZAF	2	21.27	711021	[Unwrought] Palladium

Group	Country	ISO code	Decade	Trade demand elasticity	HS code	ETM label
Developing	Tanzania	TZA	1	3.43	261690	[Ore/concentrate] Platinum, Palladium, Rhodium
Developing	Tanzania	TZA	2	1.75	261690	[Ore/concentrate] Platinum, Palladium, Rhodium
Developing	Zambia	ZMB	1	5.81	2605	[Ore/concentrate] Cobalt
Developing	Zambia	ZMB	1	14.85	8105	[Matte & more] Cobalt
Developing	Zambia	ZMB	2	7.08	2605	[Ore/concentrate] Cobalt
Developing	Zambia	ZMB	2	9.19	8105	[Matte & more] Cobalt

Sources: Author's elaboration. UN Comtrade version HS92; cleaned by CEPII published in the BACI database (2020); calculations based on the modification of Broda and Weinstein (2006) and Soderbery (2015) described in the chapter.

CHAPTER 6: CONCLUSION

Deeply decarbonizing energy is a crucial precondition to avoiding increases in global temperatures above 1.5-2°C in this century (IPCC 2021; IRENA 2019). While deep decarbonization is an environmental and innovation challenge in its own right (IEA 2020a), it also interacts with other policy priorities, making it a “grand challenge” (Anadón, Chan, et al. 2016; Mazzucato 2018). The point of departure for the research questions that guide the research in this dissertation is that we must hone our understanding of how to use government policy as a tool to transition to a globally decarbonized energy system in the coming decades, while also pursuing other objectives like sustainable and inclusive economic growth.

The diverse set of literatures that we consult and contribute to - such as innovation systems, decarbonization policy and evaluation, and criticality assessments - in relation to our research questions are usually and expectedly relatively more advanced in developed countries. All countries will need to redirect decarbonize their energy systems and economies if we are to achieve climate goals, however (Nordhaus 2019). Therefore, one important contribution of this this dissertation is that across all chapters it takes a broader geographical perspective compared to previous literature.

We frame the research questions and chapters on the economics of energy decarbonization along the stages of the ETIS conceptual framework, specifically RD&D, market formation, and diffusion and trade. In the first stages (RD&D) we focus on evaluating the *inputs* to ETIS, and in the subsequent stages (market formation and diffusion and trade), we focus on evaluating the *outcomes*. The geographical and topical breath of the research questions allows the dissertation to consider several gaps in the literature in understanding how policy can best address energy and economic goals.

6.1 MAIN RESULTS

1. **Public ERD&D expenditure requires sustained attention and impetus. Additionally, some countries should monitor and improve expenditure stability.**

Increased and stable technology-push ERD&D expenditure is widely understood to be crucial to meeting innovation and economic goals (Cohen and Noll 1991; Anadón, Chan, et al. 2016; Narayanamurti, Anadón, and Sagar 2009). However, despite a recent collaborative agreement to drastically increase ERD&D efforts called Mission Innovation, public ERD&D is at least less than half of what existing estimates say is necessary, even when including major developing countries and emitters such as China and India.

Additionally, our fixed-effects regression analysis of ERD&D expenditure growth rates shows that despite some technology-specific trends, neither the years after 2009 Financial Crisis nor the years after Mission Innovation show a statistically significant change in funding allocation towards non-fossil fuel and non-nuclear (or clean plus, CP) ERD&D in all except one group. This finding is robust across several regression specifications.

Last, four metrics of volatility across technology categories (fossil fuels including carbon capture and sequestration, nuclear, and CP) and countries point towards regional innovation systems characteristics over three groups: the United States/United Kingdom, continental Europe, and Asia. They also highlight the relative volatility and a need for increased focus on ERD&D stability and growth in the United States, UK, and India relative to the other major ERD&D spenders we focused on, France, Germany, China, Japan, and Korea.

2. **The effects of seven decarbonization policy instrument categories (PICs) on decarbonization are often negligible or negative in developing countries. However, policies that address counterparty risk have more immediate positive effects than other policies, pointing to the importance of policies that address the abilities of developing countries to secure climate financing.**

Increasing our understanding of the effect of demand-pull policies aimed at the market formation ETIS stage on ETIS *outcomes*, such as decarbonization of the energy mix, is crucial to efficiently and effectively reaching deep decarbonization.

Broad and systematic studies are relatively lacking for developing countries. We offer the first consistent attempt to identify how seven energy PICs representing 75+ policies for energy decarbonization each individually perform across a wide spectrum of developing countries over time (three, five, and seven years after implementation). To do so, we apply 2SLS with country interactions and country and time fixed effects in regional panels. The methods attempt to address a host of challenges like omitted variables and endogeneity (reverse causality and simultaneity) between PICs and outcomes. We also create several alternative representations of PICs to consider collinearity and the degree of reform between policies.

The effects of PICs are pessimistic overall, with widespread low statistical significance and negative effects. In other words, the PICs result in a *higher* share of fossil fuel sources in the developing countries' energy mix. This result is borne out in some previous research on the effects of decarbonization policies on technological effectiveness, as evidenced in our reviewed of Peñasco, Anadón, and Verdolini (2021) and the DPET dataset. In developing countries, such lackluster results may be due to a combination of the Sailing Ship Effect (Ward 1967; Gilfillan 1935), in which incumbent forces react to policies by entrenching themselves against competitors, and a difficulty in securing climate finance (as a result of several interrelated issues, including institutional quality and infrastructure) (Egli, Steffen, and Schmidt 2019; Moner-Girona et al. 2021).

Yet our results are not all negative. For instance, the effects of PICs improve with time. Additionally, policies that address counterparty risk have the most immediate positive effect on energy decarbonization. This provides further evidence of the importance of climate finance, and the importance of policies that strengthen the abilities of countries to secure it.

3. **Over the past two decades, clean and refined energy materials have held relatively larger promise for exporters than those that are traditional and unrefined. The result highlights the need for enhancing clean and refined ETM trade and capabilities in developing countries.**

Deep energy decarbonization will require a shift in the materials used in energy technologies. The changing trade patterns on a broad range of exporters are relatively unexplored, despite being an economy-wide ETIS *outcome* that interacts with other policy priorities such as sustainable growth.

Lithium carbonate (which exhibits the most beneficial trade patterns of the 30 products analyzed) is an example of a clean and refined energy material. Clean and refined energy products have experienced relatively higher growth in trade value, lower volatility of growth in trade value, and a higher exporter concentration and lower concentration over importers of trade quantity than their counterparts (traditional and unrefined products) over the past two decades. However, as per existing literature and our own analysis, these are groups of materials in which developing country exporters are generally underrepresented.

We argue that, while developing countries may still benefit from trade trends in some individual energy technology materials, trade trends over the past two decades are relatively better for products in which they are relatively less represented. As a result, developing countries would benefit from policies that strengthen trade capabilities in clean energy and refined materials.

4. **We present trade elasticities for energy technology materials. We also observe a convergence of ETM trade elasticities between developing and developed countries over the last two decades.**

Elasticities of demand and supply are a core concept in economics with far-reaching applications. Nevertheless, it is difficult to identify supply and demand curves from existing data of prices and quantities that reflect bilateral exchanges made in the market equilibrium. We propose modifications to current structural trade demand and supply price elasticities building on the methods developed by Broda and Weinstein (2006), based on Feenstra (1994) to calculate the "trade demand elasticities" (or the change in exports demanded due to a change in price) from a certain exporter and ETM product.

Our main result is a visualization with the evolution of trade elasticities over two decades for 29 products and 22 exporters, which can be used by researchers and policymakers in several settings, including integrated assessment models. As expected based on previous literature, developed countries have -weakly- statistically significantly lower ETM elasticities overall. A low trade elasticity of demand is beneficial to exporters because it is related to export stability that has impacts on a range of economic indicators. However, there are also indications of a convergence of ETM elasticities between developed and developing over the last two decades, which was not expected or reflected in the literature.

We discuss the possible reason for the convergence. The results can be attributed either to changing characteristics of the exporters and products according to importers, or to the *portfolio* of the products exported by the groups. Our discussion shows that the changes are likely due to the former. The results imply that surveilling ETM trade demand elasticities (and their changes) is relevant across the board of countries as governments position their industrial and trade policy to benefit from the energy transition.

6.2 CROSS-CHAPTER CONSIDERATIONS FOR FUTURE RESEARCH

The results of Chapter 2 on the failure of windows of opportunity to provide needed change in ERD&D can also be extended to other ETIS stages and raise the question of what it may take to reach deep decarbonization, overall and for developing countries.

Our broad set of analyses relating to the different ETIS stages, *inputs*, and *outcomes* over many regions point to the need for government to take both supply-push and demand-pull approaches, and to focus on identifying synergies with understudied areas, such as trade. Overall, the chapters therefore demonstrate the importance of a systems-wide understanding for achieving decarbonization alongside economic goals. They show the need for the adoption of evidence-based adaptive and holistic energy, technology, and environmental policy that considers the broader SDG context, with a focus on climate investment and inclusive institutions that can deliver these goals (Anadón, Chan, et al. 2016).

Areas for future research are discussed in each chapter in the context of the specific topics and ETIS stages, but there are additional questions that run across ETIS stages and/or relate to several topics at once.

ERD&D volatility has been measured previously (for example by Schuelke-Leech 2014; Winskel et al. 2014; and Baccini and Urpelainen 2012), and the importance of stable funding has been established (Norberg-Bohm 2000; Fuss et al. 2008; Anadón, Chan, et al. 2016; Guellec and Van Pottelsberghe De La Potterie 2003; Nemet 2009). We have not yet seen a cross-country econometric evaluation of the relationship between volatility (pertaining to ETIS *inputs* and ERD&D stage) and the creation of domestic markets for specific energy technologies and trade capabilities, or the relative export dominance of country-technology combinations several decades later (pertaining to ETIS *outcomes* and the Diffusion and Trade stage). Such an analysis is possible for OECD countries that have been providing data to the IEA since the 1970s. One key methodological challenge to answering this question would be in matching trade categories to ERD&D categories.

Furthermore, now that one decade has passed since the price increases of rare earth elements in 2011 and almost a decade has passed since the creation of the Critical Materials Institute in the United States in 2013, it may be possible to specifically investigate the degree of success of the industrial policies that addressed potential criticality (or security of supply) in countries like the United States and the European Union. Such an analysis could combine *output* metrics such as patent analysis and qualitative work such as process tracing.

Relatedly, in Chapter 5, we discussed the concept of "induced innovation," or the change of use in one factor of production due to a change of prices in another (Hicks 1932). One potential question that has not been explored yet, to our knowledge, is the extent to which changes in prices of ETMs have affected private and public ERD&D expenditure (ETIS *inputs*). This question can also be extended to cover the effects of the trade elasticities towards innovation *outputs* such as patents (Gallagher et al. 2011). . This question would join the topics covered in Chapters 2, 4, and 5.

The literature on innovation systems points to possible interactions between decarbonization policies and the evolution of low carbon industry. Our work lays the groundwork for such investigation. For instance, to our knowledge there is a lack of systematic research on the effects of renewable energy market formation policies (such as electricity auctions in Chile and Argentina) on the upstream export capabilities of energy technology materials (such as lithium carbonate) that are already available and exploited in the same country. This research question would allow us to study the relationships and overlaps between the Market Formation (Chapter 3) and Diffusion and Trade (Chapters 4 and 5) ETIS stages for ETMs.

Last, in addition to trade elasticities (already discussed), the outcomes of Chapter 2 on ERD&D, Chapter 3 on policies for decarbonization, and Chapter 4 on trade trends can be used as inputs to integrated assessment models. This would allow, amongst other things, to extrapolate how trends over time affect economic outcomes in all countries in different global warming scenarios.

The overall arch for future research recommendations suggests that we must continue to pose and analyze questions through a systems perspective, linking energy and broader economic development questions alongside the ETIS conceptual framework. For such questions to be resolved adequately, there is also a pointed need for high-quality data on the range of policies relating to decarbonization, as well as sufficiently granular data on energy supply and consumption, and economic indicators, especially in developing countries.

BIBLIOGRAPHY

Acar, William, and Pankaj Bhatnagar. 2003. "Re-Evaluating Diversity Measures: Calibrating for Scope to Capture the Distribution Effect." *Vikalpa* 28 (4): 9–24. https://doi.org/10.1177/0256090920030402.

Achzet, Benjamin, Christoph Helbig, Benjamin Achzet, and Christoph Helbig. 2013. *How to Evaluate Raw Material Supply Risks—an Overview*. *Resources Policy*. Vol. 38. Butterworth Scientific. https://econpapers.repec.org/article/eeejrpoli/v_3a38_3ay_3a2013_3ai_3a4_3ap_3a435-447.htm.

Ali, Saleem H., Damien Giurco, Nicholas Arndt, Edmund Nickless, Graham Brown, Alecos Demetriades, Ray Durrheim, et al. 2017. "Mineral Supply for Sustainable Development Requires Resource Governance." *Nature*. Nature Publishing Group. https://doi.org/10.1038/nature21359.

Anadón, Laura Díaz. 2012. "Missions-Oriented RD&D Institutions in Energy between 2000 and 2010: A Comparative Analysis of China, the United Kingdom, and the United States." *Research Policy* 41 (10): 1742–56. https://doi.org/10.1016/j.respol.2012.02.015.

Anadón, Laura Díaz, Erin Baker, and Valentina Bosetti. 2017. "Integrating Uncertainty into Public Energy Research and Development Decisions." *Nature Energy 2017 2:5* 2 (5): 1–14. https://doi.org/10.1038/nenergy.2017.71.

Anadón, Laura Díaz, Erin Baker, Valentina Bosetti, and Lara Aleluia Reis. 2016. "Expert Views - and Disagreements - about the Potential of Energy Technology R&D." *Climatic Change 2016 136:3* 136 (3): 677–91. https://doi.org/10.1007/S10584-016-1626-0.

Anadón, Laura Díaz, Matthew Bunn, and Venkatesh Narayanamurti. 2014. *Transforming U.S. Energy Innovation*. West Nyack: West Nyack: Cambridge University Press. https://doi.org/10.1017/CBO9781107338890.

Anadón, Laura Díaz, Gabriel Chan, Alicia G Harley, Kira Matus, Suerie Moon, Sharmila L Murthy, and William C Clark. 2016. "Making Technological Innovation Work for Sustainable Development." *Proceedings of the National Academy of Sciences of the United States of America* 113 (35): 9682–90. https://doi.org/10.1073/pnas.1525004113.

Anderson, James. 1979. "A Theoretical Foundation for Gravity Equation." *American Economic Review* 69 (February): 106–16. https://www.jstor.org/stable/1802501.

Anderson, T. W., and Herman Rubin. 1949. "Estimation of the Parameters of a Single Equation in a Complete System of Stochastic Equations." *The Annals of Mathematical Statistics* 20 (1): 46–

63. https://doi.org/10.1214/aoms/1177730090.

Andriamasinoro, Fenintsoa, and Jean Michel Angel. 2012. “Artisanal and Small-Scale Gold Mining in Burkina Faso: Suggestion of Multi-Agent Methodology as a Complementary Support in Elaborating a Policy.” *Resources Policy* 37 (3): 385–96. https://doi.org/10.1016/j.resourpol.2012.04.004.

Archibugi, Daniele, and Andrea Filippetti. 2018. “The Retreat of Public Research and Its Adverse Consequences on Innovation.” *Technological Forecasting and Social Change* 127 (February): 97–111. https://doi.org/10.1016/j.techfore.2017.05.022.

Armington, Paul S. 1969. “A Theory of Demand for Products Distinguished by Place of Production (Une Theorie de La Demande de Produits Differencies d’apres Leur Origine) (Una Teoria de La Demanda de Productos Distinguiendolos Segun El Lugar de Produccion).” *Staff Papers - International Monetary Fund* 16 (1): 159. https://doi.org/10.2307/3866403.

Arrow, Kenneth. 1962. “Economic Welfare and the Allocation of Resources for Invention.” In *The Rate and Direction of Inventive Activity: Economic and Social Factors*, 609–26. National Bureau of Economic Research, Inc. https://econpapers.repec.org/RePEc:nbr:nberch:2144.

Baccini, Leonardo, and Johannes Urpelainen. 2012. “Legislative Fractionalization and Partisan Shifts to the Left Increase the Volatility of Public Energy R&D Expenditures.” *Energy Policy* 46 (July): 49–57. https://doi.org/10.1016/j.enpol.2012.03.016.

Bacon, Robert. 2018. “Taking Stock of the Impact of Power Utility Reform in Developing Countries A Literature Review.” 8460. Policy Research Working Paper. Washington, D.C. https://openknowledge.worldbank.org/handle/10986/29889.

Bailey, Michael A, Anton Strezhnev, Erik Voeten, and Edmund A Walsh. 2017. “Estimating Dynamic State Preferences from United Nations Voting Data.” *Journal of Conflict Resolution* 61 (2): 430–56. https://doi.org/10.1177/0022002715595700.

Banerjee, Sudeshna Ghosh, Francisco Alejandro Moreno, Jonathan Edwards Sinton, Tanya Primiani, and Joonkyung Seong. 2017. “Regulatory Indicators for Sustainable Energy : A Global Scorecard for Policy Makers.” Washington, D.C. http://documents.worldbank.org/curated/en/538181487106403375/Regulatory-indicators-for-sustainable-energy-a-global-scorecard-for-policy-makers.

Barbier, Edward B. 2019. “How to Make the next Green New Deal Work.” *Nature* 565 (7737): 6–6. https://doi.org/10.1038/d41586-018-07845-5.

Bazilian, Morgan D. 2018. “The Mineral Foundation of the Energy Transition.” *Extractive Industries* *and Society*. https://doi.org/10.1016/j.exis.2017.12.002.

Behrens, Arno, Stefan Giljum, Jan Kovanda, and Samuel Niza. 2007. “The Material Basis of the Global Economy: Worldwide Patterns of Natural Resource Extraction and Their Implications for Sustainable Resource Use Policies.” *Ecological Economics* 64 (2): 444–53. https://doi.org/10.1016/J.ECOLECON.2007.02.034.

Besant-Jones, John E. 2006. “Reforming Power Markets in Developing Countries : What Have We Learned?” 19. Energy and Mining Sector Board Discussion Paper. Washington, D.C. http://documents.worldbank.org/curated/en/483161468313819882/Reforming-power-markets-in-developing-countries-what-have-we-learned.

Binz, Christian, and Laura Díaz Anadón. 2018. “Unrelated Diversification in Latecomer Contexts: Emergence of the Chinese Solar Photovoltaics Industry.” *Environmental Innovation and Societal Transitions* 28 (September): 14–34. https://doi.org/10.1016/J.EIST.2018.03.005.

Binz, Christian, and Bernhard Truffer. 2017. “Global Innovation Systems—A Conceptual Framework for Innovation Dynamics in Transnational Contexts.” *Research Policy* 46 (7): 1284–98. https://doi.org/10.1016/j.respol.2017.05.012.

Brems, Matthew. 2017. “A One-Stop Shop for Principal Component Analysis.” Towards Data Science. 2017. https://towardsdatascience.com/a-one-stop-shop-for-principal-component-analysis-5582fb7e0a9c.

Broda, Christian, Joshua Greenfield, and David Weinstein. 2006. “From Groundnuts to Globalization: A Structural Estimate of Trade and Growth.” *National Bureau of Economic Research Working Paper Series* No. 12512. https://doi.org/10.3386/w12512.

Broda, Christian, Nuno Limão, and David E. Weinstein. 2006. “Optimal Tariffs and Market Power: The Evidence.” *Policy Externalities and International Trade Agreements,* no. 2006: 13–46. https://doi.org/10.1142/9789813147980_0002.

Broda, Christian, Nuno Limao, and David E Weinstein. 2008. “Optimal Tariffs and Market Power: The Evidence.” *American Economic Review* 98 (5): 2032–65. https://doi.org/10.1257/aer.98.5.2032.

Broda, Christian, and David E Weinstein. 2006. “Globalization and the Gains From Variety*.” *The Quarterly Journal of Economics* 121 (2): 541–85. https://doi.org/10.1162/qjec.2006.121.2.541.

Brooks, Harvey. 1980. “Technology, Evolution, and Purpose.” *Daedalus* 109 (1): 65–81. http://www.jstor.org/stable/20024649.

Brown, Teresa. 2018. “Measurement of Mineral Supply Diversity and Its Importance in Assessing

Risk and Criticality.” *Resources Policy* 58 (October): 202–18. https://doi.org/10.1016/J.RESOURPOL.2018.05.007.

Buchner, Barbara, Alex Clark, Angela Falconer, Rob Macquarie, Chavi Meattle, Rowena Tolentino, and Cooper Wetherbee. 2019. “Global Landscape of Climate Finance 2019.” https://climatepolicyinitiative.org/publication/.

Bush, Vannevar. 1945. *Science - The Endless Frontier*. Washington, D.C.: United States Government Printing Office. https://www.nsf.gov/od/lpa/nsf50/vbush1945.htm.

Callon, M., P. Laredo, V. Rabeharisoa, T. Gonard, and T. Leray. 1992. “The Management and Evaluation of Technological Programs and the Dynamics of Techno-Economic Networks: The Case of the AFME.” *Research Policy* 21 (3): 215–36. https://doi.org/10.1016/0048-7333(92)90017-X.

Center, Seth, and Emma Bates. 2019. “Tech-Politik Historical Perspectives on Innovation, Technology, and Strategic Competition.” Washington, D.C. https://www.csis.org/analysis/tech-politik-historical-perspectives-innovation-technology-and-strategic-competition.

Centre for Budget and Governance Accountability, Government of India. 2019. “Open Budgets India.” 2019. https://union2019.openbudgetsindia.org/en/.

Chan, Gabriel, Anna P. Goldstein, Amitai Bin-Nun, Laura Díaz Anadón, and Venkatesh Narayanamurti. 2017. “Six Principles for Energy Innovation.” *Nature* 552 (7683): 25–27. https://doi.org/10.1038/d41586-017-07761-0.

Coase, Ronald H. 1991. “Nobel Memorial Prize in Economic Sciences Lecture.” In . https://www.nobelprize.org/prizes/economic-sciences/1991/coase/lecture/.

Cohen, Linda R., and Roger G. Noll. 1991. *The Technology Pork Barrel*. Brookings Institution Press. https://www.brookings.edu/book/the-technology-pork-barrel/.

Cooke, Philip. 2001. “Regional Innovation Systems, Clusters, and the Knowledge Economy.” *Industrial and Corporate Change* 10 (4): 945–74. https://doi.org/10.1093/icc/10.4.945.

Costantini, Valeria, and Massimiliano Mazzanti. 2012. “On the Green and Innovative Side of Trade Competitiveness? The Impact of Environmental Policies and Innovation on EU Exports.” *Research Policy* 41 (1): 132–53. https://doi.org/10.1016/J.RESPOL.2011.08.004.

Cubbin, John, and Jon Stern. 2006. “The Impact of Regulatory Governance and Privatization on Electricity Industry Generation Capacity in Developing Economies.” *World Bank Economic Review* 20 (1): 115–41. https://doi.org/10.1093/wber/lhj004.

Cunliff, Colin. 2019. "An Innovation Agenda for Hard-to-Decarbonize Energy Sectors." *Issues in Science and Technology* 36 (1): 74–79. https://doi.org/10.2307/26949082.

Dalpé, Robert, Chris DeBresson, and Hu Xiaoping. 1992. "The Public Sector as First User of Innovations." *Research Policy* 21 (3): 251–63. https://doi.org/10.1016/0048-7333(92)90019-Z.

Dechezleprêtre, Antoine, and Misato Sato. 2017. "The Impacts of Environmental Regulations on Competitiveness." *Review of Environmental Economics and Policy* 11 (2): 183–206. https://doi.org/10.1093/reep/rex013.

Deng, Hong-Mei, Qiao-Mei Liang, Li-Jing Liu, and Laura Díaz Anadón. 2018. "Co-Benefits of Greenhouse Gas Mitigation: A Review and Classification by Type, Mitigation Sector, and Geography." *Environmental Research Letters* 12 (12): 123001. https://doi.org/10.1088/1748-9326/AA98D2.

Department for International Trade, Government of the United Kindgom. 2018. "Accounting Officer System Statement." London: UK Department for International Trade, Finance and Corporate Services. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/738897/Accounting_Officer_Systems_Statement_-_FINAL_VERSION_2_ACCESSIBLE.pdf.

Department of Business Innovation and Skills, Government of the United Kingdom. 2012. "UK Trade Performance across Markets and Sectors." https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/32475/12-579-uk-trade-performance-markets-and-sectors.pdf.

Department of Energy, Government of the United States of America. 2011. "Critical Materials Strategy." https://www.energy.gov/sites/prod/files/DOE_CMS2011_FINAL_Full.pdf.

Department of Justice, Government of the United States of America. 2010. "Horizontal Merger Guidelines. Issued: 19 August 2010." https://www.justice.gov/atr/horizontal-merger-guidelines-08192010.

Dewulf, Jo, Gian Andrea Blengini, David Pennington, Philip Nuss, and Nedal T. Nassar. 2016. "Criticality on the International Scene: Quo Vadis?" *Resources Policy* 50 (December): 169–76. https://doi.org/10.1016/J.RESOURPOL.2016.09.008.

Domah, Preetum, Michael G Pollitt, and Jon Stern. 2002. "Modelling the Costs of Electricity Regulation: Evidence of Human Resource Constraints in Developing Countries." Cambridge Working Papers in Economics. Cambridge, UK: Faculty of Economics. https://doi.org/10.17863/CAM.5419.

Edquist, C. 1997. *Systems of Innovation: Technologies, Institutions and Organizations*. London: Pinter.

Egli, Florian, Bjarne Steffen, and Tobias S. Schmidt. 2019. “Bias in Energy System Models with Uniform Cost of Capital Assumption.” *Nature Communications 2019 10:1* 10 (1): 1–3. https://doi.org/10.1038/s41467-019-12468-z.

Energy Transition Institute. 2017. “Natural Resources and CO2: Hazards Ahead for Battery Electric Vehicles, ETI.” 2017. http://www.energy-transition-institute.com/Insights/NaturalResourcesandCO2.html.

Erdmann, Lorenz, and Thomas E. Graedel. 2011. “Criticality of Non-Fuel Minerals: A Review of Major Approaches and Analyses.” *Environmental Science & Technology* 45 (18): 7620–30. https://doi.org/10.1021/es200563g.

Erdoğdu, Erkan. 2011. “What Happened to Efficiency in Electricity Industries after Reforms?” *Energy Policy* 39 (10): 6551–60. https://econpapers.repec.org/RePEc:eee:enepol:v:39:y:2011:i:10:p:6551-6560.

European Commission. 2010. “Critical Raw Materials for the EU.” Brussels. https://ec.europa.eu/growth/tools-databases/eip-raw-materials/en/system/files/ged/79 report-b_en.pdf.

———. 2021. “Trade Negotiations and Agreements.” 2021. https://ec.europa.eu/trade/policy/countries-and-regions/negotiations-and-agreements/.

Fattouh, Bassam, and Lavan Mahadeva. 2013. “OPEC: What Difference Has It Made?” *Http://Dx.Doi.Org/10.1146/Annurev-Resource-091912-151901* 5 (October): 427–43. https://doi.org/10.1146/ANNUREV-RESOURCE-091912-151901.

Feenstra, Robert C. 1994. “New Product Varieties and the Measurement of International Prices.” *American Economic Review* 84 (1): 157–77. https://doi.org/10.2307/2117976.

Financial Times. 2018. “Europe Jump-Starts Effort to Take Lead in Battery Arms Race.” 2018. https://www.ft.com/content/9cac6a44-4966-11e8-8ee8-cae73aab7ccb.

Forbes. 2020. “Tesla’s Shift To Cobalt-Free Batteries Is Its Most Important Move Yet.” James Morris. July 11, 2020. https://www.forbes.com/sites/jamesmorris/2020/07/11/teslas-shift-to-cobalt-free-batteries-is-its-most-important-move-yet/.

Foster, Vivien, Elisa Portale, Daron Bedrosyan, Juliette Suzanne Georgette Besnard, and Tigran Parvanyan. 2018. “Regulatory Indicators for Sustainable Energy (RISE).” Washington, D.C. http://documents.worldbank.org/curated/en/553071544206394642/Policy-Matters-Regulatory-

Indicators-for-Sustainable-Energy.

Foster, Vivien, and Anshul Rana. 2020. "Rethinking Power Sector Reform in the Developing World." *Rethinking Power Sector Reform in the Developing World*. https://doi.org/10.1596/978-1-4648-1442-6.

Foster, Vivien, Samantha Witte, Sudeshna Ghosh Banerjee, and Alejandro Moreno. 2017. "Charting the Diffusion of Power Sector Reforms across the Developing World." *Policy Research Working Paper*, no. November. http://rise.esmap.org.

Fouquet, Roger. 2015. "The Allocation of Energy Resources in the Very Long Run." *Journal of Natural Resource Policy Research (Special Issue on William Nordhaus)* 7 (3): 147–56. https://doi.org/10.1080/19390459.2015.1050786.

Frankel, Jeffrey A. 2012. "The Natural Resource Curse: A Survey of Diagnoses and Some Prescriptions." *HKS Faculty Research Working Paper Series*. https://dash.harvard.edu/handle/1/8694932.

Freeman, C. 1987. *Technology Policy and Economic Performance: Lessons from Japan*. Edited by Pinter. London.

Fuss, Sabine, Jana Szolgayova, Michael Obersteiner, and Mykola Gusti. 2008. "Investment under Market and Climate Policy Uncertainty." *Applied Energy* 85 (8): 708–21. https://doi.org/10.1016/j.apenergy.2008.01.005.

Galeazzi, Clara. 2015. "Price and Quantity Indicators of Latin American and Caribbean Trade." Universidad Torcuato di Tella. https://repositorio.utdt.edu/handle/utdt/1963.

Galeazzi, Clara, Jevgenijs Steinbuks, and James Cust. 2020. "Africa's Resource Export Opportunities and the Global Energy Transition." 111. Live Wire. Washington, DC: World Bank, Washington, DC. https://openknowledge.worldbank.org/handle/10986/34946.

Gallagher, Kelly Sims, and Laura Díaz Anadón. 2020. "DOE Budget Authority for Energy Research, Development, and Demonstration Database." Fletcher School of Law and Diplomacy, Tufts University; Department of Land Economy, Center for Environment, Energy and Natural Resource Governance (C-EENRG), University of Cambridge; and Belfer Center for Science and International Affairs, Harvard Kennedy.

Gallagher, Kelly Sims, Laura Díaz Anadón, Ruud Kempener, and Charlie Wilson. 2011. "Trends in Investments in Global Energy Research, Development, and Demonstration." *Wiley Interdisciplinary Reviews: Climate Change* 2 (3): 373–96. https://doi.org/10.1002/wcc.112.

Gallagher, Kelly Sims, Arnulf Grübler, Laura Kuhl, Gregory F. Nemet, and Charlie Wilson. 2012.

"The Energy Technology Innovation System." *Http://Dx.Doi.Org/10.1146/Annurev-Environ-060311-133915* 37 (October): 137–62. https://doi.org/10.1146/ANNUREV-ENVIRON-060311-133915.

Gallagher, Kelly Sims, John P. Holdren, and Ambuj D. Sagar. 2006. "Energy-Technology Innovation." *Annual Review of Environment and Resources* 31 (1): 193–237. https://doi.org/10.1146/annurev.energy.30.050504.144321.

Gaulier, Guillaume, and Soledad Zignago. 2012. "BACI: International Trade Database at the Product-Level (the 1994-2007 Version)." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1994500.

Ghosh, Atish R., and Jonathan D. Ostry. 1994. "Export Instability and the External Balance in Developing Countries." *Staff Papers 1994 41:2* 41 (2): 214–35. https://doi.org/10.2307/3867507.

Gilfillan, S. C. 1935. *Inventing the Ship*. Chicago: Follett.

Gillingham, Kenneth, Richard G. Newell, and William A. Pizer. 2008. "Modeling Endogenous Technological Change for Climate Policy Analysis." *Energy Economics* 30 (6): 2734–53. https://doi.org/10.1016/J.ENECO.2008.03.001.

Global Carbon Atlas. 2021. "Emissions." http://www.globalcarbonatlas.org/en/CO2-emissions.

Glöser, Simon, Luis Tercero Espinoza, Carsten Gandenberger, and Martin Faulstich. 2015. "Raw Material Criticality in the Context of Classical Risk Assessment." *Resources Policy* 44 (June): 35–46. https://doi.org/10.1016/j.resourpol.2014.12.003.

Godin, Benoît. 2000. "Measuring Science: Is There 'Basic Research' Without Statistics?" Montréal, Canada. http://www.csiic.ca/PDF/Godin_3.pdf.

Graedel, T. E., E. M. Harper, N. T. Nassar, Philip Nuss, and Barbara K. Reck. 2015. "Criticality of Metals and Metalloids." *Proceedings of the National Academy of Sciences* 112 (14): 4257–62. https://doi.org/10.1073/PNAS.1500415112.

Grafström, Jonas, Patrik Söderholm, Erik Gawel, Paul Lehmann, and Sebastian Strunz. 2020. "Government Support to Renewable Energy R&D: Drivers and Strategic Interactions among EU Member States." *Economics of Innovation and New Technology*. https://doi.org/10.1080/10438599.2020.1857499.

Greenacre, Michael, and Raul Primicerio. 2013. "Measures of Distance between Samples: Euclidean." In *Multivariate Analysis of Ecological Data*. FBBVA. https://www.researchgate.net/publication/259890313_Multivariate_Analysis_of_Ecological_Dat a.

Groot, H.L.F. De, K. Rademaekers, K. Svatikova, M. Smith, O. Widerberg, M. Obersteiner, A. Marcarini, et al. 2012. “Mapping Resource Prices: The Past and the Future. Summary Report – Final Report for European Commission – DG Environment.” Rotterdam, Netherlands. https://ec.europa.eu/environment/enveco/resource_efficiency/pdf/studies/summary_mapping_resource_prices.pdf.

Gross, Daniel P., and Bhaven N. Sampat. 2020. “Organizing Crisis Innovation: Lessons from World War II.” *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3701812.

Grubb, Michael, Paul Drummond, Alexandra Poncia, Will McDowall, David Popp, Sascha Samadi, Cristina Penasco, et al. 2021. “Induced Innovation in Energy Technologies and Systems: A Review of Evidence and Potential Implications for CO2 Mitigation.” *Environmental Research Letters* 16 (4): 043007. https://doi.org/10.1088/1748-9326/ABDE07.

Grubb, Michael, Jean-Charles Hourcade, and Karsten Neuhoff. 2014. *Planetary Economics*. Edited by Cambridge University Press. Cambridge, UK.

Gruber, Paul W., Pablo A. Medina, Gregory A. Keoleian, Stephen E. Kesler, Mark P. Everson, and Timothy J. Wallington. 2011. “Global Lithium Availability.” *Journal of Industrial Ecology* 15 (5): 760–75. https://doi.org/10.1111/j.1530-9290.2011.00359.x.

Grübler, Arnulf, Francisco Aguayo, Kelly Sims Gallagher, Marko Hekkert, Kejun Jiang, Lynn Mytelka, Lena Neij, et al. 2012. “Policies for the Energy Technology Innovation System (ETIS).” In *Global Energy Assessment (GEA)*. https://doi.org/10.1017/cbo9780511793677.030.

Grübler, Arnulf, Nebojsa Nakicenovic, and David G. Victor. 1999. “Dyanmics of Energy Technologies and Global Change.” https://core.ac.uk/download/pdf/52947781.pdf.

Grübler, Arnulf, and Charlie Wilson. 2014. *Energy Technology Innovation: Learning from Historical Successes and Failures*. Cambridge: Cambridge University Press. http://pure.iiasa.ac.at/id/eprint/11142/.

Guellec, Dominique, and Bruno Van Pottelsberghe De La Potterie. 2003. “The Impact of Public R&D Expenditure on Business R&D.” *Economics of Innovation and New Technology* 12 (3): 225–43. https://doi.org/10.1080/10438590290004555.

Gündüç, Semra. 2019. “Diffusion of Innovation In Competitive Markets-A Study on the Global Smartphone Diffusion.” *ACTA POLONICA* 135 (3): 485–94. https://arxiv.org/abs/2103.07707.

Gunn, Gus. 2014. *Critical Metals Handbook*. Hoboken: Hoboken: American Geophysical Union. https://doi.org/10.1002/9781118755341.

Habib, Komal, Lorie Hamelin, and Henrik Wenzel. 2016. “A Dynamic Perspective of the Geopolitical Supply Risk of Metals.” *Journal of Cleaner Production* 133 (October): 850–58. https://doi.org/10.1016/J.JCLEPRO.2016.05.118.

Hahn, Jinyong, and Atsushi Inoue. 2002. “A Monte Carlo Comparison of Various Asymptotic Approximations to the Distribution of Instrumental Variable Estimators.” *Econometric Reviews* 21 (3): 309–36. https://doi.org/10.1081/ETC-120015786.

Hallak, Juan Carlos, and Peter K Schott. 2008. “Estimating Cross-Country Differences in Product Quality .” *National Bureau of Economic Research Working Paper Series* No. 13807. https://doi.org/10.3386/w13807.

Hannon, Matthew, and Ronan Bolton. 2021. “Energy Innovation and the Sustainability Transition.” In *Handbook of Energy Economics and Policy*. https://doi.org/10.1016/b978-0-12-814712-2.00008-7.

Hardin, Garrett. 1968. “The Tragedy of the Commons.” *Science*. https://doi.org/10.1126/science.162.3859.1243.

Henisz, Witold J, Bennet A Zelner, and Mauro F Guillén. 2005. “The Worldwide Diffusion of Market-Oriented Infrastructure Reform, 1977–1999.” *American Sociological Review* 70 (6): 871–97. https://doi.org/10.1177/000312240507000601.

Herfindahl, Orris C. 1951. “Concentration in the Steel Industry.” Ann Arbor: Columbia University.

Hicks, J. R. 1932. *The Theory of Wages*. London: Palgrave Macmillan UK. https://doi.org/10.1007/978-1-349-00189-7.

Hirschman, Albert O. 1945. *National Power and the Structure of Foreign Trade,*. Berkeley and Los Angeles: University of California Press.

Huenteler, Joern, Istvan Dobozi Ani, Balabanyan Sudeshna, and Ghosh Banerjee. 2017. “Cost Recovery and Financial Viability of the Power Sector in Developing Countries A Literature Review.” 8287. Policy Research Working Paper. Washington, D.C. http://econ.worldbank.org.

Intergovernmental Panel on Climate Change (IPCC). 2001. “Climate Change 2001–Mitigation: Contribution of Working Group III to the Third Assessment Report Ofthe Intergovernmental Panel on Climate Change Vol 3.” Cambridge. https://www.ipcc.ch/site/assets/uploads/2018/05/SYR_TAR_full_report.pdf.

———. 2021. “AR6 Climate Change 2021: The Physical Science Basis.” Intergovernmental Panel on Climate Change. 2021. https://www.ipcc.ch/report/sixth-assessment-report-working-group-i/.

International Energy Agency (IEA). 2020a. “Clean Energy Innovation.” Paris. https://www.iea.org/reports/clean-energy-innovation.

———. 2020b. “Energy Technology RD&D Budgets October 2020.” https://iea.blob.core.windows.net/assets/90dab698-eec6-4068-9d40-9ac4a226fcfc/RDD_Documentation1.pdf.

———. 2020c. “Energy Technology Perspectives: Special Report on Carbon, Capture, Utilisation and Storage.” Paris. https://www.iea.org/reports/ccus-in-clean-energy-transitions.

———. 2020d. “World Energy Outlook 2020.” Paris. https://www.iea.org/reports/world-energy-outlook-2020.

International Monetary Fund. 2016. "Fiscal Policies for Innovation and Growth." Washington DC. https://www.imf.org/~/media/Websites/IMF/imported-flagship-issues/external/pubs/ft/fm/2016/01/pdf/_fmc2pdf.ashx

———. 2019. “Fiscal Monitor: How to Mitigate Climate Change.”.Washington DC. https://www.imf.org/en/Publications/FM/Issues/2019/09/12/fiscal-monitor-october-2019.

International Renewable Energy Agency (IRENA). 2019. *Global Energy Transformation: A Roadmap to 2050 (2019 Edition)*. *International Renewable Energy Agency*.

———. 2021a. “Renewable Energy Statistics.” https://www.irena.org/statistics.

———. 2021b. “World Energy Transitions Outlook: 1.5 Pathway.” Abu Dhabi. https://www.irena.org/publications/2021/Jun/World-Energy-Transitions-Outlook.

IRENA and Climate Policy Initiative (CPI). 2020. “Global Landscape of Renewable Energy Finance.” Abu Dhabi. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2020/Nov/IRENA_CPI_Global_finance_2020.pdf.

Jaccard, P. 1908. “Distribution de La Flore Alpine Dans Le Bassin Des Dranses et Dans Quelques Regions Voisines.” *Bulletin de La Societé Vaudoise Des Sciences Naturelles* 37: 241–272.

Jaeger, Joel, Michael Westphal, and Corey Park. 2020. “Lessons Learned on Green Stimulus: Case Studies from the Global Financial Crisis.” *WRI Publications*. https://doi.org/10.46830/wriwp.20.00055.

Jaffe, Adam B., Richard G. Newell, and Robert N. Stavins. 2005. “A Tale of Two Market Failures: Technology and Environmental Policy.” *Ecological Economics* 54 (2–3): 164–74. https://doi.org/10.1016/j.ecolecon.2004.12.027.

Jamasb, Tooraj, Raffaella Mota, David Newbery, and Michael Pollitt. 2005. “Electricity Sector

Reform in Developing Countries: A Survey of Empirical Evidence on Determinants and Performance.” 3549. Policy Research Working Paper. Washington, D.C. https://openknowledge.worldbank.org/handle/10986/8978.

Jamasb, Tooraj, Rabindra Nepal, and Govinda R Timilsina. 2015. “A Quarter Century Effort Yet to Come of Age: A Survey of Power Sector Reforms in Developing Countries.” No. 7330. Policy Research Working Paper. Washington, D.C. https://doi.org/10.5547/01956574.38.3.tjam.

Justman, Moshe, and Morris Teubal. 1986. “Innovation Policy in an Open Economy: A Normative Framework for Strategic and Tactical Issues.” *Research Policy* 15 (3): 121–38. https://doi.org/10.1016/0048-7333(86)90007-7.

Kassouri, Yacouba, Faik Bilgili, and Aweng Peter Majok Garang. 2021. “Are Government Energy Technology Research, Development, and Demonstration Budgets Converging or Diverging? Insights from OECD Countries.” *Https://Doi.Org/10.1080/09537325.2021.1914330*. https://doi.org/10.1080/09537325.2021.1914330.

Kempener, Ruud, Laura Díaz Anadón, and Jose Condor Tarco. 2010. “Governmental Energy Innovation Investments, Policies and Institutions in the Major Emerging Economies: Brazil, Russia, India, Mexico, China, and South Africa.” Discussion Paper, 2010-16, Energy Technology Innovation Policy Project, Belfer Center. https://www.belfercenter.org/publication/governmental-energy-innovation-investments-policies-and-institutions-major-emerging.

Keohane, Robert O., and David G. Victor. 2016. “Cooperation and Discord in Global Climate Policy.” *Nature Climate Change 2016 6:6* 6 (6): 570–75. https://doi.org/10.1038/nclimate2937.

Kharrazi, Ali, and Brian D. Fath. 2016. “Measuring Global Oil Trade Dependencies: An Application of the Point-Wise Mutual Information Method.” *Energy Policy* 88 (January): 271–77. https://doi.org/10.1016/J.ENPOL.2015.10.017.

Kingdon, John W. 1984. *Agendas, Alternatives, and Public Policies*. Boston: Little, Brown.

Koopmans, Tjalling C . 1949. “Identification Problems in Economic Model Construction.” *Econometrica* 17 (2): 125–44. http://www.jstor.org/stable/1905689.

Krugman, Paul. 1979. “Increasing Returns, Monopolistic Competition, and International Trade.” *Journal of International Economics* 9 (4): 469–79. https://ideas.repec.org/a/eee/inecon/v9y1979i4p469-479.html.

———. 1980. “Scale Economies, Product Differentiation, and the Pattern of Trade.” *The American Economic Review* 70 (5): 950–59. http://www.jstor.org/stable/1805774.

Krugman, Paul, Maurice Obstfeld, and Marc Melitz. 2014. *International Economics: Theory and Policy, Global Edition*. Harlow, United Kingdom, UNITED KINGDOM: Pearson Education Limited. http://ebookcentral.proquest.com/lib/cam/detail.action?docID=5174300.

Kwoka, John E. 1977. "Large Firm Dominance and Price-Cost Margins in Manufacturing Industries." *Southern Economic Journal* 44 (1): 183–89. http://www.jstor.org/stable/1057315.

Labys, Walter C., and Chin-wei Yang. 1991. "Advances in the Spatial Equilibrium Modeling of Mineral and Energy Issues." *International Regional Science Review* 14 (1): 61–94. https://doi.org/10.1177/016001769101400104.

Leamer, Edward. 1981. "Is It a Demand Curve, or Is It a Supply Curve? Partial Identification through Inequality Constraints." *The Review of Economics and Statistics* 63 (3): 319–27. https://econpapers.repec.org/RePEc:tpr:restat:v:63:y:1981:i:3:p:319-27.

Lee, Alan David, and Zainab Usman. 2018. "Taking Stock of the Political Economy of Power Sector Reforms in Developing Countries A Literature Review." 8518. Policy Research Working Paper. Washington, D.C. http://www.worldbank.org/research.

Lee, J., M. Bazilian, B. Sovacool, K. Hund, S. M. Jowitt, T. P. Nguyen, A. Månberger, et al. 2020. "Reviewing the Material and Metal Security of Low-Carbon Energy Transitions." *Renewable and Sustainable Energy Reviews*. Elsevier Ltd. https://doi.org/10.1016/j.rser.2020.109789.

Levy, Brian, and Pablo T. Spiller. 1994. "The Institutional Foundations of Regulatory Commitment: A Comparative Analysis of Telecommunications Regulation." *Journal of Law, Economics, and Organization* 10 (2): 201–46. https://econpapers.repec.org/RePEc:oup:jleorg:v:10:y:1994:i:2:p:201-46.

Lewis, Joanna I. 2013. "Green Innovation in China." In *Green Innovation in China: China's Wind Power Industry and the Global Transition to a Low-Carbon Economy*, 1–4. Columbia University Press. http://www.jstor.org/stable/10.7312/lewi15330.8.

Liu, Peiran R., and Adrian E. Raftery. 2021. "Country-Based Rate of Emissions Reductions Should Increase by 80% beyond Nationally Determined Contributions to Meet the 2 °C Target." *Communications Earth & Environment 2021 2:1* 2 (1): 1–10. https://doi.org/10.1038/s43247-021-00097-8.

Lopez, R A. 2005. "Trade and Growth: Reconciling the Macroeconomic and Microeconomic Evidence." *Journal of Economic Surveys* 19 (4): 623–48. https://onlinelibrary.wiley.com/doi/abs/10.1111/j.0950-0804.2005.00264.x.

Lundvall, B.A., ed. 1992. *National Systems of Innovation: Towards a Theory of Innovation and*

Interactive Learning. London: Pinter.

Macal, Charles M., and Lawrence G. Hill. 1985. “Metal Price and Supply Effects of Electric Vehicle Commercialization.” *Resources and Energy* 7 (3): 259–82. https://doi.org/10.1016/0165-0572(85)90021-0.

Malerba, F, ed. 2004. *Sectoral Systems of Innovation*. Cambridge: Cambridge University Press.

Marangoni, Giacomo, Gauthier De Maere, Valentina Bosetti, and Fondazione Eni Enrico Mattei. 2017. “Optimal Clean Energy R&D Investments Under Uncertainty.” https://ideas.repec.org/p/ags/feemmi/256056.html.

Macquarie, Rob, Baysa Naran, Paul Rosane, Matthew Solomon, Cooper Wetherbee, Barbara Buchner, June Choi, Elysha Davila, Caroline Dreyer, and Angela Falconer. 2019. “Updated View on the Global Landscape of Climate Finance 2019.” https://www.climatepolicyinitiative.org/wp-content/uploads/2020/12/Updated-View-on-the-2019-Global-Landscape-of-Climate-Finance-1.pdf.Marangoni, Giacomo, and Massimo Tavoni. 2014. “The Clean Energy R&D Strategy for 2°C.” *Climate Change Economics* 5 (1): 1440003. https://www.worldscientific.com/doi/abs/10.1142/S201000781440003X.

Margolis, Robert M., and Daniel M. Kammen. 1999a. “Evidence of Under-Investment in Energy R&D in the United States and the Impact of Federal Policy.” *Energy Policy* 27 (10): 575–84. https://econpapers.repec.org/RePEc:eee:enepol:v:27:y:1999:i:10:p:575-584.

———. 1999b. “Underinvestment: The Energy Technology and R&D Policy Challenge.” *Science (New York, N.Y.)* 285 (5428): 690–92. https://doi.org/10.1126/SCIENCE.285.5428.690.

Mazzucato, Mariana. 2018. “Mission-Oriented Innovation Policies: Challenges and Opportunities.” *Industrial and Corporate Change* 27 (5): 803–15. https://doi.org/10.1093/icc/dty034.

McCullough, Erin, and Nedal T Nassar. 2017. “Assessment of Critical Minerals: Updated Application of an Early-Warning Screening Methodology.” *Mineral Economics* 30 (3): 257–72. https://doi.org/10.1007/s13563-017-0119-6.

Ministry of Finance, Government of India. 2020a. “Demands for Grants of Central Government Union Budget of India.” 2020. https://www.indiabudget.gov.in/budget2019-20/demands_grants_central_government.php.

———. 2020b. “Summary of Expenditure Profile 2019-2020.” 2020. https://www.indiabudget.gov.in/budget2019-20/doc/eb/stat1.pdf.

Mission Innovation. 2020. “Mission Innovation Country Highlights.” http://mission-innovation.net/wp-content/uploads/2020/09/3.-MI-Country-Highlights-2020.pdf.

Mohler, Lukas. 2009. “On the Sensitivity of Estimated Elasticities of Substitution.” 038. Trade Patterns. Basel. https://www.freit.org/WorkingPapers/Papers/TradePatterns/FREIT038.pdf.

Moner-Girona, M., A. Bender, W. Becker, K. Bódis, S. Szabó, A. G. Kararach, and Laura Díaz Anadón. 2021. “A Multidimensional High-Resolution Assessment Approach to Boost Decentralised Energy Investments in Sub-Saharan Africa.” *Renewable and Sustainable Energy Reviews* 148 (September): 111282. https://doi.org/10.1016/J.RSER.2021.111282.

Murray, Cherry. 2017. “Public Funding of Energy Research.” *Joule* 1 (2): 204–8. https://doi.org/10.1016/J.JOULE.2017.09.002.

Murray, Michael P. 2006. “Avoiding Invalid Instruments and Coping with Weak Instruments.” *The Journal of Economic Perspectives* 20 (4): 111–32. https://www.aeaweb.org/articles?id=10.1257/jep.20.4.111.

Myslikova, Zdenka, and Kelly Sims Gallagher. 2020. “Mission Innovation Is Mission Critical.” *Nature Energy 2020 5:10* 5 (10): 732–34. https://doi.org/10.1038/s41560-020-00694-5.

Nagayama, Hiroaki. 2009. “Electric Power Sector Reform Liberalization Models and Electric Power Prices in Developing Countries: An Empirical Analysis Using International Panel Data.” *Energy Economics* 31 (3): 463–72. https://econpapers.repec.org/RePEc:eee:eneeco:v:31:y:2009:i:3:p:463-472.

Narayanamurti, Venkatesh, Laura Díaz Anadón, and Ambuj D. Sagar. 2009. “Transforming Energy Innovation.” *Issues in Science and Technology* 26 (1): 57–64. https://www.hks.harvard.edu/publications/transforming-energy-innovation.

Narins, Thomas P. 2017. “The Battery Business: Lithium Availability and the Growth of the Global Electric Car Industry.” *The Extractive Industries and Society* 4 (2): 321–28. https://doi.org/10.1016/J.EXIS.2017.01.013.

Nassar, N. T., T. E. Graedel, and E. M. Harper. 2015. “By-Product Metals Are Technologically Essential but Have Problematic Supply.” *Science Advances* 1 (3): e1400180. https://doi.org/10.1126/SCIADV.1400180.

National Research Council. 2008. *Minerals, Critical Minerals, and the U.S. Economy*. Washington, D.C.: National Academies Press. https://doi.org/10.17226/12034.

Nelson, Richard. 1959. “The Simple Economics of Basic Scientific Research.” *Journal of Political Economy* 67. https://econpapers.repec.org/RePEc:ucp:jpolec:v:67:y:1959:p:297.

———. 1993. *National Innovation Systems: A Comparative Analysis*. New York: Oxford University Press.

Nemet, Gregory F. 2009. “Demand-Pull, Technology-Push, and Government-Led Incentives for Non-Incremental Technical Change.” *Research Policy* 38 (5): 700–709. https://doi.org/10.1016/J.RESPOL.2009.01.004.

Nemet, Gregory F., and Evan Johnson. 2012. “Do Important Inventions Benefit from Knowledge Originating in Other Technological Domains?” *Research Policy* 41 (1): 190–200. https://doi.org/10.1016/J.RESPOL.2011.08.009.

Nemet, Gregory F., and Daniel M. Kammen. 2007. “U.S. Energy Research and Development: Declining Investment, Increasing Need, and the Feasibility of Expansion.” *Energy Policy* 35 (1): 746–55. https://doi.org/10.1016/j.enpol.2005.12.012.

Nemet, Gregory F., Vera Zipperer, and Martina Kraus. 2018. “The Valley of Death, the Technology Pork Barrel, and Public Support for Large Demonstration Projects.” *Energy Policy* 119 (August): 154–67. https://doi.org/10.1016/j.enpol.2018.04.008.

Norberg-Bohm, Vicki. 2000. “Creating Incentives for Environmentally Enhancing Technological Change: Lessons from 30 Years of U.S. Energy Technology Policy.” *Technological Forecasting and Social Change* 65 (2): 125–48. https://doi.org/10.1016/S0040-1625(00)00076-7.

Nordhaus, William. 2019. “Climate Change: The Ultimate Challenge for Economics.” *American Economic Review*. https://doi.org/10.1257/aer.109.6.1991.

North, Douglass C. 1990. *Institutions, Institutional Change and Economic Performance*. *Institutions, Institutional Change and Economic Performance*. https://doi.org/10.1017/cbo9780511808678.

Nuclear Energy Agency. 2021. “Unlocking Financing for Nuclear Energy Infrastructure in the COVID-19 Economic Recovery.” Paris. https://read.oecd-ilibrary.org/view/?ref=135_135910-ndj38lclqb&title=Unlocking-financing-for-nuclear-energy-infrastructure-in-the-COVID-19-economic-recovery.

Nuss, Philip, E. M. Harper, N. T. Nassar, Barbara K. Reck, and T. E. Graedel. 2014. “Criticality of Iron and Its Principal Alloying Elements.” *Environmental Science and Technology* 48 (7): 4171–77. https://doi.org/10.1021/es405044w.

Olivetti, Elsa A., Gerbrand Ceder, Gabrielle G. Gaustad, and Xinkai Fu. 2017. “Lithium-Ion Battery Supply Chain Considerations: Analysis of Potential Bottlenecks in Critical Metals.” *Joule* 1 (2): 229–43. https://doi.org/10.1016/J.JOULE.2017.08.019.

Peñasco, Cristina, Laura Díaz Anadón, and Elena Verdolini. 2021. “Systematic Review of the Outcomes and Trade-Offs of Ten Types of Decarbonization Policy Instruments.” *Nature Climate Change*. Nature Research. https://doi.org/10.1038/s41558-020-00971-x.

Popp, David. 2002. “Induced Innovation and Energy Prices.” *The American Economic Review* 92 (1): 160–80. http://www.jstor.org/stable/3083326.

———. 2019. “Environmental Policy and Innovation: A Decade of Research.” http://www.nber.org/papers/w25631.

Popp, David, Richard G. Newell, and Adam B. Jaffe. 2010. *Energy, the Environment, and Technological Change*. *Handbook of the Economics of Innovation*. Vol. 2. Elsevier B.V. https://doi.org/10.1016/S0169-7218(10)02005-8.

Quéré, Corinne Le, Robert B. Jackson, Matthew W. Jones, Adam J. P. Smith, Sam Abernethy, Robbie M. Andrew, Anthony J. De-Gol, et al. 2020. “Temporary Reduction in Daily Global CO2 Emissions during the COVID-19 Forced Confinement.” *Nature Climate Change 2020 10:7* 10 (7): 647–53. https://doi.org/10.1038/s41558-020-0797-x.

Rauch, James E. 1999. “Networks versus Markets in International Trade.” *Journal of International Economics* 48 (1): 7–35. https://doi.org/10.1016/S0022-1996(98)00009-9.

Renner, Sven, and Friedrich W. Wellmer. 2019. “Volatility Drivers on the Metal Market and Exposure of Producing Countries.” *Mineral Economics*. https://doi.org/10.1007/s13563-019-00200-8.

Resnick Institute. 2011. “Critical Materials For Sustainable Energy Applications.” https://www.seia.org/sites/default/files/resources/ri_criticalmaterials_report.pdf.

Reuter, Benjamin, Johannes Riedl, Thomas Hamacher, Markus Lienkamp, and Alex Bradshaw. 2014. “Future Resource Availability for the Production of Lithium-Ion Vehicle Batteries.” In . COFAT 2014, At Munich, Volume: 3. https://www.researchgate.net/publication/263888647_COFAT_2014_-_Future_Resource_Availability_for_the_Production_of_Lithium-Ion_Vehicle_Batteries.

Reuters. 2018. “Congo Declares Cobalt ‘Strategic’, Nearly Tripling Royalty Rate | Reuters.” Reuters. December 3, 2018. https://www.reuters.com/article/us-congo-cobalt-idUSKBN1O220D.

Riahi, Keywan, Detlef P. van Vuuren, Elmar Kriegler, Jae Edmonds, Brian C. O’Neill, Shinichiro Fujimori, Nico Bauer, et al. 2017. “The Shared Socioeconomic Pathways and Their Energy, Land Use, and Greenhouse Gas Emissions Implications: An Overview.” *Global Environmental Change* 42 (January): 153–68. https://doi.org/10.1016/j.gloenvcha.2016.05.009.

Robiou du Pont, Yann, M. Louise Jeffery, Johannes Gütschow, Joeri Rogelj, Peter Christoff, and Malte Meinshausen. 2016. “Equitable Mitigation to Achieve the Paris Agreement Goals.” *Nature Climate Change 2017 7:1* 7 (1): 38–43. https://doi.org/10.1038/nclimate3186.

Rogelj, Joeri, Drew Shindell, and Kejun Jiang. 2018. "Chapter 2: Mitigation Pathways Compatible with 1.5°C in the Context of Sustainable 4 Development." https://www.ipcc.ch/site/assets/uploads/2018/11/sr15_chapter2.pdf.

Rogge, Karoline S., and Kristin Reichardt. 2016. "Policy Mixes for Sustainability Transitions: An Extended Concept and Framework for Analysis." *Research Policy* 45 (8): 1620–35. https://doi.org/10.1016/j.respol.2016.04.004.

Rufín, Carlos. 2003. *The Political Economy of Institutional Change in the Electricity Supply Industry: Shifting Currents*. Cheltenham, UK: Edward Elgar.

Runci, Paul J., and James J. Dooley. 2004. "Research and Development Trends for Energy." Encyclopedia of Energy, Volume 5. 2004. https://reader.elsevier.com/reader/sd/pii/B012176480X004770?token=2359E33E0D591BED7199DBBB1DF6CAC4F884193FB942B89217973DFCAD962D70E970890F5DB0F57A88471996B7E5AE88&originRegion=eu-west-1&originCreation=20210607163029.

Sagar, Ambuj D. 2002. "India's Energy and Energy R&D Landscape: A Brief Overview 2002-08." BCSIA Discussion Paper, Energy Technology Innovation Project. https://www.belfercenter.org/sites/default/files/legacy/files/india_erd_landscape4.pdf.

———. 2004. "Technology Innovation and Energy." *Encyclopedia of Energy* 6: 27–43. https://doi.org/10.1016/b0-12-176480-x/00447-2.

Samuelson, P. A., and W. D. Nordhaus. 1998. *Economics*. Boston, Massachusets: Irwin/McGraw-Hill.

Samuelson, Paul A. 1954. "The Pure Theory of Public Expenditure." *The Review of Economics and Statistics* 36 (4): 387. https://doi.org/10.2307/1925895.

Samuelson, Paul, and William Nordhaus. 2009. *Economics*. 19th ed. Boston, Massachusets: McGraw-Hill Education.

Schmidt, Tobias S., and Sebastian Sewerin. 2019. "Measuring the Temporal Dynamics of Policy Mixes – An Empirical Analysis of Renewable Energy Policy Mixes' Balance and Design Features in Nine Countries." Research Policy 48 (10): 103557. https://doi.org/10.1016/j.respol.2018.03.012.

Schock, Robert N., William Fulkerson, Merwin L. Brown, Robert L. San Martin, David L. Greene, and Jae Edmonds. 1999. "How Much Is Energy Research and Development Worth as an Insurance?" *Http://Dx.Doi.Org/10.1146/Annurev.Energy.24.1.487* 24 (November): 487–512. https://doi.org/10.1146/ANNUREV.ENERGY.24.1.487.

Schrijvers, Dieuwertje, Alessandra Hool, Gian Andrea Blengini, Wei Qiang Chen, Jo Dewulf, Roderick Eggert, Layla van Ellen, et al. 2020. "A Review of Methods and Data to Determine Raw Material Criticality." *Resources, Conservation and Recycling* 155 (April): 104617. https://doi.org/10.1016/J.RESCONREC.2019.104617.

Schuelke-Leech, Beth Anne. 2014. "Volatility in Federal Funding of Energy R and D." *Energy Policy* 67 (April): 943–50. https://doi.org/10.1016/j.enpol.2013.12.057.

Sen, Anupama, Rabindra Nepal, and Tooraj Jamasb. 2016. "Reforming Electricity Reforms? Empirical Evidence from Asian Economies." *The Oxford Institute for Energy Studies (OIES)*. Oxford, UK. https://www.oxfordenergy.org/publications/reforming-electricity-reforms-empirical-evidence-from-asian-economies/.

Shaffer, Christopher. 2015. "Platinum Group Metals on the Move: Transportation & Energy Applications." 2015. https://www.thermofisher.com/blog/metals/platinum-group-metals-on-the-move-transportation-and-energy-applications/.

Soderbery, Anson. 2010. "Investigating the Asymptotic Properties of Import Elasticity Estimates." *Economics Letters* 109 (2): 57–62. https://doi.org/https://doi.org/10.1016/j.econlet.2010.08.006.

———. 2015. "Estimating Import Supply and Demand Elasticities: Analysis and Implications." *Journal of International Economics* 96 (1): 1–17. https://doi.org/10.1016/j.jinteco.2015.01.003.

———. 2018. "Trade Elasticities, Heterogeneity, and Optimal Tariffs." *Journal of International Economics* 114 (September): 44–62. https://doi.org/10.1016/j.jinteco.2018.04.008.

Soete, Luc, Bart Verspagen, and Bas Ter Weel. 2010. *Systems of Innovation*. *Handbook of the Economics of Innovation*. Vol. 2. Elsevier B.V. https://doi.org/10.1016/S0169-7218(10)02011-3.

Sovacool, Benjamin K. 2019. "The Precarious Political Economy of Cobalt: Balancing Prosperity, Poverty, and Brutality in Artisanal and Industrial Mining in the Democratic Republic of the Congo." *The Extractive Industries and Society*, July. https://doi.org/10.1016/J.EXIS.2019.05.018.

Speirs, Jamie, Marcello Contestabile, Yassine Houari, and Robert Gross. 2014. "The Future of Lithium Availability for Electric Vehicle Batteries." *Renewable and Sustainable Energy Reviews* 35 (July): 183–93. https://doi.org/10.1016/J.RSER.2014.04.018.

Speirs, Jamie, Yassine Houari, and Robert Gross. 2013. "Comparison of Material Criticality Studies-Methodologies and Results Working Paper III." www.ukerc.ac.uk/support/TheMeetingPlace.

StataCorp. 2021. "Stata 17 Base Reference Manual." College Station, TX: Stata Press.

Steckel, Jan Christoph, Michael Jakob, Christian Flachsland, Ulrike Kornek, Kai Lessmann, and Ottmar Edenhofer. 2017. “From Climate Finance toward Sustainable Development Finance.” *Wiley Interdisciplinary Reviews: Climate Change* 8 (1): e437. https://doi.org/10.1002/WCC.437.Steinmueller, Edward W. 2010. *Economics of Technology Policy*. *Handbook of the Economics of Innovation*. Vol. 2. Elsevier B.V. https://doi.org/10.1016/S0169-7218(10)02012-5.

Stern, Nicholas, and Joseph E Stiglitz. 2021. “The Social Cost of Carbon, Risk, Distribution, Market Failures: An Alternative Approach.” *National Bureau of Economic Research Working Paper Series* No. 2847. http://www.nber.org/papers/w28472.

Stock, James H., and Mark W. Watson. 2011. *Introduction to Econometrics, 3rd Edition*. Pearson.

Surana, Kavita, and Laura Díaz Anadón. 2015. “Public Policy and Financial Resource Mobilization for Wind Energy in Developing Countries: A Comparison of Approaches and Outcomes in China and India.” *Global Environmental Change* 35 (November): 340–59. https://doi.org/10.1016/j.gloenvcha.2015.10.001.

Teece, David J. 1986. “Profiting from Technological Innovation: Implications for Integration, Collaboration, Licensing and Public Policy.” *Research Policy* 15 (6): 285–305. https://doi.org/10.1016/0048-7333(86)90027-2.

United Nations Conference on Trade and Development (UNCTAD). 2018a. “Export Market Concentration Index.” 2018. https://unctadstat.unctad.org/EN/IndicatorsExplained/statie2018d1_en.pdf.

———. 2018b. “Import Market Concentration Index.” 2018. https://unctadstat.unctad.org/en/IndicatorsExplained/statie2018d2_en.pdf.

———. 2020. “Commodities at a Glance: Special Issue on Strategic Battery Raw Materials.” Geneva. https://unctad.org/system/files/official-document/ditccom2019d5_en.pdf.

———. 2021. “Carbon Emissions Anywhere Threaten Development Everywhere.” June 2, 2021. https://unctad.org/news/carbon-emissions-anywhere-threaten-development-everywhere.

United Nations Development Programme (UNDP). 2020. “Human Development Report 2020.” *UNDP: New York, NY, USA*.

United Nations Environment Programme (UNEP). 2019. *Emissions Gap Report 2019*. Nairobi: UNEP.

United Nations Statistics Division (UNSD). 2020. “UN Comtrade Database.” United Nations Statistical Office. 2020. https://comtrade.un.org/.

United States Geological Survey (USGS). 2016. “Ore.” 2016. https://www.usgs.gov/news/earthword-–-ore.

———. 2021. “What Is the Difference between a Rock and a Mineral?” 2021. https://www.usgs.gov/faqs/what-difference-between-a-rock-and-a-mineral?qt-news_science_products=0#qt-news_science_products.

Urpelainen, Johannes. 2018. “RISE to the Occasion? A Critique of the World Bank’s Regulatory Indicators for Sustainable Energy.” *Energy Research and Social Science*. https://doi.org/10.1016/j.erss.2017.10.034.

Urpelainen, Johannes, Joonseok Yang, and Di Liu. 2018. “Power Sector Reforms and Technical Performance: Good News from an Instrumental Variable Analysis.” *Review of Policy Research* 35 (1): 120–52. https://doi.org/10.1111/ropr.12275.

Wamukonya, Njeri. 2003. “Power Sector Reform in Developing Countries: Mismatched Agendas.” *Energy Policy* 31 (12): 1273–89. https://doi.org/10.1016/S0301-4215(02)00187-8.

Ward, W H. 1967. *The Sailing Ship Effect*. Institute of Physics and The Physical Society. https://books.google.co.uk/books?id=mIQkMwAACAAJ.

Warner, Rebecca. 2007. “Applied Statistics: From Bivariate Through Multivariate Techniques.” *Components*. https://doi.org/10.1017/CBO9781107415324.004.

Watari, Takuma, Benjamin C. McLellan, Damien Giurco, Elsa Dominish, Eiji Yamasue, and Keisuke Nansai. 2019. “Total Material Requirement for the Global Energy Transition to 2050: A Focus on Transport and Electricity.” *Resources, Conservation and Recycling* 148 (September): 91–103. https://doi.org/10.1016/J.RESCONREC.2019.05.015.

Weil, Marcel, Saskia Ziemann, and Jens Peters. 2018. “The Issue of Metal Resources in Li-Ion Batteries for Electric Vehicles.” In , 59–74. https://doi.org/10.1007/978-3-319-69950-9_3.

Weiss, Charles, and William B. Bonvillian. 2009. *Structuring an Energy Technology Revolution*. The MIT Press.

Weitzman, Martin L. 2011. “Fat-Tailed Uncertainty in the Economics of Catastrophic Climate Change.” *Review of Environmental Economics and Policy* 5 (2): 275–92. https://doi.org/10.1093/reep/rer006.

Williams, J. H., and R. Ghanadan. 2006. “Electricity Reform in Developing and Transition Countries: A Reappraisal.” *Energy* 31 (6–7): 815–44. https://doi.org/10.1016/j.energy.2005.02.008.

Wilson, C, A Grübler, N Bento, S Healey, S De Stercke, and C Zimm. 2020. “Granular Technologies to Accelerate Decarbonization." *Science* 368 (6486): 36–39. https://doi.org/10.1126/science.aaz8060.

Winskel, Mark, Jonathan Radcliffe, Jim Skea, and Xinxin Wang. 2014. "Remaking the UK's Energy Technology Innovation System: From the Margins to the Mainstream." *Energy Policy* 68: 591–602. https://doi.org/10.1016/j.enpol.2014.01.009.

Winter, Sidney G., and Richard R. Nelson. 1982. "An Evolutionary Theory of Economic Change." https://papers.ssrn.com/abstract=1496211.

Wooldridge, Jeffrey M. 2001. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, Massachusetts: The MIT Press.

World Bank. 2015. "Commodity Markets Outlook. A World Bank Quarterly Report." Washington, D.C. http://www.worldbank.org/content/dam/Worldbank/GEP/GEPcommodities/GEP2015a_commodity_Jan2015.pdf.

———. 2017. "The Growing Role of Minerals and Metals for a Low Carbon Future." http://documents.worldbank.org/curated/en/207371500386458722/The-Growing-Role-of-Minerals-and-Metals-for-a-Low-Carbon-Future.

———. 2020a. "New World Bank Country Classifications by Income Level: 2020-2021." July 1, 2020. https://blogs.worldbank.org/opendata/new-world-bank-country-classifications-income-level-2020-2021.

———. 2020c. "Minerals for Climate Action - The Mineral Intensity of the Clean Energy Transition." Washington, DC. http://pubdocs.worldbank.org/en/961711588875536384/Minerals-for-Climate-Action-The-Mineral-Intensity-of-the-Clean-Energy-Transition.

———. 2020b. "Doing Business 2020." *Doing Business 2020: Comparing Business Regulation in 190 Economies*. https://doi.org/10.1596/978-1-4648-1440-2.

———. 2021a. "World Development Indicators." 2021. https://databank.worldbank.org/source/world-development-indicators.

———. 2021b. "Worldwide Governance Indicators (WGI) Project." Washington, D.C. https://info.worldbank.org/governance/wgi/.

World Bank, Energy Sector Management Assistance Program (ESMAP). 1999. "Global Energy Sector Reform in Developing Countries: A Scorecard." Washington, D.C. https://www.esmap.org/sites/default/files/esmap-files/Rpt_GBLscorecaredesm219.pdf.

———. 2014. “Readiness for Investment in Sustainable Energy, Pilot Report.” Washington, D.C. https://rise.worldbank.org/reports.

———. 2018. “Policy Matters: Regulatory Indicators for Sustainable Energy.” Washington, D.C. http://documents1.worldbank.org/curated/en/553071544206394642/pdf/132782-replacement-PUBLIC-RiseReport-HighRes.pdf.

Yeo, Sophie. 2019. “Where Climate Cash Is Flowing and Why It’s Not Enough.” *Nature* 573 (7774): 328–31. https://doi.org/10.1038/D41586-019-02712-3.

Yim, Odilia, and Kylee T Ramdeen. 2015. “Hierarchical Cluster Analysis: Comparison of Three Linkage Measures and Application to Psychological Data.” Vol. 11.

Yu, Zhou, William Lazonick, and Yifei Sun. 2016. *China as an Innovation Nation*. *China as an Innovation Nation*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780198753568.001.0001.

Zahariadis, Nikolaos. 2007. “The Multiple Streams Framework: Structure, Limitations, Prospects.” In *Theories of the Policy Process*, edited by Paul A. Sabatier. Boulder, Colorado: Westview Press.

Zhang, Fang, Kelly Sims Gallagher, Zdenka Myslikova, Easwaran Narassimhan, Rishikesh Ram Bhandary, and Ping Huang. 2021. “From Fossil to Low Carbon: The Evolution of Global Public Energy Innovation.” *Wiley Interdisciplinary Reviews: Climate Change*, e734. https://doi.org/10.1002/WCC.734.

Zhang, Kuangyuan, Andrew N. Kleit, and Antonio Nieto. 2017. “An Economics Strategy for Criticality – Application to Rare Earth Element Yttrium in New Lighting Technology and Its Sustainable Availability.” *Renewable and Sustainable Energy Reviews*. Elsevier Ltd. https://doi.org/10.1016/j.rser.2016.12.127.