From Relatedness to Complexity in Regional Industrial Evolution

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Declaration

This thesis 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. I further state that no substantial part of my thesis has already been submitted, or, is being concurrently submitted for any such degree, diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the Preface and specified in the text. It does not exceed the prescribed word limit for the relevant Degree Committee.

Abstract

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If division is the starting point to understand regional industrial structure, complexity may be a stage in its evolutionary trajectory. 'Regional' emphasises the geographical context for economic activities, while 'industrial' is defined as a meso level compared with a micro firm level or a macro aggregate level. 'Complexity' provides a quality measure of regional industrial structure, while 'evolution' stands for a dynamic dimension to view ups and downs. The goal is to understand the role of complexity in economic performance within an evolutionary framework. An underlying mechanism through which complexity matters is a path-dependent evolutionary trajectory underpinned by relatedness. The Chinese case is used for the empirical work. Three studies are intended to shed light on different aspects of this topic: (*i*) multiplicity of mechanisms for evolution, (*ii*) the role of complexity in times of crisis, and (*iii*) the role of relatedness in relation to local market conditions.

The first study explores how productivity is associated with sources of regional industrial path development. A conceptual framework for the heterogeneity of path development in a qualitative sense is transformed to a quantitative one to empirically test the existence of sources of path development and their association with productivity. The second study turns its attention to the economic shock with an attempt to explore the patterns, mechanisms, and necessities of regional resilience through a 'complexity' lens. A difference-in-difference framework is adopted to examine how the global financial crisis influenced economic growth in Chinese cities differently depending on their complexity. The third study investigates the extent to which regional industrial relatedness accounts for spatial disparities in state-granted land prices in China and the relevance of local market-orientedness for the role of relatedness. A co-occurrence measure of relatedness is used, whereas local market-orientedness is captured as a city's innovation and entrepreneurship.

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Introduction

1 Research objective

Back to Adam Smith, it is acknowledged that the division of labour can act as the underlying mechanism for why the specialisation or comparative advantage at the regional industry level can promote economic efficiency (Smith 1776). With local endowments catalysed by global connection, the regional industrial structure can diverge across space in terms of its diversification pattern or the allocation of resources among various industries. As a result of deepening division and increasing diversity, local economic interactions and knowledge spillovers can accumulate to a degree that the prospect for growth and development tends to depend on the diversity of non-tradable capabilities already present in a spatial economy, or the complexity of the regional economic structure (Hidalgo and Hausmann 2009). Such capabilities can involve both internal and external sources of growth (e.g. labour, capital, technologies, institutions, natural resources) and create values through a combinational process due to their interdependence (Hidalgo 2018; Romer 1994; Solow 1956). Accordingly, the proximity between a pair of industries is associated with the similarity in the capabilities that they require. The relatedness of an industry to a region refers to the extent to which the industry composition of the region can signal the availability of all the requisite capabilities that go into the industry (Hidalgo and Hausmann 2009). The role of complexity on predicting a region's future growth may result from the fact that the evolution of the productive structure may exhibit path dependence, that is, a region is more likely to diversify into industries whose requisite capabilities are related to a region's previously available capabilities.

The objective of the thesis is to understand the role of complexity in economic development and growth within an evolutionary framework in a systematic manner from three aspects, which can help fill corresponding gaps in the literature. First, multiple factors are associated with regional industrial evolution and performance. Second, complexity can account for the spatial variations in the influence of a crisis. Third, the importance of relatedness is contingent on regional market conditions. Specifically, the first study intends to understand path branching underpinned by related variety in an integrated theoretical framework that distinguishes different types of pathways with their main sources identified, and empirical evidence is further found with regard to the relative importance of each source for path development and productivity at the regional industry level. The second study aims at examining the relationship between economic complexity and regional resilience in terms of how cities at different complexity levels keep their economic growth momentum in times of a crisis compared with their pre-crisis state, and further testing how cities at low- and high-complexity levels rely on different mechanisms to resist and recover from the shock. The third study attempts to address the relevance of regional market-orientedness for relatedness externalities reflected in land prices, and one underlying mechanism is further tested with respect to how the complementarity of complexity and relatedness in accounting for spatial disparities in land values is contingent on regional market-orientedness.

2 Background and motivation

2.1 Theoretical background

The key concepts in evolutionary economic geography, i.e. place dependence and path dependence, can lay the foundation to delve into the topic of this research (Boschma et al. 2017). Both concepts involve an evolutionary notion in that pre-existing events can affect the probability of future events to occur. Place dependence stresses the importance of a place-specific context with certain regional capabilities for economic development, whereas path dependence pays attention to the relevance of a globally shared socio-technical regime for the development trajectory in a particular sector. Hence, with regard to economic evolution, these two concepts place a focus on the regional level and industrial level, respectively. Normally, path dependence refers to regional path dependence in terms of the place-dependent evolutionary pathway of an industrial sector (Martin 2010).

Along this line of literature, related variety as one dimension of regional industrial structure takes off with substantial evidence achieved on its role in economic performance and evolution (Boschma 2017; Content and Frenken 2016; Frenken et al. 2007; Saviotti and Frenken 2008). Tacit knowledge and skills are more likely to be absorbed and recombined by related activities due to the close cognitive distance. According to a path-dependent regional branching model underpinned by relatedness, regional diversification follows a self-reinforcing trajectory in terms of the role of industrial structure in industrial dynamics, because new related industries are able to develop where pre-existing industrial structures with a sufficient level of related variety have the potential to provide the assets that these news industries require (Boschma and Frenken 2006).

An emerging body of studies are based on a novel measure of relatedness subject to geographical hierarchy instead of the industrial classification system when defining pairwise proximity between different industry domains (Neffke et al. 2011a; Rocchetta et al. 2022b; Whittle and Kogler 2020). Such proximity derived from geographical co-occurrence patterns of different economic activities can reveal between-industry similarities ranging from inputs and outputs, value chains, production processes, worker flows, to institutions, not limited to their positions in the classification system (Hidalgo et al. 2007a). Co-occurrence proximity of industry pairs naturally embodies a geographical element when it comes to the role of a diverse environment in its formation. Stemming from the proximity values in the industrial space, regional industrial relatedness can indicate how an industry is connected to the existing strengths and competences of regional industry composition.

Based on the same building blocks as relatedness, economic complexity as an indicator of capability endowments is a quality measure of diversity (Hidalgo and Hausmann 2009; Hidalgo 2018, 2021). Complexity thinking is not a recent theory (Anderson et al. 1988) and tends to view the economic landscape as a complex system that exhibits self-organisation, emergence, adaptation and the like (Martin and Sunley 2007). The research interest in complex systems is recently revived by a strand of literature that focuses on a novel index of place and product complexity developed by Hidalgo and Hausmann (2009). Economic complexity of a place can not only indicate the diversity of its capabilities to produce products but also captures the non-ubiquity of its products. Economic diversity is an aggregate proxy for the productive structure of an economic system in terms of its variety (the number of sectors), balance (the quantity of sectors), disparity (the differentiation among sectors), and quality (comparative advantages or the non-ubiquity of sectors). Accordingly, different indicators of diversity can have different focuses: entropy measures variety and balance, the Hirschman-Herfindahl Index measures concentration and balance, and complexity measures quality (Hartmann 2014). Diversification emphasises the dynamic dimension of such diversity in terms of the changes in number, type, and quality of economic sectors. When it comes to the evolution of industry composition, the productive structure can become more complex with productive capabilities accumulating.

Evolutionary economic geography can help provide the theoretical foundation to introduce the abovementioned key concepts in this thesis. However, relevant work is still required to support or enrich the theoretical framework for the role of complexity in economic development and growth. Specifically, research on the mechanism through which complexity matters can be illuminated from various aspects, in terms of the multiplicity of mechanisms for economic performance and evolution, the role of complexity in times of crisis, and the role of relatedness in relation to local institutional arrangements.

First, regional path dependence should be viewed in a more comprehensive framework to understand its scope and limitations with respect to its role in regional economic evolution and performance. Theoretical research recently articulates the heterogeneity in how evolutionary pathways may differ and establishes a systematic classification to unveil different forms of regional industrial path development driven by differentiated mechanisms (Grillitsch et al. 2018a; Hassink et al. 2019; Martin and Sunley 2006). Although extensive research on a path-dependent branching process has been done (Content and Frenken 2016; Whittle and Kogler 2020), a relatively small body of work elaborates on other types of path development, let alone the comparison analysis among different types in terms of their key sources not limited to related variety (Grillitsch et al. 2018a). Moreover, the importance of institutions as a driver of path development is not fully understood, particularly in a transitional economy's context (Boschma 2017; Boschma et al. 2017; Hassink et al. 2019).

Second, the role of economic complexity in economic performance and evolution should be examined in times of crisis to understand the mechanism through which complexity can promote growth in the course of a spatial economy's both ups and downs. The vision of complex systems can be used to conceptualise the notion of resilience in an evolutionary model (Martin and Sunley 2007, 2011, 2015). However, an evolutionary approach to probe into regional resilience tends to highlight how the importance of related variety or relatedness for employment growth can change after the burst of a shock (Cainelli et al. 2019; Grabner and Modica 2022; Hane-Weijman et al. 2021; Rocchetta et al. 2022a; Rørheim and Boschma 2022). The relationship between economic complexity and regional resilience appears to be underexplored and warrants more attention to illuminate how complexity is associated with regional growth differently before, during and after the shock and why (Hane-Weijman et al. 2021).

Third, whether the importance of relatedness can be attributed to a place-specific context should be investigated to understand the market conditions for relatedness externalities to take place, due to the complementarity of relatedness and complexity. Evolutionary economic geography adopts a local innovation systems approach to understand the role of the context in conditioning the evolutionary path dependent development of a new industrial sector in an urban economy, and argues that markets as a form of innovation system can fundamentally shape modern economic production and drive the evolution of knowledge (Martin and Sunley 2007; Martin and Simmie 2008). The differentiated relationships between the institutional environment and related versus unrelated diversification can thus rest on the relevance of institutions for the nature of the innovation process (Boschma et al. 2017; Boschma and Capone 2015a). Although empirical evidence in developed countries confirms that institutional arrangements can influence the importance of relatedness as a driver of diversification, the underlying reason for such relationship is rarely examined in an explicit way, particularly in terms of how the complementarity of relatedness and complexity (Balland et al. 2019a; Davies and Maré 2021) can be contingent on the institutional context. Apart from that, limited attention has been paid to transitional economies, where the market conditions can be distinguished from those in developed areas (Li 2015).

2.2 Analytical background

In a multi-level economic system, evolutionary approaches address the spatial evolution of industries and networks at the meso-level of the economy, and the evolution of territorial units at the macro-level is analysed in a framework of structure change in terms of the rise and decline of sectors (Boschma and Frenken 2006). In economic terms, economies at a micro-, meso-, and macro-level are generally understood to indicate firms, sectors, and the spatial economy as a whole, with the higher level depending on the lower level to form (Figure 1). As the core of this micro–meso–macro architecture (Dopfer 2012; Dopfer et al. 2016), the meso level can present agglomeration patterns with broad implications of economic activities. Agglomeration may result from evolutionary processes in which chance events become magnified by positive feedbacks at the firm level. Agglomeration may also be the result of increasing returns at the regional level, in which agglomeration economies act as both an incentive and a selection mechanism (Boschma and Frenken 2006). In this sense, an evolutionary approach is more interested in how agglomeration economies arise from knowledge spillovers and underlines the importance of related variety for development, as some degree of cognitive proximity is required to enable effective interactive learning (Boschma and Frenken 2011, 2006, 2018).

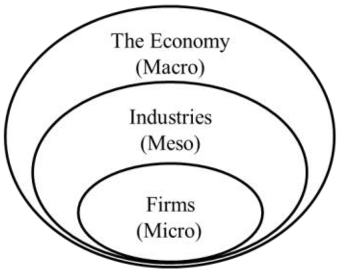

Figure 1. Micro–Meso–Macro System

Source: Dopfer 2012; Dopfer et al. 2016

Previous empirical studies have illuminated the relationship between the different levels of a multi-level system across firms–industries–cities (e.g. Andersson et al. 2019, Rocchetta and Mina 2019, Power et al. 2019). What seems to be overlooked in this empirical strand of literature is that these levels may not necessarily act in an additive way when we consider their importance for the evolutionary pathways. We argue that they act in an interactive fashion, i.e. an industry and the city in which it operates are not orthogonal to each other, and hence the combination of the two should be studied as the unit of observation rather than treating them as two levels of a system. Although this idea of multiplicity across the levels of a system is implicitly or explicitly recognised in previous studies, most of the empirical work still treats them as additive features of a system, or in other words divisible parts of a system.

This interaction between the different levels in the firm–industry–city system is analogous to the concept of indivisibility proposed by Adam Smith (Smith 1776). As one source of internal scale economies, indivisibility relates to one property of input factor (e.g. machinery). A reduced output level does not necessarily mean a decrease in capital input because machines cannot be divided into smaller parts to operate. Meanwhile, doubling output may not require doubling capital input, as one additional unit of factor input (e.g. one machine) could result in more than proportional increase in output. In a broader sense, a mix of different machines working together makes production possible. Each machine as an indivisible component of a factory could not work in its own right. Similar to a machine in a factory, a firm or an industry in a city is an indivisible part of the urban economy. The firm or industry interacts with other components of this local economy to operate and cannot simply relocate to another city to perform equally well. Furthermore, external scale economies (e.g. localisation and urbanisation economies) may occur so that relevant economic activities located in close proximity can enjoy positive externalities (Duranton and Puga 2004). From this indivisibility perspective, a city is like a factory while industries located in this city are like machines in the factory.

In this thesis, we look at this city–industry unit that combines an industry and a city in an interactive way instead of an additive fashion from various aspects to deepen our understanding of this unit of observation. The first study directly adopts regional industries as units of analysis and emphasises the indivisibility of an industry in a locality. We justify the relative independence of a specific regional industry by exploring the balance between path development and productivity at the regional industry level based on a MEME (meso–meso) model. Path development and productivity can be regarded as two complementary elements of the regional structural change that can contribute to economic growth at the regional level. The second study then examines this relationship between industry composition and regional economic growth based on a MEMA (meso–macro) model. The city–industry indivisibility constitutes the foundation to measure the explanatory variable of interest, i.e. economic complexity as a proxy of industry composition. The relevance of economic complexity for regional productivity and diversification can further act as the underlying mechanisms through which economic complexity can influence regional economic growth. The role of complexity may result from the importance of regional industrial relatedness as a driver of diversification or a source of agglomeration externalities, due to the same city–industry indivisibility underpinning complexity and relatedness. The third study subsequently investigates the association between regional industry-level characteristics and firm-level behaviour based on a MEMI (meso–micro) model. We hypothesise that a firm operating in an industry more related to the local industrial structure is likely to invest in more valuable land resources. Additional analysis shows that relatedness externalities as a form of agglomeration economies are contingent on regional market-orientedness to occur based on a MEMAMI (meso-macro-micro) model, implying that meso–micro links can vary depending on the macro-level conditions. In sum, to understand the role of complexity within an evolutionary framework, the importance of the city-industry unit should be emphasised to delve into the interactions across different levels in the micro-meso-macro system, as the combination of an industry and a locality can serve as the building block of complexity.

2.3 The Chinese case

China can provide an extraordinary case as a transitional economy to study regional industrial evolution characterised by both path dependence and path breaking with multi-actor and multi-scalar sources involved. Over the past forty years, the fast pace of industrial growth in China might combine both a break of and a continuation of historical industrial base (Li et al. 2019; Zhu et al. 2017b). On the one hand, China began to establish external linkages in global industrial systems as an emerging market and served as ‘the world’s factory’. On the other hand, it might be a burst of entrepreneurship after centuries of seclusion. Such emergence of industries across space in China may be a mix of different diversification trajectories, instead of one single dominant type of transplantation at the first glance (Guo and He 2017; Zhu et al. 2019c). Industrial diversification in China is also a multi-level process with multi-agents engaged in, such as national and local governments, the global market, firms with different attributes in ownership, size, and age (He et al. 2018; He and Zhu 2018; Zhu et al. 2019b). Inevitably, as this trend goes on, one issue that may arise is whether the industrialisation would face the issue of embeddedness. The conflicts between pre-existing and burgeoning business cultures may seem extreme for the first generation. The diffusion process might take several generations until it forms a sense of identity in local culture. This embeddedness of manufacturing sets urban governance a demanding task in terms of how to sustain the industrial development effectively.

The Chinese case can provide unique evidence on the influence of the institutional context on regional industrial development, particularly in terms of how local institutions may incorporate the market power as one critical driving force of regional industrial restructuring and transformation (Boschma and Frenken 2018; MacKinnon et al. 2009). The importance of local institutions may lie in their capabilities to rectify inefficient path-dependent processes and to introduce path-breaking development opportunities, despite political lock-in as some scholars have criticised (Boschma et al. 2017; Hassink 2010; Martin 2010). To reduce foreseeable uncertainty and increase short-term marginal profits, businesses tend to pursue a production strategy related to existing production. However, sometimes this evolutionary direction may not be efficient compared with alternative path-breaking trajectories in the long run. In contrast, long-term prosperity across a wider scale of space can be the departure point of governments' action. The state may have the risk-taking capability to address market failure and are willing to take initiatives to make alternative evolutionary pathways possible such as making vast investment in unrelated industries at the initial stage. Government involvement has been considered as one key determinant in shaping the spatially unbalanced development in China (Fan and Sun 2008; He et al. 2017b), as Chinese cities present significant spatial variations in local protectionism, privatisation and globalisation. 'Market-based allocation of resources' is recognised as the prevailing institutional setting for economic development in current China, which calls for further insights into relevant opportunities and challenges. In particular, despite the top-down market-oriented reform initiated by the central government, land marketisation is a rather bottom-up arrangement dominated by municipal governments with quite uneven outcomes achieved across space (Liu et al. 2016). In terms of the relevance of regional institutions for economic evolution and performance, previous studies show that relatedness can contribute to new firm survival (Guo et al. 2018), path-dependent regional industrial change (Guo and He 2017), new industry entry (He et al. 2018) in highly market-oriented places. However, the relevance of institutional arrangements for the role of relatedness in the land market has drawn scant attention.

The manufacturing development in China has been experiencing a transition from a quantity stage to a quality stage. As China is striving to develop a knowledge economy, innovative capabilities are playing an increasingly important role in economic performance. The past four decades have witnessed the remarkable development of manufacturing in China and can be roughly divided into four stages with their distinct features: from 1978 to 1990, reform of the economic system and opening to foreign trade; from 1990 to 1999, socialist market economy with soaring state budget and influx of foreign capital; from 1999 to 2008, copy to China, rapid urbanisation; from 2008 to present, innovation for China. The government's focus has shifted from an only GDP-growth strategy to pursuing better quality growth in terms of socio-economic equality and environmental sustainability through a more diversified structural reform and transition (Green and Stern 2015). Local governments used to adopt a variety of policies to attract investment and boost growth. At the initial stage, relatively adequate resources fuelled burgeoning start-up scene. For example, low-cost resources (e.g. land) and different forms of subsidies (e.g. tax) were utilised to create enabling conditions for entrepreneurial activities (Howell et al. 2018; Tian and Ma 2009). Now, it seems that demand is increasing faster than supply. Industrial projects have begun to compete for limited available resources. At a stage when industrial development is increasingly stimulated by continual innovations as intrinsic motivations for industrial behaviour, how to effectively allocate limited land resources to meet the needs of industrial transformation is still an unanswered question. The Chinese economy is also evolving towards a more complex stage in terms of its industry composition. As an indicator of capability endowments, complexity may be predictive of economic sustainability in a more uncertain future (Balland et al. 2019a; Balland and Rigby 2017; Hidalgo and Hausmann 2009). But there is a long way to go in term of industrial transformation and upgrading in China.

Chinese manufacturing resilience can be of importance not only for the Chinese economy but also for the worldwide supply chain. When it comes to sustainability, resilience is one important feature of economies at the sectoral or regional level (Martin and Sunley 2015). From a manufacturing perspective to delve into resilience is of great practical significance. Manufacturing is an integral part of the national economic system. For example, in 2020, manufacturing accounts for 26.3% of China's GDP in terms of value added. The importance of manufacturing has also been highlighted globally in recent years, such as revitalisation of Industry 4.0 among Germany, America, and the UK (Kang et al. 2016). Similarly, Made in China 2025 is a national strategy to update Chinese manufacturing capabilities and develop technology-intensive industries. In addition to its strategic meaning, manufacturing is also closely concerned with daily life. This is more obvious in times of a crisis, particularly in this era when more places worldwide rely on interregional or international trade. For example, the rapid coronavirus outbreak in China in the early months of year 2020 imposed high requirements for manufacturing capabilities. Resilience of manufacturing relevant necessities (e.g. face masks) is of particular importance in terms of meeting the high demand nationwide or even worldwide. Meanwhile, the stability of the Chinese economy can help sustain the global economic growth momentum in a broad sense, although this is also a time when inter-regional mobility of urgent materials is hindered by the epidemic and the global demand can shrink to a degree that can lead to great pressure of economic downturn for China. The situation at home and abroad urges us to reconsider how to strengthen the resilience of Chinese manufacturing in the face of a shock.

3 Chapters of the thesis

3.1 Study 1: Sources of productivity in regional industrial path development

This study examines how sources of regional industrial path development are associated with productivity. A conceptual framework is established regarding the multiple types of regional industrial path development (i.e. path extension, upgrading, branching, diversification, importation, and creation) and their multi-actor and multi-scalar sources to account for the multiplicity of mechanisms for path development. This study identifies six key sources (i.e. specialisation, related variety, unrelated variety, external linkages, innovation, and institutions) for analysis, due to their relative independence as a single source and their completeness as a whole. The relative importance of each key source for productivity and path development as two complementary aspects of regional structural change is estimated using two-way fixed effect models. The unit of analysis in this study is at the city–industry level.

Empirical analysis is conducted on manufacturing industries in 338 Chinese cities over the period 1998–2013 at different levels of aggregation (i.e. two/three/four-digit). The results show that contributors to path development may not necessarily promote productivity, and vice versa. Related variety promotes new sector emergence but not productivity in new sectors and has a relatively short-term effect on sustaining comparative advantages of existing industries. Unrelated variety presents a positive association with productivity in general and helps sustain existing industries but not the development of new sectors. Specialisation exhibits a stronger positive relationship with productivity when industries are more aggregated. Institutions effectively promote the emergence of new sectors but undermine efficiency for path development. Innovation and external linkages are positively associated with productivity and path development at a moderate level.

The contributions of this study are threefold: the mechanisms for different forms of regional industrial path development are distinguished by transforming a qualitative conceptual framework into a quantitative analytical one; the sources for productivity are evaluated in the context of regional industrial path development by virtue of a multi-scalar and multi-actor approach; and the balance between path development and productivity at the regional industry level is established through the operation of their common sources.

3.2 Study 2: Economic complexity and regional resilience: Economic growth in Chinese cities in times of crisis

This study explores how regional resilience during an exogenous shock varies among cities at different degrees of economic complexity. Empirically, we investigate how the 2007–08 global financial crisis influenced economic growth in Chinese cities depending on their complexity. We adopt a difference-in-difference framework to estimate the marginal effect of the shock conditional on complexity after controlling for global and domestic demand. The shock captured by a period dummy is the treatment variable and complexity acts as the moderator. Two stages of resilience are distinguished (i.e. resistance in the crisis period and recovery in the post-crisis period), whereas two outcome variables are used (i.e. employment and output growth). Last but not least, we examine how three mechanisms of resilience (i.e. reduction in productivity improvement, deceleration in industrial dynamics, and redistribution of comparative advantages) may apply to cities at different complexity levels differently.

In terms of the results, first, we find that the relevance of complexity for resilience is not a linear one. Low complexity can contribute to resistance in employment growth, whereas medium complexity can help resistance in output growth. Recovery can be found at every complexity level and can somewhat decrease with complexity. Second, global demand can moderate the influence of the shock, whereas domestic demand cannot. The relationship between the global and domestic markets may change in times of crisis. Third, temporary sacrifice of productivity growth alongside the redistribution of comparative advantages are found in low-complexity cities after the burst of the crisis. Cities at a high complexity level tend to sustain their pre-crisis structure and decelerate industrial dynamics in the face of a shock.

This study addresses complexity as an inherent characteristic of industrial structure that can shape regional resilience. This study may contribute to the existing literature by providing a conceptual framework and empirical design to look at the relationship between economic complexity and regional resilience.

3.3 Study 3: Spatial disparities in state-granted land prices: The role of regional industrial relatedness and market-orientedness

This study explores the role of regional industrial relatedness in spatial disparities in state-granted land prices and the relevance of regional market-orientedness for such relatedness externalities in a transitional economy China. We hypothesise that a firm operating in an industry more related to the local economic composition may invest in more valuable land resources, and this positive association can be stronger in highly market-oriented cities. We employ the Annual Survey of Industrial Firms dataset covering all manufacturing firms above a designated size and match these firms with the parcel-level land transfer dataset obtained from the China land market website to acquire the information on which firms acquire land at what prices between 2011 to 2013. Regional industrial relatedness in terms of how related one industry is to the existing industries of a locality is calculated based on co-occurrence patterns of industries at the city level. City market-orientedness is measured by a comprehensive indicator to capture city-level innovation and entrepreneurship. When estimating relatedness externalities, we also control for the city and firm characteristics in addition to the government involvement variables. The results show that a firm operating in an industry with higher relatedness in a locality may be willing to pay a higher price to acquire land. Whereas this positive association between land prices and relatedness is stronger in highly market-oriented cities, relatedness externalities tend to be negative in low market-oriented cities. The complementarity of relatedness and complexity can be an underlying mechanism for the relevance of local market-orientedness for the role of relatedness in generating a land premium.

This study can contribute to the literature by investigating how regional market-orientedness can condition relatedness externalities in a transitional economy. This study can also provide empirical evidence on how industrial characteristics at the local level can account for spatial disparities in state-granted land prices through the lens of regional industrial relatedness.

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Study 1 Sources of productivity in regional industrial path development

Abstract This study examines how the sources for regional industrial path development are associated with productivity, using data on industries at different aggregation levels in Chinese cities between 1998 and 2013. Results show that contributors to path development are not necessarily those to productivity. Related variety stimulates new sector emergence but not its efficiency, whereas unrelated variety promotes productivity but not new sector development. Specialisation has a stronger positive relationship with productivity at a higher aggregation level. Institutions are positively associated with new sector emergence but not productivity and sustainability. Innovation and external linkages moderately boost path development and efficiency.

Keywords: Regional industrial path development, productivity, new sector emergence, sustaining a comparative advantage, city–industry level

1 Introduction

Industrial evolution and regional development tend to be investigated separately or connected in the way that industrial structural changes can influence regional economic performance or regional economic situations can shape industrial dynamics (Hidalgo et al. 2007; Saviotti and Frenken 2008; Saviotti et al. 2020; Tyler et al. 2017). This tradition is in line with the acknowledgement of industrial heterogeneity and regional heterogeneity. However, a regional industry with the combination of a region and an industry should be viewed as a relatively independent unit of analysis. Such region–industry pair is proposed based on the interdependence between an industry and the region in which this industry is anchored. Over the past decade, the concept of regional industrial path development has been gradually recognised with the accumulation of case studies in related topics such as the evolutionary pathway of a specific regional industry or a group of industries within a specific territory (Fredin et al. 2019; Vanthillo et al. 2018). In particular, recent work can be a critical step taken forward through systematising the differentiated typologies of regional industrial path development conceptually and methodologically (Grillitsch et al. 2018; Hassink et al. 2019; Martin and Sunley 2006). However, the link between regional industrial evolution and performance may not be well discovered and established in a systematic matter, and this may undermine the potential of this concept to our understanding of regional industries theoretically and practically. Thus, this study intends to fill this gap by connecting regional industrial path development and productivity, which are concrete representations of economic evolution and performance. Specifically, the common key sources for path development and productivity are identified and could act as the bridge between these two aspects of regional industries.

The six key sources identified refer to specialisation, related variety, unrelated variety, external linkages, innovation, and institutions, which altogether constitute a relatively complete set to shed light on three dimensions of regional industrial evolution and performance (i.e. economic, spatial, and dynamic). These three dimensions can be viewed individually or in combination to explore a regional industry from diverse perspectives (i.e. economic; spatial; dynamic; spatial and economic; dynamic and economic; spatial, dynamic, and economic). The six key sources can be introduced consecutively along this line of thought:

(i) Economic: As a foundation in economics-related regional science, division of labour (Saviotti et al. 2020; Smith 1776) can be the starting point to understand a regional industry, which may embody specificity when contextualised or generality when standardised.

(ii) Spatial: Beyond a local arena, external linkages (Ricardo 1817) can not only allow for the international trade of concrete inputs and outputs but also enable inflows and outflows of technologies and capabilities in a non-local space.

(iii) Dynamic: In a history-specific context, institutions (North 1990) can be interwoven and coevolve with the local economy, which could largely determine to what degree economic evolution is a self-reinforcing process.

(iv) Spatial and economic: When localised, division of labour for a specific production process can gather together in the forms of not only specialisation by accumulating competences and routines but also diversification by adding variety to a spatial economy (Jacobs 1969; Marshall 1890).

(v) Dynamic and economic: The rise and fall of products, firms, and industries can be regarded as a process of creative destruction, in which innovation is positioned at the core of economic cycles (Schumpeter 1942).

(vi) Spatial, dynamic, and economic: The source of diversification can be further divided into related variety and unrelated variety to imply a dichotomy between path-dependent and path-breaking evolutionary trajectories of a regional economy (Hidalgo et al. 2007; Neffke et al. 2011a).

Thus, the six key sources can be reflected in regional industrial development. Although the relevance of each key source for an economic system has been investigated intensively from various aspects, these sources as a whole hardly serve as a direct link between economic evolution and performance, let alone at a regional industry level.

To fill this gap with respect to how the six key sources as a complete set can connect regional industrial evolution and performance in a systematic manner, this study transforms a conceptual framework for the heterogeneity of regional industrial path development in a qualitative sense into a quantitative one to test empirically how sources of regional industrial path development can be associated with productivity. In particular, this study adopts the concept of regional industrial path development to capture the development of new and existing industries in a region, in accordance with its interpretation in previous work (Grillitsch et al. 2018; Hassink et al. 2019; Martin et al. 2019). Owing to its relative importance, regional industrial path development, compared with productivity and key sources, may constitute the point of departure with regard to the contribution of this study to the literature.

In a broad sense, the contribution of this study may lie in its attempt to explore regional industrial path development and productivity as two sides of a coin in an integrated framework of effectiveness and efficiency, which can influence the structural change of a macro economic system and be incorporated into its growth model as well. On the one hand, efficiency is defined as how efficiently a specific industry operates in a region and may be used to capture the quantity improvement of regional industries. Efficiency can be proxied by productivity and measured as the ratio of outputs to inputs when outputs is qualitatively stable. On the other hand, effectiveness is defined as how effectively a specific industry progresses in a region and may be adopted to capture the quality improvement of regional industries. Effectiveness can be represented by regional industrial path development and proxied by not only the emergence and growth of new industries but also the continuation of existing industries in terms of their comparative advantages. Previous research has not explicitly used the word 'effectiveness' but 'creativity' to reflect the qualitative changes involved in new and existing industries, and placed innovation at the core of this concept (Saviotti et al. 2020). This study replaces 'creativity' with 'effectiveness' by acknowledging various key sources for path development apart from innovation. Saviotti et al. (2020) argue that a balance exists between creativity and efficiency in a regional economic system because new industries can absorb and use the displaced employment and resources due to the efficiency increase in old industries. For the purpose of this study, the balance between effectiveness and efficiency at the regional industry level exists for the same logic but in different contexts of path development, which means the common key sources can act as the bridge to link these two aspects in various scenarios (**mechanism**).

In a narrow sense, three concrete pieces of work are conducted and connected with one another to contribute to the overarching goal of this study. They are the multiple forms of regional industrial path development, their multi-actor and multi-scalar sources, and the relevance of key sources for productivity in the context of path development. The three parts of this study are linked by their interplay: (*i*) the first part can provide various causal mechanisms for the regional structural change to take place in the second one, (*ii*) the extent of such structural change in the second part can rest on its two complementary aspects explored in the third one, and (*iii*) the third part in terms of the relative importance of each key source for effectiveness and efficiency can help justify various mechanisms listed in the first one.

Specifically, the three parts of this study are organised to fit in the literature. First, recent studies have carried out fine-grained conceptual work to disentangle multiple types of regional industrial evolutionary pathways that depend on different combinations of factors to take effect (Grillitsch et al. 2018; Hassink et al. 2019). For analysis, this study identifies six key sources due to their relative independence as a single source and their completeness as a whole to account for the multiplicity of mechanisms for path development. Second, in terms of the sources of structural change that can be incorporated into models of regional economic performance as an explicit mechanism (Saviotti et al. 2020; Tyler et al. 2017), the dichotomy of related variety and unrelated variety has been found to affect economic performance at different time scales and to benefit regional adaption to shocks in different ways (Bishop 2019; Saviotti and Frenken 2008). To take a step further by illuminating more sources for evolution, this study investigates and measures the multi-actor and multi-scalar sources for regional industrial path development based on their firm-level statistics in a comprehensive framework. Third, scholars have come to acknowledge the balance between efficiency and creativity as two complementary aspects of the regional structural change, particularly in the field of evolutionary economics (Saviotti and Frenken 2008; Saviotti et al. 2020). This study not only expands the applicable scope of this balance from a regional level to a regional industry level but also develops the concept of creativity to a broader one of effectiveness by accounting for a variety of development drivers instead of innovation alone.

With respect to the empirical test, what makes the Chinese case distinguish from other empirical studies can be greatly attributed to the role that institutions may play in regional industrial path development. The significance of institutions in new path development has unfolded in recent years, as scholars have devoted closer attention to institutional elements, conditions, and dynamics that can act as either enabling or constraining factors for the rise of new sectors (Hassink et al. 2019). As implied by Boschma et al. (2017), when an economy industrialises, institutions can play an active role in determining whether regions diversify into related sectors or unrelated sectors. In line with this study on advanced economies, the empirical work on Chinese regions can help illustrate that path-breaking and path-dependent evolutionary trajectories may exist in an emerging economy as well (He et al. 2018; Li et al. 2019; Zhu et al. 2017a). Based on this previously proven finding, this study might further argue that institutions can operate at the same regional industry level as other key sources for path development. Particularly, in a transition economy such as China, institutions may serve as a substitute for other key sources (e.g. related variety) in processes of resource allocation and can directly influence investments and selection of activities. On the one hand, governments can help create favourable conditions for new ventures and emerging industries through a variety of measures, such as industrial policies, infrastructure, and financial support. On the other hand, the expectations and visions of certain industries can be incorporated into institutions and further reflected in the behavior of state-owned enterprises, which can directly act as market pioneers in industrial growth paths. In this sense, to understand the industrialisation in China, what role institutions play may warrant particular attention (He et al. 2018; He and Zhu 2018). Furthermore, the conceptualisation of regional industrial path development has enriched a related and unrelated diversification dichotomy to various mechanisms for evolution, which can lead to a more comprehensive understanding of the Chinese case in terms of its heterogeneous growth patterns.

Empirical analysis is conducted on manufacturing industries in 338 Chinese cities over the period 1998–2013 at different levels of aggregation (i.e. two/three/four-digit). The results show that contributors to path development may not necessarily promote productivity, and vice versa. Related variety promotes new sector emergence but not productivity in new sectors and has a relatively short-term effect on sustaining comparative advantages of existing industries. Unrelated variety presents a positive association with productivity in general and helps the continuity of existing industries but not the growth of new sectors. Specialisation exhibits a stronger positive relationship with productivity when industries are more aggregated. Institutions effectively promote the emergence of new sectors but undermine the efficiency for path development. Innovation and external linkages are positively associated with productivity and path development at a moderate level.

The study is organised as follows. Section 2 presents the conceptual framework based on the mechanisms and sources for various forms of regional industrial path development. Section 3 introduces the dataset and presents the methods adopted to measure productivity, new industries and existing industries, key sources for path development, and city–industry-level and city-level control variables. Section 4 presents the empirical design and model specifications. Section 5 provides and discusses the results. Section 6 presents the conclusions.

2 Conceptual framework

Inspired by the conceptual work of Grillitsch et al. (2018) on different forms of regional industrial path development, the following six paragraphs elaborate on each form of path development in terms of its definition, mechanism, sources, and relevant empirical work.

Path extension stresses the continuity of an existing path. Its corresponding development is fuelled by incremental product and process innovation in current industries. Innovative activities mainly rely on the experience and tacit knowledge of employees to enhance the region’s manufacturing base. Owing to relatively weak innovation capabilities, firms tend to pursue a cost-effective strategy and emphasise process innovation by using capital-intensive and mass production processes, which may raise entry barriers and reduce production costs. While the continuity of the industry composition might pose a danger of path exhaustion or ‘lock-in’ for the local economy (Isaksen 2015), it can also prevent an industry from falling into decline (Luhas et al. 2019; Vanthillo et al. 2018). The research of Květoň and Blažek (2018) finds that for less developed regions, such as central Europe, the presence of regional stakeholders might play a role in the maintenance of existing industries and restraining regional actors and institutions from creating new path types.

Path upgrading refers to the change of an existing development path into a new direction, via one of the following three mechanisms. First, path renewal can be facilitated when new technologies, firm strategies, and business models are adopted (Coenen et al. 2015). Second, the development of the regional industry within global production networks can promote value enhancement (MacKinnon et al. 2019). Finally, path upgrading can also result from the development of niches in mature industries. Moodysson et al. (2016) argue that the adaptation and continuity of policy approaches to support innovation at multi-scalar levels can help promote path renewal. Njøs et al. (2017) find that extra-regional linkages may have a non-negligible effect on cluster renewal through multinational corporation practices. Hauge et al. (2017) demonstrate that organisationally thick and diversified regions may stimulate regional renewal by promoting the capability of firms to innovate across industries. Miörner and Trippl (2019) highlight the influence of being connected with global innovation systems on the transformation of existing local industries.

Path importation, also known as path transplantation, denotes the emergence of a new sector that is not present in the region but already exists globally. In this process, external sources may play a key role compared with the existing local capability base and institutional setting. External linkages with inter-regional and global sources (e.g. foreign direct investment) as a critical mechanism can help attract and absorb knowledge generated elsewhere (Trippl et al. 2018). New industries may also rely on exogenous factors (e.g. transport, natural resources, and input costs) in place rather than regional capabilities (Boschma et al. 2017). With respect to the access to differentiated knowledge sources, Martin (2013) argues that industries with an analytical knowledge base tend to rely on innovation inputs from a wider geographical scale than those with a synthetic or symbolic knowledge base. Considering regions at different development stages (Carvalho and Vale 2018), this type of path development is relatively appropriate for peripheral regions and developing countries, which lack a strong industrial base and tend to adopt a ‘catch-up’ strategy. In this sense, path importation is an actor-driven process, and regime incumbents (e.g. multinational corporations) and government agencies normally take an active role in creating enabling conditions for regimes from outside to be accepted locally (Boschma et al. 2017).

Path branching is defined as regional diversification into a (technologically) related industry; that is, the rise and fall of the industry can be subject to how it is related to the local industrial structure. This form arises because a region where the existing industry composition presents a sufficient level of related variety to a new sector is more likely to provide favourable assets and conditions for this sector to grow (Boschma 2017). Klepper (2007) points out three firm-level routes to path branching, i.e. spinoffs from incumbent firms, setting up new firms based on competences in existing sectors, and diversification of incumbent firms into new sectors based on redeploying existing assets and capabilities. Brekke (2015) examines three branching mechanisms (i.e. entrepreneurship, mobility, and social networks) that new industries can arise from and suggests policy action to encourage knowledge transfer between industries. Liang (2017) finds that industrial relatedness still matters in the time of an economic downturn by allowing for shock-induced path-dependent industrial branching. According to the finding of Xiao et al. (2018), while relatedness can increase the likelihood of a region developing specialisation in an industry, the effect of relatedness is less evident in regions where the presence of high innovation intensity is more likely to promote path-breaking development.

Path diversification represents the emergence of a new industry based on previously unrelated knowledge combinations. Diversity of local industries can allow for path breaking to avoid 'lock-in' and to realise revitalisation (Boschma 2005). Ng (2007) identifies an organisation's 'three pillars' (i.e. dynamics capabilities, absorptive capacity, and weak ties) to promote unrelated diversification. Boschma and Capone (2015) argue that institutions can influence the direction of diversification in that compared with coordinated market economies, liberal market economies are more likely to diversify into unrelated industries. Unrelated variety may be relevant for innovation processes in that combinations of three different knowledge bases (i.e. analytical, synthetic, and symbolic knowledge) in firms, industries, or even regions can promote novel ideas to arise (Asheim et al. 2017). In line with this relevance, Miguelez and Moreno (2018) find that related technologies can help generate incremental innovations, whereas unrelated activities can promote radical innovations. Similarly, Xiao et al. (2018) show that the intensity of innovation can complement the effect of relatedness in new industrial specialisation development. Janssen and Frenken (2019) suggest that policy makers could pay attention to unrelated variety and promote cross-specialisation by developing linkages between strong but unrelated knowledge bases.

Path creation implies the emergence of industries new to the world based on most radical innovations (e.g. radically new technologies, scientific discoveries, and social innovations). Such innovations can stem from intense research activities, active policy interventions (e.g. creation of supportive organisational and institutional structures), strong knowledge exchange and networking, and spin-off dynamics (Grillitsch et al. 2018). Owing to its inconsistency with the local established knowledge base and existing global regimes, heterogeneous actors in different places may need to be involved in the new growth path. An empirical investigation by Wink et al. (2017) indicates that institutional transformation on the local policy level aiming at the integration of new actors or coordination mechanisms could facilitate the emergence of start-ups and the growth of young firms in new industries. When deviating from place dependence, agents with non-local roots may help regions introduce unrelated novel activities, although entrepreneurs may face a relatively high risk of failure compared with new subsidiaries of existing industries (Neffke et al. 2018). With regard to long-term survival, while outsiders tend to exert a greater influence at the early stage of path development in the short term, their interplay with regional preconditions and existing actors could determine the sustainability of its influence in the long run (Fredin et al. 2019).

This study extends the opportunity space for regional industrial path development proposed by Grillitsch et al. (2018) to establish an integrated framework that can distinguish different forms of path development based on their respective mechanisms (see Figure 1). The multiplicity of mechanisms can reflect different degrees of continuity and change underpinning the heterogeneity of evolutionary trajectories. The six key sources for path development involved in these mechanisms consist of three elements (i.e. specialisation, related variety, and unrelated variety) in the opportunity space for regional structural change and three additional factors (i.e. external linkages, innovation, and institutions). Before delving deeper into the six key sources, many sources going beyond these six could account for different forms of path development, as evidenced by the above empirical work. In addition, one source can take effect in several forms of path development (e.g. unrelated variety in path upgrading/diversification/creation), whereas several sources can operate together in a single form (e.g. specialisation and external linkages in path upgrading). Admittedly, other methods may present multiple forms of path development based on a differentiated selection of sources, such as the opportunity space. Thus, why are these six sources key in this study?

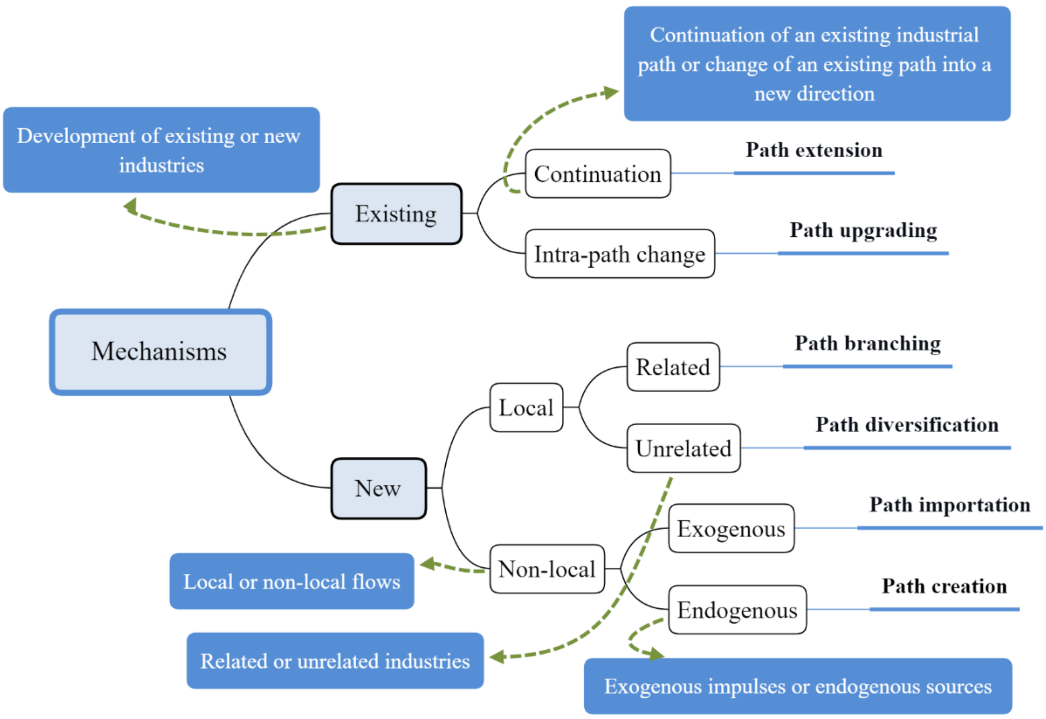

Figure 1. Mechanisms and sources for various forms of regional industrial path development
Source: Authors' elaboration, inspired by Grillitsch et al. (2018).

Three aspects may matter. First, these six sources are relatively independent of one another and are fundamental in the mechanisms of regional industrial path development. The independent nature means that these sources not only refer to qualitatively different characteristics of regional industries but also have their own quantitative measurements (for description, see Section 3.2.3). The fundamental nature means that in each form of path development, the key source(s) involved can act as a point of departure to distinguish one mechanism from the others (for elaboration, see Section 3.2.2). These independent, fundamental sources suffice to constitute different combinations to grasp how different forms of path development can operate. Second, six is the minimum number of sources to capture the heterogenous mechanisms of path development, such that moving along each line of logic leads to only one form of path development without overlapping or absence (see Figure 1). Although the correspondence between the source and the form is not one to one, these six sources as a whole make exploring path development in variegated contexts feasible by examining several sets of regressions, as displayed in Sections 5 and 6. Finally, the emphasis of identifying key sources is not on the link between the sources and corresponding forms of path development, but on the connection between productivity and path development through the operation of the common sources. In this sense, these key sources are selected due to their importance in evolution and performance at the regional industry level. Nevertheless, key sources are deeply embedded in various mechanisms of path development.

To illustrate better how the conceptual framework is transformed into an analytical one, Table 1 reports the multi-actor and multi-scalar sources for different forms of regional industrial path development in a comprehensive framework inspired by Hassink et al. (2019). It comprises agency at different levels (i.e. firm, industry, and system) in the local space and external linkages in the non-local space. Based on this framework, the six key sources for path development are captured at the regional industry level and have their respective micro foundations. In terms of their relative importance in different forms of path development, the three elements relevant for regional industrial structure (i.e. specialisation, related variety, and unrelated variety) can act as the key source of path extension/upgrading, path branching and path diversification, respectively. Innovation plays a key role in path creation, whereas external linkages primarily lead to path importation. To distinguish between path extension and path upgrading, the former has a tendency of increasing capital intensity, whereas the latter may be featured by a higher degree of innovation, external linkages, or unrelated variety.

Table 1. Multi-actor and multi-scalar sources for regional industrial path development

	Path extension	Path upgrading	Path importation	Path branching	Path diversification	Path creation
Local space						
Firm level (micro foundations)						
Firm actor	Existing establishments (Květoň and Blažek 2018)	Existing establishments (Grillitsch et al. 2018)	New entrants (Boschma et al. 2017; Carvalho and Vale 2018)	Spin-offs from incumbents or new entrants (Klepper 2007)	New entrants (Ng 2007)	New entrants (Grillitsch et al. 2018)
Knowledge and innovation	Experience-based existing knowledge, incremental innovation (Grillitsch et al. 2018)	Development of skills, technologies, business models, and niches (Coenen et al. 2015)	Non-local competences and innovation (Boschma et al. 2017; Martin 2013)	Similar competences to existing industries (Boschma et al. 2017)	Radical innovation unrelated to existing knowledge base (Miguelez and Moreno 2018)	Rooted in an excellent scientific base and interactions of individuals (Grillitsch et al. 2018)
Industry level						
Industrial structural	Specialisation (Grillitsch et al. 2018)	Specialisation Unrelated variety (Hauge et al. 2017)	Unrelated variety (Boschma et al. 2017).	Related variety (Boschma 2017)	Unrelated variety (Boschma 2005)	Unrelated variety (Boschma et al. 2017)
Industrial life cycle	Dynamic and declining industries (Luhas et al. 2019; Vanthillo et al. 2018)	Mature and dynamic industries (Grillitsch et al. 2018)			Relatively new industry composition (Boschma et al. 2017)	Old and new industries (Boschma et al. 2017; Martin and Simmie 2008)
System level						
Institutions	Relatively weak local knowledge network (Isaksen 2015)	Regional innovation system reconfiguration (Miörner and Trippl 2019)	Explicit strategy by regional and national governments (Boschma et al. 2017)	'Non-market' coordination (Boschma and Capone, 2015)	Overarching institutional framework, crossover interfaces (Boschma and Capone 2015; Janssen and Frenken 2019)	Creation in institutional work at regional and global levels (Boschma et al. 2017)
Non-local space						
Extra-regional linkages	Global industry-specific institutions and technologies (Boschma et al. 2017)	Renewal and niche development (Boschma et al. 2017; MacKinnon et al. 2019; Njøs et al. 2017)	Foreign direct investment, foreign-owned companies, and extra-regional partnerships (Trippl et al. 2018)	Investments from non-local actors active in related industries (Boschma et al. 2017)	Globally accepted technologies, standards, and regulations (Boschma et al. 2017)	Inflows of individuals, entrepreneurs, and firms from outside (Boschma et al. 2017)

Source: Authors' elaboration, inspired by Grillitsch et al. (2018) and Hassink et al. (2019).

In terms of system-level agency for path development, a wide range of actions by institutions can result in the institutionalisation of emerging paths, such as the incorporation of new practices and resources into an existing system (Hassink et al. 2019). System-level actors such as governments can shape the environment in which regional industries develop. In particular, pioneering governments are required to adapt existing institutions or to establish new institutions for the creation of new paths (Simmie 2012). To illustrate the relevance of institutions for path development in this regard, the role of related variety can pave the way. Relate variety as a source of regional industrial path development can be either endogenous or exogenous. In the former case, related variety resembles agglomeration economies in terms of creating knowledge spillover effects on technologically related economic activities. In the latter case, related variety enables the shift of competences and resources from declining to dynamic industries in a local economy based on their similar capability base. State actors can complement the latter role of related variety in processes of resource allocation but in aspects other than competitiveness and innovativeness, particularly when it comes to emerging markets where related activities are absent. Despite their similarities in terms of their functions in path development, institutions and related variety are totally distinct notions with regard to their corresponding mechanisms. Thus, the relative independence of each key source is conducive to demonstrating one mechanism or another, and deeper investigation into the potential interplay between these six sources goes beyond the focus of this study but deserves more attention in future work.

3 Data and measurement methods

3.1 Data

Data employed in this study is obtained from the Annual Survey of Industrial Firms (ASIF) maintained by the State Statistical Bureau in China. The database covers all enterprises in manufacturing industries with annual sales of more than 5 million RMB (approximately US$600,000) from 1998 to 2010 and 12 million RMB from 2011 to 2013 in China. The sample of enterprises accounts for more than 90% of the total industrial output (Brandt et al. 2014). This database provides detailed firm-level data with many indicators such as firm location, industry code, employment, asset value, fixed capital, output, new product output, entry year, wages, shareholding status, and registration type. It has been used in previous studies to investigate a wide range of issues at multiple levels empirically, such as firm performance (Howell 2017), industrial evolution (He et al. 2018), and regional institutions (Zhu et al. 2019a). The unit of analysis in this study is the city–industry level, and corresponding variables are calculated based on firm-level statistics at the spatial scale of cities[1] during the period 1998–2013. The method developed by Brandt et al. (2014) is adopted to help clean the data and match enterprises through the years. The database contains 338 cities, with 30 two-digit industries, 169 three-digit industries, and 482 four-digit industries [2] distinguished[3], respectively, covering a period from 1998 to 2013. The China City Statistical Yearbooks (CCSY) and China Statistical Yearbooks for Regional Economy (CSYRE) are also used to provide city-level data.

3.2 Measurement methods

3.2.1 Productivity

Productivity refers to the ratio of output to input as a measure to capture the efficiency of production (Diewert and Nakamura 2007). Output could be denoted by gross output or value added, and only the former accounts for the contribution of intermediated products. Despite their slightly different outcomes at the industry level (Hulten 1978), recent research implies that gross output-based and value added-based productivity measures could always coincide (Balk 2009). Thus, this study employs gross output due to the unavailability of valued added in several years. The association of the key sources with productivity is evaluated using the Solow residual approach. This approach allows for a wide range of factors that could influence technological progress to enter the residual term, whereas stochastic frontier analysis accounts for technological efficiency going beyond the scope of this study (Comin 2010; Diaz and

[1] At a more aggregated province level, an entry–exit pattern of industries is rare because almost all provinces have all types of industries over time. At a more disaggregated prefecture level, agglomeration externalities hardly exist due to a relatively small population (Glaeser et al. 1992). A wide range of data on socio-economic conditions are also available at the city level.

[2] Unalanced panel.

[3] All firms in this dataset are classified according to the China Industry Classification standard (GB/T 4754). To make the data for each year comparable, all industry codes (two/three/four-digit) are merged according to the standard applied from 2003 to 2012, which is the longest period compared with 1998–2002 and 2013 in our database.

Sanchez 2008; Kim and Han 2001). For simplicity, this study adopts a Cobb–Douglas production function, and labour productivity is measured as gloss output per employee (Öner 2018). A log-transformed production function is estimated as follows[4]:

$$\ln\left(\frac{Q_{jit}}{L_{jit}}\right) = \alpha_0 + \beta_1 * \ln(L_{jit}) + \beta_2 * \ln(K_{jit}) \tag{1}$$

where $\frac{Q_{jit}}{L_{jit}}$ is the ratio of output to labour used as a proxy for productivity in industry *j* in city *i* in year *t*; Q_{jit} is the output in terms of gross value in current price; $\log(L_{jit})$ is the log-form amount of labour, and its parameter β_1 is expected to have a negative sign due to the law of diminishing marginal returns to labour in output when all other factors are held fixed in the original Cobb–Douglas model; $\ln(K_{jit})$ is the amount of physical capital in log form, and its parameter β_2 measures the elasticity of output to capital; and α_0 is the residual productivity gap, which represents the technical term to capture the relevance of multiple factors for productivity.

3.2.2 New industries and existing industries

The multiple types of regional industrial path development cannot be simply modelled mathematically. In this case, a set of key sources are required to capture the fundamental differences between various mechanisms of path development. However, their contribution to effectiveness does not necessarily demonstrate the existence of corresponding forms of regional development but at least potentially proves their respective mechanisms. Different forms of path development can be centred on either developing or maintaining a considerable level of specialisation in a city industry. In this regard, industries are split into new industries, in which cities acquire a comparative advantage over time, and existing industries, in which cities already have a comparative advantage[5].

[4] The original Cobb–Douglas production function is defined as $Q = AL^{\alpha}K^{\beta}$, where α and β are supposed to be above 0 and below 1, due to the decreasing marginal returns to labour and capital. Its log form is obtained as: $\ln(Q/L) = a + b \ln L + c \ln K$, where $b = \alpha - 1$, and $c = \beta$.

[5] The industry membership in the city is defined from a comparative advantage angle, as shown by Neffke et al. (2011b), which is originally designed to capture sector entry.

The following equation is adopted to capture the revealed comparative advantage (or the location quotient[6], which implies the export–import flows for an industry in a region):

$$RCA_{jit} = \frac{Employment_{jit} / \sum_j Employment_{jit}}{\sum_i Employment_{jit} / \sum_{i,j} Employment_{jit}} \quad (2)$$

where $Employment_{jit}$ is the number of employees in industry *j* in city *i* in year *t*. RCA_{jit} measures whether the share of industry *j*'s production in city *i* is above the average level of Chinese cities in year *t* (RCA_{jit}>1), indicating the level of specialisation in that industry *j* in city *i*.

A considerable level of specialisation can reflect not only the relative importance of one industry in a local economy compared with other local industries but also the associated favourable environment that can reinforce the growth of such industry. On the one hand, existing industries can be used to distinguish between path extension and path upgrading, which both present a level of specialisation above 1, but these two forms are different in terms of how cities could succeed in sustaining a comparative advantage in existing industries over a period of time. Path extension could be evidenced by the efforts to lower production costs by increasing capital investment. In this respect, an industry with a higher capital labour ratio is more likely to maintain its existing path and to present more than proportionate importance in a city. By contrast, path upgrading is characterized by the propensity to enhance innovation, cross-industry knowledge transfer, and external linkages as a way of redirecting an existing regional industrial path. On the other hand, the isolation of new industries may enable testing other forms of path development in relation to sector entry (i.e. path branching, path diversification, path importation, and path creation), which all indicate a rise in the specialisation degree of an industry above 1, but they differ with respect to how a city can build up a comparative advantage in a new industry. Specifically, these four forms of path development need the involvement of external linkages, related variety, unrelated variety, and innovation in their respective mechanisms. In addition, institutions as a key source for regional industrial path development could take part in

[6] According to the economic base model, the location quotient based on employment indicates whether the output of an industry located in a region could be exported to other regions because it already ensures sufficient local supply (location quotient is above 1), or the region needs to import more goods in this sector from outside because local supply could not meet local demand (location quotient is below 1).

multiple forms of path development with different roles to play and its form-specific relevance in an empirical sense is still underexplored (Boschma et al. 2017).

3.2.3 Sources of regional industrial path development

Sources of path development (i.e. specialisation, related variety, unrelated variety, innovation, external linkages, and institutions) constitute the variables of interest. Specialisation is measured by using the concept of location quotient in Equation (2) and signals comparative advantages to display the relative importance of one industry in the local economy. To respond to the interpretation of specialisation that stresses the interdependencies between economic activities (Grillitsch et al. 2018), this measure is calculated at different levels of industrial aggregation (i.e. two/three/four-digit) instead of only one level considering the potential interdependency issue involved in sector grouping.

Related variety is one explanatory variable in this study with respect with its indication of path-dependent trajectories (Neffke et al. 2011a). Related variety has been measured in diverse ways in the literature based on different implications of relatedness, such as sectoral classifications (Frenken et al. 2007), co-occurrence patterns (Neffke et al. 2011a), and input–output relationships (Cainelli and Iacobucci 2012). This study follows the relatedness index developed by Hidalgo et al. (2007), which has been widely used in recent studies (Balland et al. 2019b; Boschma et al. 2012; Cortinovis et al. 2017; Innocenti and Lazzeretti 2019). This concept derives from the co-location patterns of industries and can indicate not only industrial spatial proximity but also their production similarities, including the intensity of labour/capital/land, the level of technical sophistication, the input–output relationship in the value chain, and the requisite institutions.

The first step in measuring related variety is to examine the extent to which every pair of industries is related by calculating the proximity between them, as shown in Equation (3):

$$\phi_{jkt} = min\{P(RCA_{jit} > 1|RCA_{kit} > 1),\ P(RCA_{kit} > 1|RCA_{jit} > 1)\} \qquad (3)$$

where the proximity ϕ_{jkt} between industry *j* and industry *k* in year *t* is the minimum of the pairwise conditional probabilities of a city *i* having a comparative advantage in one industry given that it also presents a comparative advantage in another industry in year *t*; RCA_{jit} refers to the revealed comparative advantage, as calculated in Equation (2).

The second step in measuring related variety is to calculate how related one industry is to the industry composition in a locality, as shown in Equation (4):

$$Related\_variety_{jit} = \frac{\sum_k x_{kit} \emptyset_{jkt}}{\sum_k \emptyset_{jkt}} \tag{4}$$

where $Related\_variety_{jit}$ refers to the summed proximity values between industry *j* and each industry in which city *i* has a comparative advantage in year *t*, divided by the sum of proximity values between industry *j* with all the industries in city *i*; $\emptyset_{jkt}$ refers to the proximity between industry *j* and industry *k* in year *t*; and $x_{kit} = 1$ if city *i* has a comparative advantage in industry k in year t ($RCA_{kit} > 1$) or 0 otherwise. In accordance with the product space developed by Hidalgo et al. (2007), new products are new to the country but not to the world because the product space is made up of existing product categories in the world. With the same logic adopted in this study, the notion of new sector formation is a relative concept in that this new sector still shares certain degree of relatedness with existing local industries as captured by the index of related variety.

This notion of related variety focuses on the degree of specialised variety at the city–industry level and captures the weighted average of comparative advantages around the focal industry. Its value can be high when the share of existing industries with comparative advantages is large and the proximity between local industrial strengths and the focal industry is close. On the one hand, the measurement of related variety is based on co-occurrence matrices and does not depend on the hierarchical structure of industrial classification (Whittle and Kogler 2020). Hence, related variety can be measured at every level of aggregation. On the other hand, the notion of related variety is distinguished from co-occurrence relatedness that tends to be higher in a more diversified environment. Instead, it can have a positive correlation with specialisation and a negative correlation with unrelated variety (see correlation matrices in Tables A3–A6 in the Appendix). An underlying reason is that this index is calculated in a relative term at the local level when the proximity values in relation to the focal industry in the denominator are only centred on existing local industries rather than all the industries in the industrial space nationwide (see Hidalgo et al., 2007, for the latter measurement). Another reason is that this index has a relative meaning different from the concept of relative relatedness that is obtained by standardising the absolute relatedness around the local option set (see Pinheiro et al. 2022, for the latter measurement) so that the distribution of related variety values can differ across cities depending on the existing industry composition of a locality.

Unrelated variety denoted as Div_{jit} is calculated, as shown in Equation (5):

$$Div_{jit} = \sum_j \left(\frac{Employment_{jit}}{\sum_j Employment_{jit}} \ln \frac{\sum_j Employment_{jit}}{Employment_{jit}}\right) \tag{5}$$

where entropy is used as a proxy to measure heterogeneity and distribution, with higher values indicating a higher number of industry types in a city and a more uniform distribution of labour across industries.

Innovation is measured by the output share of new products in a city industry to indicate the intensity of innovative activities. New products tend to represent a radical level of innovation compared with new models of existing products. In this sense, the figure of new products can be a more appropriate indicator for path upgrading or path creation, in which the latter may exhibit a higher degree of creativity by giving rise to a totally new sector in a locality.

External linkages of one regional sector are captured as the output share of foreign-invested and Hong Kong, Macau, and Taiwan (HMT)-invested enterprises in the regional sector. The role of institutions in one local industry is measured by the market share of state-owned enterprises in the total output of the local industry. This index captures the extent to which the government might help industries overcome entry barriers and promote the development of new industries that cannot build on pre-existing production capabilities of a city (Boschma et al. 2017; He et al. 2017c; Zhu et al. 2017a).

3.2.4 City–industry and city control variables

City–industry characteristics that may influence regional industrial development are controlled for, including industrial concentration, maturity, dynamism, and business models. Industrial concentration relates to economic performance in that a higher level of industrial structure concentration indicates a dominance of large firms, and the resultant lower competitiveness may hamper productivity of firms in that industry, especially small firms (Drucker and Feser 2012). The level of concentration in a given industry is captured using the Herfindahl–Hirschman Index (Ramaswamy 2001), which adds up the squared shares of each firm belonging to the same industry in a city. A high value of the Herfindahl–Hirschman Index can indicate a highly concentrated structure and low competition among firms in a regional industry.

Industrial maturity is another industrial feature that can interact with path dependence because the ‘lock-in’ issue could arise in old industrial areas where mature industries may face the need to realise revitalisation (Coenen et al. 2015; Grillitsch et al. 2018). Industrial maturity as a proxy for the industrial life cycle stage is measured as the market share of old firms (i.e. firms aged 10 or more) in the local industry when controlling the changes in the overall plant turnover over the years (Neffke et al. 2011c). When the industry is at a young or rejuvenated stage characterised by strong technological renewal, young firms are likely to retain large shares of the market. By contrast, if an industry is mature with a stable technological trajectory, old firms might be unaffected by new entrants’ threats and tend to capture a large share of the market (Nelson and Winter 1982).

Industrial dynamism may transform local economies through introducing novel establishments (Grillitsch 2019) or through incumbent’s growth and decline (Neffke et al. 2018). To measure industrial dynamism, instead of the net flow of firms, this study adopts the churn of firms with the entry rate and exit rate added together. The gross flow captured by the churn implies that high levels of entry and exit may occur at the same time (Austin and Rosenbaum 1990). Churn plays a critical role in job creation and productivity growth in the sense that economic resources from less productive firms could be reallocated to more productive firms (Haltiwanger 2012). Thus, churn as measure of industrial dynamism may provide more accurate information on the effects of firm dynamics on industrial productivity.

Innovative business models can help enhance the firm’s management efficiency and expand its market share. Business model innovation is measured as the growth rate of expenditures on operational activities (e.g. marketing, advertising, and cost of sales) in a local industry. Business models may differ among firms and even differ among different products produced by the same firm. To quantify it explicitly, the increase in operating expenditures is adopted to capture the efforts in pursuing innovative channels of marketing and services (Backman et al. 2017).

Four variables to measure city characteristics include GPD per capita, manufacturing share, population density, and average wage. GDP per capita in logarithmic form is used to control for uneven distribution of economic prosperity across cities, whereas manufacturing share in GDP is adopted to capture the level of industrialisation in each city. Population density in log form is employed to control for urbanisation economies. The average wage level in a city is calculated as a proxy for the cost of living and the quality of the workforce:

$$Wage_{it} = \sum_j \frac{Employment_{jit}}{Employment_{it}} \frac{wage_{jit}}{\overline{wage_{Jt}}} \tag{6}$$

where $wage_{jit}$ is the average wage in industry *j* in city *i* in year *t*, and $\overline{wage_{Jt}}$ is the average wage nationwide in industry *j* in year *t*. Local employment share is used as the weight to calculate a weighted average wage. Table 2 presents the description of all the variables in the empirical analysis (for descriptive statistics and correlation matrices, see Tables A1–A6 in the Appendix).

Table 2. Variables used in the empirical analysis

Variable	Measure	Computation	Source and Year [a]
Outcome variables at the city–industry level			
Productivity	Efficiency	Ratio of gross output to the number of employees	ASIF, 1998–2013
Emergence and growth of new sectors	Effectiveness	The location quotient of one new industry in a city rises above 1 in a five-year interval	ASIF, 2003–2013
Sustaining existing industries		Probability that an existing industry successfully maintains its location quotient above 1 over a four-year interval	ASIF, 2002–2013
Explanatory variables			
Labour	Inputs of production	Number of employees	ASIF, 1998–2013
Capital		Total investment in fixed assets	ASIF, 1998–2013
Key sources of path development			
Specialisation	Path extension/upgrading	Location quotient measured as the labour share of one sector in a city compared with the national average	ASIF, 1998–2013
Related variety	Path branching	Relatedness between one sector with the composition of local industries	ASIF, 1998–2013
Unrelated variety	Path diversification	Entropy measure calculated by taking the logarithm of the reciprocal of the share of a sector in a city, multiplying this number with the share, and then summing these values	ASIF, 1998–2013
External linkages	Path importation	Market share of foreign-invested and HMT-invested enterprises in a local industry	ASIF, 1998–2013
Innovation	Path creation	Market share of new products in a local industry	ASIF, 1998–2003, 2005–2007, 2009–2010
Institutions	Multiple paths	Market share of state-owned enterprises in a local industry	ASIF, 1998–2013
City–industry characteristics			
Herfindahl-Hirschman Index	Concentration	Herfindahl–Hirschman Index calculated by squaring the output share of every firm in a local sector and then summing the resulting numbers	ASIF, 1998–2013
Maturity	Life cycle stage	Market share of old plants (no less than 10 years old) divided by the national average	ASIF, 1998–2013
Churn	Dynamism	Ratio of the number of firms that enter or exit the local industry during one year to the total number of firms at the beginning of this year	ASIF, 1999–2013
Innovative business models	Business model innovation	Annual growth rate of expenditures on operational activities for a local sector	ASIF, 1999–2013
City characteristics			
GDP per capita	Prosperity	GDP per capita in a city	ASIF, CCSY, CSYRE, 1998–2013
Manufacturing share	Industrialisation	Market share of manufacturing in local GDP	
Population density	Urbanisation economies	Number of people per square kilometre	
Average wage	Wage level	Sum (weighted by labour share) of the ratio of the local industry wage to the national average	ASIF, 1998–2008, 2011–2013

Note: Missing years for certain variables are due to the lagged effects of variables or the unavailability of corresponding indicators in the original database.

4 Empirical design

All estimations are conducted at the city–industry level based on different degrees of industrial aggregation (i.e. two/three/four-digit). The first set of regressions is to examine how the key sources of regional industrial path development are associated with productivity. A log-transformed Cobb–Douglas production function is performed with factors of productivity entering the residual term. The dataset could be treated in a data structure of either independently pooled cross sections or panel data. To control for unobserved characteristics of city–sector pairs in the longitudinal data, panel data analysis is performed. Hausman test is additionally conducted, and its result shows that the fixed-effect estimator is more efficient than the random-effect estimator. Two-way fixed effect models are carried out to control for both unit-specific and time-specific confounders. The baseline model takes the following form:

$$\log\left(\frac{Q_{jit}}{L_{jit}}\right) = \alpha_0 + \beta_1 \log(L_{jit}) + \beta_2 \log(K_{jit}) + \gamma V'_{jit} + \delta S'_{jit} + \zeta C'_{it} + \eta_{ji} + \theta_t + \varepsilon_{jit} \tag{7}$$

where V'_{jit} is a vector of key variables that capture the key sources for different forms of regional industrial path development in industry j of city i in year t, including specialisation, related variety, unrelated variety, external linkages, innovation, and institutions; S'_{jit} is a vector of the variables for city–industry characteristics, including industrial concentration, maturity, dynamism, and innovative business models; C'_{it} is a vector of city characteristics in city *i* in year *t*, ranging from prosperity, industrialisation, and urbanisation economies to wage level; η_{ji} are city–industry fixed effects to control for time-invariant unobservable heterogeneity of city–industry pairs; θ_t denotes time fixed effects to control for year-specific factors common to all industries in the sample; and ε_{jit} is an error term. The γ parameters are of main interest and indicate the relevance of key sources in path development for productivity. The model is first estimated without the city–industry-level and city-level control variables, and then these variables are included to control for their connection with productivity.

A linear probability model is further used to assess the probability that a city keeps the specialisation of an industry above 1 over a period of time. This set of regressions aims to examine the mechanisms of path extension and upgrading. This empirical strategy extends the classical model developed by Neffke et al. (2011a) by incorporating a time scale into the model. Specifically, for an industry whose revealed comparative advantage is above 1 in year t, the dependent variable takes 1 if this industry can keep its comparative advantage above 1 until year $t+4$ and 0 otherwise. The value of the outcome variable depends on whether this city–industry pair can present continuity and stability in terms of its relative importance in the regional economy in a five-year interval. The model takes the same form as Equation (7), except that the explanatory variables for labour and capital as inputs of production are dropped from the regression; the outcome variable is replaced by the dummy variable to capture the probability of sustaining a comparative advantage; the variable for specialisation is also dropped, and capital labour ratio is used to signal the mechanism of path extension; alongside a high level of specialisation, external linkages, innovation, and unrelated variety can indicate the mechanism of path upgrading. Different time intervals (i.e. three/four/five years) are adopted as a robustness check of the time scales at which regional industrial path development takes place.

Similar to the model specification for existing industries, another set of regressions is estimated to examine the mechanisms of remaining types of regional industrial path development (i.e. path importation, path branching, path diversification, and path creation). These types can be represented by a process during which a city successfully builds up a comparative advantage in a new industry. This model design is based on previous studies that have investigated new sector emergence, which is regarded as a process of specialisation growth (Boschma et al. 2013; Cortinovis et al. 2017). The dependent variable is the specialisation level of an industry. Only industries whose location quotient is below 1 in the first four years but exceeds 1 in the last year in a five-year interval are included in the regression. The progressive development of new comparative advantages is estimated as a proxy for the emergence of new industries. This model design can separate new from existing industries by focusing on the years when industries grow to a substantial size, thereby minimising the overlap between new industries and existing industries.

5 Estimation results

5.1 Sources of productivity

Table 3 shows the association between sources of regional industrial path development and industrial productivity for industries at different levels of aggregation. The first three columns are the estimations without control variables that capture city–industry-level and city-level characteristics. The last three columns provide the estimates of the full model with all variables added to the regression. In terms of six key sources, the significance and magnitude of their estimated coefficients do not change markedly when control variables are incorporated into the model. Interpretation of their association with productivity is mainly based on the results obtained from the full model.

Table 3. Productivity of all industries in the two-way fixed effect model

	Baseline Model			Full Model		
	(1) Two-digit	(2) Three-digit	(3) Four-digit	(4) Two-digit	(5) Three-digit	(6) Four-digit
Variable	Output per employee	Output per employee	Output per employee	Output per employee	Output per employee	Output per employee
Inputs						
Labour (log)	–0.447***	–0.419***	–0.412***	–0.405***	–0.411***	–0.418***
	(0.004)	(0.002)	(0.002)	(0.005)	(0.003)	(0.002)
Capital (log)	0.311***	0.269***	0.257***	0.269***	0.240***	0.235***
	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
Core variables						
Specialisation (path extension/upgrading)	0.017***	0.001***	0.000	0.015***	0.001***	0.000**
	(0.002)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
Related variety (path branching)	0.090***	0.220***	0.298***	0.122***	0.297***	0.403***
	(0.024)	(0.021)	(0.019)	(0.027)	(0.024)	(0.021)
Unrelated variety (path diversification)	0.699***	0.675***	0.649***	0.736***	0.597***	0.535***
	(0.025)	(0.014)	(0.011)	(0.028)	(0.016)	(0.013)
External linkages (path importation)	0.104***	0.118***	0.122***	0.073***	0.115***	0.126***
	(0.012)	(0.007)	(0.005)	(0.013)	(0.007)	(0.006)
Innovation (path creation)	0.131***	0.156***	0.134***	0.133***	0.174***	0.160***
	(0.021)	(0.012)	(0.009)	(0.022)	(0.013)	(0.010)
Institutions (multiple paths)	–0.687***	–0.786***	–0.767***	–0.537***	–0.663***	–0.670***
	(0.009)	(0.006)	(0.005)	(0.011)	(0.007)	(0.006)
City–industry characteristics						
Herfindahl–Hirschman Index				0.048***	–0.127***	–0.201***
				(0.014)	(0.008)	(0.007)
Maturity				–0.079***	–0.056***	–0.027***
				(0.003)	(0.002)	(0.001)
Churn				0.012***	0.009***	0.007***
				(0.003)	(0.002)	(0.001)
Innovative business models				0.000***	0.000***	0.000***
				(0.000)	(0.000)	(0.000)
City characteristics						
GDP per capita (log)				0.359***	0.341***	0.325***
				(0.013)	(0.009)	(0.008)
Manufacturing share				0.263***	0.260***	0.259***
				(0.010)	(0.007)	(0.006)
Population Density (log)				–0.006	–0.006	–0.002
				(0.006)	(0.006)	(0.006)
Average wage				–0.002*	–0.003*	–0.005***
				(0.001)	(0.001)	(0.002)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
City–industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.566***	3.454***	3.375***	0.443***	0.679***	0.778***
	(0.033)	(0.024)	(0.022)	(0.126)	(0.093)	(0.081)
Observations	90,461	293,820	479,837	73,266	238,344	388,739
R-squared	0.644	0.554	0.497	0.613	0.520	0.465
Number of codes	8,979	36,857	72,625	8,664	34,545	67,125

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

First, with respect to the differences among six key sources, specialisation, related variety, unrelated variety, external linkages, and innovation have a significantly positive relationship with industrial productivity, but institutions have a negative one. The relatively weak effect of specialisation may be because location quotient is used as a measure of specialisation, whereas an absolute measure (e.g. density or amount) can lead to a stronger association (Frenken and Boschma 2015). In line with previous studies, the relationship with productivity is positive for related variety (Aarstad et al. 2016; Quatraro 2010), unrelated variety (Andersson et al. 2019; Jacobs 1969), external linkages (Wang et al. 2016), and innovation (Cassiman et al. 2010). Regarding one standard deviation increase in each key source (Tables A1–A3 in the Appendix), unrelated variety is associated with approximately 18% increase in productivity, followed by related variety (2%–6%), external linkages (2%–4%), innovation (2%) and specialisation (1%–4%). However, a 10% increase in the market share of state-owned enterprises is correlated with an approximately 2% decrease in productivity. This result may justify the reform of state-owned enterprises as an attempt to improve their economic performance (Howell 2017; Zhu et al. 2020).

Then, to what extent the results may differ at different aggregation levels (i.e. two/three/four-digit) is examined. Additional t-tests indicate that the coefficients of every key source (specialisation, related variety, unrelated variety, external linkages, and institutions) change significantly in their magnitudes across different levels, except for those of innovation. With a one standard deviation increase in specialisation (Tables A1–A3 in the Appendix), industrial productivity rises more at a higher aggregation level (e.g. 1% at four-digit and 4% at two-digit). An opposite pattern is observed for the figures of unrelated variety, which is 18.3% at four-digit and 16.8% at two-digit. However, the same indicator at different aggregation levels might have slightly different meanings. In terms of specialisation, a two-digit level can capture the effect of co-location of upstream and downstream activities in a production chain compared with the four-digit level, which may only reflect the production of particular products (Andersson et al. 2019). Regarding unrelated variety proxied by entropy, unrelated variety at a lower level of aggregation (e.g. four-digit) can be the sum of unrelated variety and semi-related variety at a higher aggregation level (e.g. three-digit) (Saviotti and Frenken 2008). The results also show that productivity's relationships with related variety, external linkages, institutions, and innovation become stronger at a more disaggregated level. These four could be regarded as rather industry-specific factors, which are more likely to have spillover effects when considered in a narrower-aggregation context.

Regarding the relevance of city–industry level control variables, industrial concentration measured by the Herfindahl–Hirschman Index at the three- or four-digit level exhibits a negative association with productivity as predicted, due to the lack of competition (Drucker and Feser 2012). The figure at the two-digit level is positive though small. The Herfindahl–Hirschman Index in a broad sector grouping (e.g. two-digit) may be the sum of within-sector and between-subsector concentration, in which the latter resembles related variety and has an effect offsetting that of the within concentration. Industrial maturity has a significant and negative association with productivity in all estimations, demonstrating that higher market shares of old firms in the industry could undermine productivity due to weaker motivation for updating technologies and introducing new products. This result is consistent with the finding of Potter and Watts (2011) that Marshall's agglomeration economies have a negative effect on economic performance at later stages of industrial life cycle. This evidence may reflect the risk of path 'lock-in' faced by declining industries in many parts of China (Wei et al. 2009). The significant positive coefficient of churn as a proxy for industrial dynamism indicates that new ventures may be more productive, and resources are likely to be reallocated efficiently (Aghion et al. 2009; Fritsch and Changoluisa 2017) when other observable factors are held constant. With respect to the growth rate of operational expenditures to capture innovative business models, its coefficient is almost zero though positive, implying its role in promoting productivity (Johnson and Lafley 2010) but limited in manufacturing.

With regard to the relationship between city economic conditions and industrial productivity, the result shows that industrial productivity is likely to be higher in more prosperous or more industrialised areas, but not necessarily in densely populated or high-paying cities (Fu and Hong 2011). Additional regressions show that the productivity–density relationship is statistically significant positive until year and city–industry fixed effects are all included in the regression. Thus, urban economies might be absorbed by these fixed effects because population density is almost a time-invariant variable. The coefficient of average wage remains markedly small probably due to sufficient supply of labour, which could stagnate wage growth but boost productivity

(Dosi et al. 2020). Additional regressions show that average wage has a significant positive association with productivity when innovation is not included in the regression, implying that innovation could pick up the average wage's positive relationship with productivity.

5.2 Heterogeneity in path development and discussion

The empirical emphasis of this study is to investigate the association between sources of regional industrial path development and productivity. Among the six forms of path development identified, two forms refer to the development of existing industries (i.e. path extension and path upgrading), and the other four represent the emergence of new industries (i.e. path branching, path diversification, path importation, and path creation). The baseline model with the full sample does not limit the estimation to the processes of path development; hence the estimated coefficient of each source is a mixed association resulting from multiple forms or even beyond the scope of path development. To separate the various mechanisms for path development, existing industries where cities have a comparative advantage and new industries in which cities gain a comparative advantage over time are then isolated from the full sample. The first two sets of regressions are conducted to demonstrate the sources of path development for new and existing industries, respectively. These results are further combined with another set of regressions on productivity estimated in these two groups to interpret the relative importance of every key source in path development and productivity in various contexts of regional industrial path development.

To display the results of the three sets of regressions briefly, Table B1 in the Appendix demonstrates the existence of the mechanisms for path extension and path upgrading, in which the former is evidenced by the positive coefficient of capital labour ratio and and the latter is by those of innovation, external linkages, and unrelated variety. The effects of a one standard deviation increase in these sources are approximately equal in size, associated with an approximately 1% increase in the probability of sustaining an existing comparative advantage. By contrast, an existing industry with a higher market share of state-owned enterprises has more difficulty maintaining its competitiveness. The evidence on related variety is mixed, with its coefficients being positive only within a short time horizon (no more than three years). Then, Table B2 provides evidence of external linkages, related variety, and innovation as sources of new sector emergence, implying that path importation, path branching, and path creation may take place. Industries owned by the state to a greater extent are more likely to acquire a substantial size in the local economy. Unrelated variety underpinning path diversification does not act as a stimulus to new sector development. Next, Table B3 provides productivity estimations in existing industries and new industries as a robustness check of estimations in Table 3. The results for existing industries are similar to those for the full sample in that all sources of regional industrial path development except for institutions are positively associated with productivity. For new industries, related variety is found to be negatively associated with productivity.

Table 4. Key sources for path development and productivity

	Existing industries		New industries	
	Path development	Productivity	Path development	Productivity
Specialisation	+ (path extension)	+		+
Related variety	+ (short-term)	+	+ (path branching)	–
Unrelated variety	+ (path upgrading)	+	– (path diversification)	+
External linkages	+ (path upgrading)	+	+ (path importation)	+
Innovation	+ (path upgrading)	+	+ (path creation)	+
Institutions	–	–	+	–

Note: This table reports the obtained signs in regressions with respect to the association between key sources of path development and productivity.

Combining the evidence from these three tables (Tables B1–B3 in the Appendix), Table 4 exhibits the sources of path development and productivity in the context of different forms of regional industrial path development. In line with the findings in previous studies, related industries are more likely to enter and less likely to exit (Neffke et al. 2011a), but their existence is probably not long lasting. Related variety does not make new industries more productive when they grow. Thus, their emergence is probably not driven by the positive effect of related variety on efficiency but by the instantaneous demands generated by pre-existing related industries. This finding may partly explain why the advantage of related industries in keeping their competitiveness in the local market disappears over a short time span (Saviotti and Frenken 2008). Hence, related variety may not guarantee long-lasting competitiveness when industries achieve a substantial size. They should rely on other sources of path development (e.g. innovation, external linkages) to maintain their relative importance. Overall, path branching as a way of regional diversification into related sectors can promote the productivity of industries via increasing backward linkage effects. While path branching is a demand-driven process, path diversification is a relatively supply-driven one, in which unrelated variety can make new economic activities more productive via expanding the scope of learning and innovation (Fritsch and Kublina 2018). However, new sector specialisation is less likely to develop in a diversified economy as the saturation point has not been reached in terms of the demand of the pre-existing industries. Resources are less likely to be redistributed from old to new economic activities to make room for considerable growth of new sectors. Not limited to new industries, unrelated variety known as a source of urbanisation economies also supports existing industries. Transferring capabilities and resources of pre-existing industries to unrelated sectors can be more difficult (Content et al. 2019), but unrelated combinations might be a necessary requirement of long-term development (Saviotti and Frenken 2008). Similarly, path importation and path creation are also driven by supply in the sense that external linkages and innovation as constant boosters for productivity can lead to industrial emergence as well as comparative advantage maintenance (path upgrading) (Zhu et al. 2017a). Moreover, the estimated coefficients of innovation and external linkages are always maintained at a moderate level compared with those of other factors (e.g. the extremely large coefficient of related variety in new sector development, and that of unrelated variety in productivity), which may partly explain why development paths fuelled by these two sources also present efficiency because these two factors have no extreme effects. A characteristic of industrial dynamics in China is that institutions always play a fundamental role in promoting industrial development due to the relative efficiency of state start-ups (Zhou et al. 2017), although state ownership in general may not act as a stimulus to industrial productivity (Zhu et al. 2019a). Compared with other sources, the association between specialisation and productivity remains small in most regressions, but this point can demonstrate the complementary relationship between path development and productivity because specialisation growth itself reflects path development as a process of acquiring comparative advantages. The relatively large magnitude of specialisation at a higher aggregation level is partly because the specialisation measure in a broader industry grouping can capture some degree of related variety.

6 Conclusion

This study empirically aims to examine how six key sources for regional industrial path development are associated with productivity. Despite the emphasis of previous studies on the importance of related variety for regional industrial dynamics, relatively few studies explore the multiplicity of mechanisms in regional industrial evolution and their differentiated connections with economic performance in a systematic manner. Therefore, the contributions of this study are threefold. First, effectiveness can be measurable because the mechanisms for different forms of regional industrial path development can be distinguished by transforming a qualitative conceptual framework into a quantitative analytical one. Second, efficiency can be testable because the sources for productivity can be evaluated in the context of regional industrial path development by virtue of a multi-scalar and multi-actor approach. Finally, the balance between effectiveness and efficiency at the regional industry level can be systematically established with respect to each key source simultaneously underpinning path development and productivity[7]. In terms of the city–industry level as the unit of analysis, this study may shed light on the moderately different results when conducting the analysis at different industrial aggregation levels. The multiple sources of path development can have different economic interpretations at different industry grouping levels.

Consistent with what previous research suggests, an interdependent relationship exists between productivity and path development due to their common sources (i.e.

[7] With respect to the relevance of regional industries as units of analysis for the balance mentioned here, in previous work (Saviotti and Frenken 2008; Saviotti et al. 2020), regional structural change can contribute to economic growth based on a MEMA (meso–macro) model, which assumes that interactions (e.g. resource reallocation) can exist between different industries within a region and that efficiency improvement may take place after the emergence of new sectors at the regional level. By comparison, in this paper, the balance between effectiveness and efficiency exists at the regional industry level based on a MEME (meso–meso) model, which argues for the relative independence of a specific regional industry. Effectiveness and efficiency as two parallel processes may be simultaneously tied in a complementary manner through finite potential of every key source involved.

the six key sources). Unrelated variety is positively associated with productivity in general but negatively with new sector development. By contrast, institutions proxied by the share of state-owned enterprises can effectively promote the rise of new sectors, but state involvement may not be efficient in terms of industrial productivity. Related variety can considerably promote the emergence of new sectors but not in a productive manner, and it cannot sustain the comparative advantages of existing industries for long. Innovation and external linkages have a positive association with productivity and sustainability of path development in a moderate manner. Specialisation is more likely to have a positive association with productivity in a broader industry grouping.

The study has its limitations. First, the work on the identification of different forms of path development is far from complete owing to diverse sources operating in every type of regional industrial path development. More factors could be accounted for if relevant data are available, such as human capital and R&D. Second, spatial dependences could be further explored by capturing the connections between cities at a larger spatial scale, where agglomeration economies could take place in a network of cities. Third, future work could be performed in combination with a qualitative case study to illustrate the relevance of multiple sources for different types of path development better. Fourth, empirical tests could be further carried out in other institutional settings to help justify any generality and specificity issue involved in the relationship between effectiveness and efficiency.

Despite its limitations, the study may have several policy implications in terms of how to improve industrial path development and boost productivity. The sources of productivity and path development could not be taken for granted but need to be placed in a broader picture of regional economic landscapes and at a longer time scale. For example, despite the positive association between related variety and new sector development, relatedness may not help new industries become more productive and sustain long-term competitiveness unless other sources of productivity exist to promote path development, such as unrelated variety and innovation. Policies targeted at linkages between strong but unrelated industries may be a more efficient catalyst for knowledge spillovers. State involvement is indeed an effective way to build up new sectors in local economies in the Chinese context, but its efficiency and sustainability may not be evidenced. Policy makers could rethink the role of state involvement in regional economies at different development stages to avoid its inefficiency and make good use of its effectiveness. For example, when industries with state involvement are established locally, the inefficiency issue can be foreseen and other sources for compensation purpose could be nurtured.

Appendix

A. Descriptive statistics and pairwise correlations

Table A1. Descriptive statistics for two-digit industries

Variable	Obs.	Mean	Std. Dev.	Min	Max
Output per employee (log)	120233	5.373	1.186	–4.416	14.736
Sustaining a comparative advantage (four-year)	34289	0.792	0.406	0	1
Specialisation	120233	1.423	2.985	0.000	102.187
Related variety	120233	0.389	0.159	0.007	1
Unrelated variety	120233	1.000	0.228	0	1.372
External linkages	120233	0.162	0.262	0	1
Innovation	120233	0.036	0.122	0	5.251
Institutions	120233	0.142	0.285	0	1
Capital labour ratio	120233	160.230	5261.513	0	1786248
Labour (log)	120233	7.592	1.870	0	14.657
Capital (log)	120040	11.884	2.292	0	19.258
Herfindahl–Hirschman Index	120233	0.382	0.325	0	1
Maturity	120233	0.919	0.741	0	8.408
Churn	112888	0.467	0.713	–0.833	57.667
Innovative business models	112888	0.930	94.231	–114.500	29577.250
GDP per capita (log)	117524	9.593	0.900	6.852	12.833
Manufacturing share	118952	0.811	0.524	0.000	6.902
Population density (log)	116905	5.674	1.083	–1.349	11.852
Average wage	104011	1.973	42.686	0.000	2284.289

Table A2. Descriptive statistics for three-digit industries

Variable	Obs.	Mean	Std. Dev.	Min	Max
Output per employee (log)	397543	5.385	1.218	–6.856	15.077
Sustaining a comparative advantage (four-year)	137398	0.732	0.443	0	1
Specialisation	397543	2.439	10.808	0.000	1524.907
Related variety	397543	0.434	0.140	0.059	1
Unrelated variety	397543	1.398	0.306	0	1.900
External linkages	397543	0.164	0.301	0	1
Innovation	397543	0.032	0.135	0	5.251
Institutions	397543	0.122	0.291	0	1
Capital labour ratio	397543	156.974	5248.604	0	1989131
Labour (log)	397543	6.449	1.698	0	13.752
Capital (log)	396242	10.584	2.155	0	19.252
Herfindahl–Hirschman Index	397543	0.566	0.344	0.003	1
Maturity	397543	0.904	0.991	0	235.639
Churn	374655	0.415	0.780	–0.938	65
Innovative business models	374655	1.080	81.302	–114.500	29577.250
GDP per capita (log)	391211	9.732	0.883	6.852	12.833
Manufacturing share	394648	0.902	0.526	0.000	6.902
Population density (log)	390284	5.880	0.927	–1.349	11.852
Average wage	341733	1.280	14.480	0.000	849.458

Table A3. Descriptive statistics for four-digit industries

Variable	Obs.	Mean	Std. Dev.	Min	Max
Output per employee (log)	658532	5.413	1.224	–7.125	15.077
Sustaining a comparative advantage (four-year)	247166	0.650	0.477	0	1
Specialisation	658532	3.821	23.859	0.000	3568.689
Related variety	658532	0.515	0.145	0.108	1
Unrelated variety	658532	1.583	0.342	0	2.154
External linkages	658532	0.173	0.326	0	1
Innovation	658532	0.031	0.142	–0.183	5.251
Institutions	658532	0.112	0.290	0	1
Capital labour ratio	658532	155.790	4361.583	0	1989131
Labour (log)	658532	6.008	1.599	0	13.370
Capital (log)	655534	10.069	2.083	0	19.252
Herfindahl–Hirschman Index	658532	0.660	0.334	0.003	1
Maturity	658532	0.911	1.697	0	858.341
Churn	623573	0.364	0.818	–0.958	167
Innovative business models	623573	0.992	60.206	–114.500	29577.250
GDP per capita (log)	650055	9.854	0.880	6.852	12.833
Manufacturing share	654686	0.968	0.533	0.000	6.902
Population density (log)	649224	5.997	0.863	–1.349	11.852
Average wage	561971	1.075	4.553	0.000	295.169

Table A4. Correlation matrix for two-digit industries

	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*	*i*	*j*	*k*	*l*	*m*	*n*	*o*	*p*	*q*	*r*	*s*
a	1																		
b	0.154*	1																	
c	0.019*	–0.017*	1																
d	0.065*	0.108*	0.351*	1															
e	0.201*	0.042*	0.021*	–0.162*	1														
f	–0.414*	–0.089*	0.062*	0.070*	–0.155*	1													
g	0.117*	0.040*	–0.069*	–0.043*	0.181*	–0.221*	1												
h	–0.010*	0.007	–0.024*	–0.004	0.062*	0.027*	0.020*	1											
i	0.055*	0.041*	0.004	0.003	–0.002	0.007*	–0.001	0.000	1										
j	0.238*	0.240*	0.168*	0.216*	0.373*	–0.161*	0.229*	0.073*	–0.017*	1									
k	0.455*	0.257*	0.195*	0.237*	0.314*	–0.158*	0.202*	0.091*	0.020*	0.887*	1								
l	–0.173*	–0.184*	–0.082*	–0.027*	–0.354*	0.252*	–0.160*	0.003	0.011*	–0.702*	–0.601*	1							
m	–0.244*	–0.062*	0.005	0.042*	–0.026*	0.330*	–0.070*	0.036*	0.000	0.056*	0.012*	0.067*	1						
n	0.066*	0.006	–0.001	0.001	0.021*	–0.088*	–0.008*	–0.029*	0.000	0.047*	0.040*	–0.112*	–0.092*	1					
o	0.004	0.003	0.004	0.001	0.002	0.012*	–0.003	0.001	0.000	–0.003	–0.001	0.011*	0.001	0.022*	1				
p	0.156*	0.033*	–0.260*	–0.161*	0.473*	–0.136*	0.205*	0.071*	–0.005	0.368*	0.299*	–0.316*	0.022*	0.025*	–0.004	1			
q	0.017*	0.001*	0.018*	0.001	–0.020*	–0.003	–0.003	–0.006*	0.002	0.001	0.010*	0.000	–0.007*	0.002	0.000	–0.002	1		
r	0.590*	–0.040*	–0.140*	–0.040*	0.127*	–0.365*	0.234*	–0.044*	0.010*	0.351*	0.424*	–0.266*	–0.123*	0.058*	–0.007*	0.172*	0.022*	1	
s	0.220*	–0.097*	–0.279*	–0.097*	0.165*	–0.118*	0.236*	–0.008*	0.000	0.380*	0.333*	–0.268*	0.021*	0.016*	–0.001	0.421*	0.001	0.466*	1

Notes: *a*: Output per employee (log). *b*: Sustaining a comparative advantage (four-year). *c*: Specialisation. *d*: Related variety. *e*: Unrelated variety. *f*: External linkages. *g*: Innovation. *h*: Institutions. *i*: Capital labour ratio. *j*: Labour (log). *k*: Capital (log). *l*: Herfindahl–Hirschman Index. *m*: Maturity. *n*: Churn. *o*: Innovative business models. *p*: GDP per capita (log). *q*: Manufacturing share. *r*: Population density (log). *s*: Average wage. * $p<0.05$.

Table A5. Correlation matrix for three-digit industries

	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*	*i*	*j*	*k*	*l*	*m*	*n*	*o*	*p*	*q*	*r*	*s*
a	1																		
b	0.176*	1																	
c	–0.009*	0.058*	1																
d	–0.114*	–0.012*	0.242*	1															
e	0.211*	0.051*	–0.137*	–0.254*	1														
f	0.116*	0.046*	–0.025*	–0.122*	0.180*	1													
g	–0.006*	0.034*	0.006*	–0.019*	0.041*	0.021*	1												
h	–0.432*	–0.081*	0.038*	0.120*	–0.165*	–0.187*	0.024*	1											
i	0.054*	0.037*	0.000	0.008*	–0.007*	0.000	0.001	0.003	1										
j	0.123*	0.267*	0.132*	–0.009*	0.279*	0.193*	0.057*	–0.081*	–0.016*	1									
k	0.353*	0.275*	0.125*	0.010*	0.238*	0.194*	0.081*	–0.094*	0.029*	0.844*	1								
l	–0.179*	–0.232*	–0.030*	0.084*	–0.310*	–0.130*	0.012*	0.174*	0.010*	–0.687*	–0.592*	1							
m	–0.194*	–0.051*	0.027*	0.011*	–0.016*	–0.039*	0.019*	0.270*	0.000	0.073*	0.024*	0.023*	1						
n	0.061*	0.022*	0.005*	–0.018*	0.040*	0.011*	–0.017*	–0.073*	0.000	0.124*	0.107*	–0.205*	–0.061*	1					
o	0.001	–0.002	0.003*	0.003*	–0.002	–0.001	0.001	0.005*	0.000	0.001	0.001	0.007*	0.000	0.017*	1				
p	0.525*	0.059*	–0.060*	–0.281*	0.253*	0.226*	–0.033*	–0.343*	0.013*	0.300*	0.358*	–0.281*	–0.077*	0.071*	–0.009*	1			
q	0.192*	0.044*	–0.098*	–0.407*	0.289*	0.227*	–0.013*	–0.120*	0.000	0.288*	0.236*	–0.251*	0.021*	0.042*	–0.003	0.489*	1		
r	0.132*	0.036*	–0.151*	–0.454*	0.510*	0.178*	0.049*	–0.122*	–0.012*	0.244*	0.189*	–0.249*	0.027*	0.043*	–0.003	0.223*	0.418*	1	
s	0.016*	0.019*	0.000	0.024*	–0.012*	0.001	–0.004*	0.000	0.002	0.004*	0.014*	0.003	–0.005*	0.004*	0.000	0.023*	0.004*	–0.004*	1

Notes: *a*: Output per employee (log). *b*: Sustaining a comparative advantage (four-year). *c*: Specialisation. *d*: Related variety. *e*: Unrelated variety. *f*: External linkages. *g*: Innovation. *h*: Institutions. *i*: Capital labour ratio. *j*: Labour (log). *k*: Capital (log). *l*: Herfindahl–Hirschman Index. *m*: Maturity. *n*: Churn. *o*: Innovative business models. *p*: GDP per capita (log). *q*: Manufacturing share. *r*: Population density (log). *s*: Average wage. * $p<0.05$.

Table A6. Correlation matrix for four-digit industries

	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*	*i*	*j*	*k*	*l*	*m*	*n*	*o*	*p*	*q*	*r*	*s*
a	1																		
b	0.181*	1																	
c	–0.152*	–0.040*	1																
d	–0.020*	0.033*	0.178*	1															
e	0.211*	0.055*	–0.422*	–0.119*	1														
f	–0.425*	–0.091*	0.136*	0.031*	–0.171*	1													
g	0.110*	0.055*	–0.166*	–0.023*	0.189*	–0.178*	1												
h	–0.004*	0.038*	–0.013*	0.009*	0.035*	0.024*	0.017*	1											
i	0.062*	0.048*	0.009*	0.002	–0.007*	0.001	0.003*	0.002	1										
j	0.058*	0.291*	–0.058*	0.098*	0.214*	–0.048*	0.166*	0.051*	–0.019*	1									
k	0.307*	0.288*	–0.042*	0.088*	0.181*	–0.065*	0.179*	0.076*	0.037*	0.809*	1								
l	–0.151*	–0.259*	0.160*	–0.018*	–0.263*	0.147*	–0.107*	0.015*	0.010*	–0.657*	–0.554*	1							
m	–0.110*	–0.028*	0.002	0.024*	–0.007*	0.156*	–0.018*	0.011*	–0.002	0.046*	0.013*	0.010*	1						
n	0.054*	0.052*	–0.042*	0.007*	0.049*	–0.061*	0.016*	–0.015*	–0.002	0.155*	0.129*	–0.245*	–0.034*	1					
o	0.002	–0.001	0.005*	0.000	–0.002	0.005*	–0.001	0.004*	0.000	0.003*	0.003*	0.002	0.000	0.024*	1				
p	0.123*	0.039*	–0.506*	–0.133*	0.539*	–0.118*	0.176*	0.040*	–0.012*	0.177*	0.129*	–0.202*	0.026*	0.047*	–0.003*	1			
q	0.014*	0.013*	0.011*	–0.001	–0.001	0.000	0.015*	–0.003	0.003*	0.012*	0.021*	–0.004*	–0.001	0.004*	0.000	0.003*	1		
r	0.483*	0.078*	–0.399*	–0.054*	0.339*	–0.327*	0.226*	–0.031*	0.013*	0.240*	0.290*	–0.248*	–0.042*	0.076*	–0.007*	0.269*	0.034*	1	
s	0.178*	0.038*	–0.505*	–0.081*	0.364*	–0.125*	0.219*	–0.015*	–0.002	0.223*	0.164*	–0.214*	0.013*	0.050*	–0.001	0.421*	0.021*	0.499*	1

Notes: *a*: Output per employee (log). *b*: Sustaining a comparative advantage (four-year). *c*: Specialisation. *d*: Related variety. *e*: Unrelated variety. *f*: External linkages. *g*: Innovation. *h*: Institutions. *i*: Capital labour ratio. *j*: Labour (log). *k*: Capital (log). *l*: Herfindahl–Hirschman Index. *m*: Maturity. *n*: Churn. *o*: Innovative business models. *p*: GDP per capita (log). *q*: Manufacturing share. *r*: Population density (log). *s*: Average wage. * $p<0.05$.

B. Heterogeneity in path development and productivity

Table B1. Path development of existing industries in the linear probability model

	Outcome variable: probabilities of specialisation maintenance [a]								
	Two-digit			Three-digit			Four-digit		
Variable	(1) Three-year interval	(2) Four-year interval	(3) Five-year interval	(4) Three-year interval	(5) Four-year interval	(6) Five-year interval	(7) Three-year interval	(8) Four-year interval	(9) Five-year interval
Capital labour ratio	0.000***	0.000**	0.000	0.000**	0.000***	0.000***	0.000***	0.000***	0.000***
(path extension)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unrelated variety	0.085***	0.048*	0.037	0.044***	0.017	0.001	0.039***	0.022**	0.020*
(path upgrading)	(0.027)	(0.028)	(0.028)	(0.014)	(0.015)	(0.014)	(0.011)	(0.011)	(0.011)
External linkages	0.022	0.018	0.025	0.036***	0.031***	0.027***	0.035***	0.023***	0.008
(path upgrading)	(0.017)	(0.018)	(0.018)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)
Innovation	0.041*	0.053**	0.053**	0.055***	0.037***	0.055***	0.051***	0.028***	0.028***
(path upgrading)	(0.024)	(0.025)	(0.025)	(0.012)	(0.012)	(0.012)	(0.008)	(0.009)	(0.008)
Institutions	–0.019*	–0.027**	–0.005	–0.018***	–0.010	0.006	–0.034***	–0.025***	–0.016***
(both)	(0.011)	(0.012)	(0.012)	(0.006)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)
Related variety	0.074**	–0.054*	–0.085***	0.081***	0.021	–0.047**	0.057***	0.021	–0.089***
(both)	(0.029)	(0.031)	(0.031)	(0.022)	(0.022)	(0.022)	(0.018)	(0.019)	(0.018)
Constant	1.061***	1.160***	1.256***	1.021***	1.003***	1.104***	1.077***	0.999***	1.105***
	(0.116)	(0.123)	(0.122)	(0.077)	(0.079)	(0.078)	(0.064)	(0.065)	(0.063)
Observations	27,767	27,767	27,767	102,781	102,781	102,781	200,026	200,026	200,026
R-squared	0.034	0.052	0.069	0.049	0.054	0.057	0.060	0.062	0.064
Number of codes	4,473	4,473	4,473	20,033	20,033	20,033	43,884	43,884	43,884

Notes: [a] This table shows how an existing industry sustains its comparative advantage over a period of time (i.e. three/four/five-year interval). The underlying model is a linear probability model that includes year dummies, city–industry fixed effects, and the same control variables as in the full model specification in Table 3. Only the results for the core factors associated with path development are reported. The dependent variable is a dummy variable that is 1 if an industry maintains its specialisation in a city above 1 for three/four/five years and 0 otherwise. The robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B2. Path development of new industries in the two-way fixed effect model

	Full Model		
	(1) Two-digit	(2) Three-digit	(3) Four-digit
Variable	Specialisation	Specialisation	Specialisation
Core variables			
Related variety (path branching)	2.421***	4.847***	7.657***
	(0.117)	(0.269)	(0.403)
Unrelated variety (path diversification)	-0.390**	–0.401*	–0.733**
	(0.178)	(0.233)	(0.308)
External linkages (path importation)	0.126*	0.274***	0.117
	(0.0749)	(0.0881)	(0.107)
Innovation (path creation)	0.193*	0.396***	0.401**
	(0.114)	(0.137)	(0.168)
Institutions (multiple paths)	0.302***	0.158**	0.315***
	(0.0616)	(0.0779)	(0.107)
Observations	10,024	43,465	83,082
R-squared	0.194	0.065	0.035
Number of codes	2,623	13,672	31,309

Notes: This table shows how the specialisation of a new industry rises above 1 during a five-year period. The underlying model is a two-way fixed effect model that includes year dummies, city–industry fixed effects, and the same control variables as in the full model specification in Table 3. Only the results for the core factors associated with path development are reported. The dependent variable is the level of specialisation proxied by location quotient. The robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B3. Productivity of existing and new industries in the two-way fixed effect model

	Existing industries				New industries		
	(1) Two-digit	(2) Three-digit	(3) Four-digit		(4) Two-digit	(5) Three-digit	(6) Four-digit
Variable	Output per employee	Output per employee	Output per employee		Output per employee	Output per employee	Output per employee
Core variables							
Specialisation (path extension/upgrading)	0.013***	0.000*	0.000		0.037***	0.003*	–0.000
	(0.001)	(0.000)	(0.000)		(0.007)	(0.001)	(0.001)
Related variety	0.020	0.338***	0.312***	(path branching)	–0.135**	–0.129**	–0.068
	(0.036)	(0.026)	(0.027)		(0.062)	(0.063)	(0.057)
Unrelated variety (path upgrading)	0.338***	0.505***	0.456***	(path diversification)	0.719***	0.861***	0.654***
	(0.033	(0.015)	(0.016)		(0.091)	(0.054)	(0.043)
External linkages (path upgrading)	0.052**	0.112***	0.149***	(path importation)	0.200***	0.129***	0.111***
	(0.021	(0.010)	(0.008)		(0.038)	(0.020)	(0.015)
Innovation (path upgrading)	0.157***	0.145***	0.168***	(path creation)	0.007	0.089***	0.142***
	(0.029)	(0.016)	(0.012)		(0.058)	(0.031)	(0.023)
Institutions (both)	–0.212***	–0.411***	–0.457***	(all paths)	–0.362***	–0.618***	–0.680***
	(0.014)	(0.008)	(0.007)		(0.0314)	(0.018)	(0.015)
Observations	27,749	136,033	199,626		10,014	43,358	82,788
R-squared	0.721	0.663	0.504		0.372	0.288	0.257
Number of codes	4,472	22,730	43,817		2,622	13,650	31,237

Notes: This table shows how the sources for path development of existing and new industries are associated with productivity. The same source could refer to different types of path development when examined in existing and new industries. The underlying model is the same two-way fixed effects model as the full model specification in Table 3. Only the results for the core factors associated with path development are reported. The robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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Study 2 Economic complexity and regional resilience: Economic growth in Chinese cities in times of crisis

Abstract This study explores the relationship between city-level economic complexity and regional resilience during an exogenous shock. Based on the Annual Survey of Industrial Firms dataset in China, we examine the extent to which the 2007–08 global financial crisis influenced economic growth in Chinese cities depending on their complexity level. We focus on how the marginal effect of the shock on employment and output growth is conditional on the city complexity level in crisis and post-crisis periods after controlling for domestic and global demand. The results show that both resistance and recovery vary with complexity. Employment growth is resistant in less complex cities, whereas output growth is resistant in medium-complexity cities. Recovery is found at every complexity level and tends to decrease as complexity increases.

Keywords: Economic complexity, regional resilience, economic growth, global financial crisis

1 Introduction

This study focuses on the association between economic complexity and regional resilience from an industrial development perspective. Resilience of urban economies has caused great concern for academia and policy-making across a wide range of disciplines, particularly following the 2007–08 global financial crisis (Meerow et al. 2016). The recent stream of work has paid particular attention to the role of industrial structure in regional differential resistance and recovery pathways (Breathnach et al. 2015; Martin et al. 2016). In this strand of literature, scholars have investigated different aspects of the industrial composition, such as diversity, related variety, and specialisation (Bishop 2019; Boschma 2015; Cuadrado-Roura and Maroto 2016; Karlsson et al. 2021). One nature of industrial structure could be the complexity of the industry/product/knowledge space in the local economy (Hidalgo and Hausmann 2009). Such notion of complexity has recently captured the attention of decision makers and regional analysts in terms of interpreting variations in regional economic development (Balland et al. 2019a). Yet, its correlation with economic resilience still lacks theoretical framework and empirical testing, although relevant work has arisen. For example, Innocenti et al. (2021) argue that Italian areas at the forefront of economic complexity can effectively favour fertility and adapt to the negative outcomes of globalisation.

Resilience has been increasingly recognised as a fundamental dimension of regional development rather than a faddish concept. This is due to the fact that resilience deals with inevitable elements of a free market, such as shocks and disruptions, and can be critical to better understanding instability and its implications. The role that resilience can play in times of shocks is more effective compared with the measures and policies following disruptions and challenges. Resilience is different from the concepts of competitiveness and sustainability in that resilience emphasises the capacity to withstand the impact of shocks in an economy (Martin and Sunley 2015). Competitiveness and sustainability may also exert an influence on regional resilience, but the concept of resilience extends beyond a local economy's competitiveness.

Perceived as a dynamic process, the notion of resilience deals with short-term sensitivity to accommodate shocks, mid-term recovery from shocks, and also long-term adaptation to generate new paths (Joan et al. 2017). The regional capability to absorb external shocks differs from place to place and could be associated with a set of factors in a locality (Martin and Sunley 2015). Joan et al. (2017) argue that economic composition, knowledge networks, and institutional settings are three critical sources of the regional capability to be resilient. Fratesi and Rodríguez-Pose (2016) claim that open, dynamic, and competitive economies compared with sheltered and protected economies are more capable of recovering and generating new employment after the crisis. Bishop and Shilcof (2017) find that new firm birth rates are positively correlated with regional resilience during an exogenous shock. Bristow and Healy (2018) highlight the importance of innovation capability for regional resilience to external shocks. Cainelli (2019) provides evidence on the positive effects of related variety on regional resilience. Ruiz-Fuensanta and Bellandi (2019) show that district firms tend to be more resilient to a recessionary shock compared with their out-district counterparts. Ezcurra and Rios (2019) hold that the link between government quality and regional reaction to the crisis is positive and could be shaped by the spatial spillovers of government quality in neighbouring areas. Chacon-Hurtado et al. (2020) demonstrate that the resilient capacity of regions is positively associated with transportation accessibility during and after the Great Recession. Grabner and Modica (2021) point out that metropolitan US counties are more likely to keep diversifying and create new industrial specialisations in response to the 2008 economic shock than rural counties. Wang and Wei (2021) find that industrial diversity, human capital, trade openness, and financial liberalisation can enhance regional economic resilience in China to the 2008 subprime crisis.

These studies help researchers and policy makers better elaborate on the factors that are associated with economic competitiveness prior to an economic crisis. On the one hand, more resilient regions are also those that show stronger competitiveness in ordinary times (Fratesi and Rodríguez-Pose 2016). On the other hand, regions after crisis could change their regional development trajectory which is associated with pre-crisis trajectory determinants (Martin and Sunley 2015; Simmie and Martin 2010). One of such key factors is complexity, which is strongly associated with economic growth and development in the sense that (*i*) complexity reveals the mix of capabilities available in a place, (*ii*) complexity has strong correlation with income per capita, (*iii*) complexity could indicate future growth, and (*iv*) complexity is predictive of the complexity of exports (Hidalgo and Hausmann 2009). Complexity thinking is not a recent theory (Anderson et al. 1988) and a paucity of empirical work may be due to lack of appropriate measures of complexity (Hidalgo and Hausmann 2009). Thus, Hidalgo and Hausmann (2009) develop a place and product complexity index (Balland et al. 2019a; Balland and Rigby 2017). This index is different from the concept of diversification in the sense that complexity of a place not only indicates the diversity of its capabilities to produce products but also captures the non-ubiquity of its products. Balland et al. (2019) propose that a relatively high level of relatedness could reduce the risk of new business formation, while developing high-complexity technologies could lead to a high expected rate of return. Hidalgo (2021) conduct a review on economic complexity theory and applications in terms of the increasing amount of work on the causes and consequences of complexity metrics. Recent work has also enriched the foundation of economic complexity from such dimensions as mathematical interpretations (Mealy et al. 2019), robust methodologies (Sciarra et al. 2020), and prediction exercise (O'Clery et al. 2022). The field of complexity is still in its infancy. Particularly, more theoretical and empirical work may be required to reveal the relevance of complexity for economic performance (Felipe et al. 2012; Fritz and Manduca 2021; Guan and Cheng 2020; Hartmann et al. 2017; Tacchella et al. 2013).

Building on the previous literature, this study explores how the patterns, mechanisms, and necessities of regional resilience in times of an exogenous shock vary among cities at different degrees of economic complexity. For descriptive analysis, we illustrate the influence of the global financial crisis, divide Chinese cities into three groups by complexity (i.e. low, medium, and high), and identify differences between these groups in terms of economic growth and its sources. For econometric analysis, we estimate how the marginal effect of the shock is conditional on complexity based on a difference-in-difference framework (or multiplicative interaction models). Apart from complexity and the shock, we also control for global and domestic demand. Further, we examine the extent to which reduction in productivity growth, deceleration in industrial dynamics, and redistribution of comparative advantages vary with a city's complexity in times of crisis.

Specifically, two stages of resilience are distinguished, i.e. resistance in the crisis period and recovery in the post-crisis period. Two indicators of economic performance (i.e. employment and output growth) serve as outcome variables separately. Resistance (recovery) refers to whether cities increase their growth momentum during (after) the crisis compared with that before the crisis. The shock dummy is incorporated into the model as the treatment variable, whereas complexity acts as the moderator. The coefficient of their interaction term is the difference-in-difference estimator, whose marginal forms are of fundamental interest. Different model specifications are examined consecutively in terms of explanatory variables, including global and domestic demand and their interaction effects with the shock.

The results of descriptive analysis show that the relevance of complexity for resilience is not a linear one, meaning that cities at a higher or lower level of complexity might not necessarily perform better in times of crisis. The results of econometric analysis show that the association between complexity and resilience varies not only at two phases of resilience (i.e. resistance and recovery) but also for two outcome variables (i.e. employment and output growth). Whereas cities with lower complexity are more likely to show resistance in employment growth, medium complexity cities are resistant in output growth. Recovery is found at every complexity level and tends to decrease with complexity, regardless of the growth indicator. Global and domestic demand, we argue, should be incorporated into the model in different forms. They have different relationships with not only complexity but also the nature of the shock.

Specifically, global demand has a positive correlation with complexity and can also modify the influence of the shock. Domestic demand has no correlation with complexity and does not interact with the shock. The relationship between global demand and domestic demand can constitute complements during the shock and substitutes after the shock. We find that the mechanisms for resilience may differ among cities at different complexity levels. Low complexity cities reduce their productivity during the crisis. Cities with higher complexity are less likely to keep their momentum in industry entry and exit in both resistance and recovery periods. The ability to maintain comparative advantages in existing industries strengthens in the face of the shock, particularly for high complexity cities. Low complexity cities tend to increase their number of specialisations in times of crisis. Although high complexity cities to some extent used to be low complexity cities, their pathways to resilience may present different patterns contingent on the corresponding time scales or space zones. They may not only be of the same origin but also evolve towards the same direction that can unite different types of growth paths.

The remainder of the study is organised in the following way. In Section 2, we introduce the conceptual framework for the relationship between complexity and resilience. In Section 3, we elaborate on the conceptualisation of the empirical design from several aspects. In Section 4, we describe the data and variables. In Section 5, we present the econometric analysis and results. In Section 6, we conclude.

2 Conceptual framework

2.1 Complexity

Industrialisation, urbanisation, and globalisation go hand in hand, which is the direction of economic evolution. Division, agglomeration, and connection are their foundations. With respect to the relationship between the three: division is an economics-specific concept; agglomeration is the spatial version of division; connection is the bridge between division and agglomeration. Industrialisation is a process during which one brings two, two brings three, three brings all. The ‘one’ is division. Urbanisation happens alongside industrialisation as urban areas provide the place of production. The ‘place’ is agglomeration. Globalisation promotes industrialisation and urbanisation as the global market constitutes the base of their further development. The ‘base’ is connection.

When industrialisation is viewed in a spatial context, it is a process when specialisation brings diversification, diversification brings complexity, and complexity brings all. Specialisation and diversification used to be considered as two distinctions of agglomeration, but in this study they are regarded as two early stages of complexity. In other words, agglomeration still matters as it is a transition phase towards the stage of complexity. Specialisation is measured on the basis of comparative advantages, which emphasise the relative importance of an economic division in a spatial economy. The opposite existence of specialisation is diversification. Where there is specialisation, there is diversification. What connects specialisation and diversification is relatedness. The accumulation of specialisation can lead to either related or unrelated diversification. The relatedness itself can evolve over time. Complexity is the stage at which diversification is made most use of given a matrix of relatedness between industries. But the evolution of relatedness never stops, so does complexity. Last but not least, relatedness and complexity are increasingly reshaping the economic landscape as an ‘invisible’ hand in this globalised context. This is because urbanisation is increasingly being accompanied or somewhat replaced by globalisation. The former initially promotes industrialisation by acknowledging the distinction between urban and rural areas, whereas the latter can accelerate the connection to be established between places of production and consumption worldwide. In this regard, globalisation may have a tendency of breaking every potential man-made or even natural ‘boundary’ to establish connection. Relatedness and complexity change before we can seize them.

Along this line of thought, two strands of literature can be observed from an empirical standpoint. On the one hand, complexity in the context of industrialisation has been put into practice as a principle to follow. Activities (e.g. products and patents) or economies (e.g. cities and countries) with a high level of complexity can be regarded as an advanced form of existence with high technology and knowledge intensity. In this regard, empirical work has covered a wide range of topics. Of these, some studies emphasise the role of complexity in comparison with that of relatedness, while others elaborate on the formation of complexity. The former normally takes industrial policies as a point of departure or motivation, and the involved topics include but not limited to the complementary role of relatedness and complexity in economic growth (Davies and Maré 2021), the actual implementation of industrial policies with a focus on complexity and relatedness (Deegan et al. 2021), the balance between complexity and relatedness in achieving path breaking (De Noni et al. 2021), optimal design of industrial policies based on complexity and relatedness (Restrepo et al. 2022). The latter also covers a set of aspects such as the role of local related capabilities in developing complex technological activities (Balland et al. 2019a), the importance and stages of developing complex industries in countries' catch-up (Hartmann et al. 2021), the effect of policy interventions in diversifying into complex industries in a locality (Dong et al. 2022), and the relative importance of firm and local knowledge in the production of complex knowledge (Zhang and Rigby 2022).

On the other hand, complexity as a mirror of industrialisation has been investigated with respect to its association with urbanisation and globalisation as well. Balland et al. (2020) show that complex economic activities tend to concentrate disproportionately in large cities and the spatial concentration of complex activities may increase over time in the United States. This finding suggests that complexity and agglomeration cannot divorce and the mechanisms for economic growth may be the same as those for unevenness growth between and within cities. Such spatial inequality in the distribution of complex activities among large and small cities has also been found in other countries such as New Zealand (Davies and Maré 2021). Moreover, Di Clemente et al. (2021) show that the complexity of the exports in a country's productive system may present a positive relation with the urbanisation process during the early stages of a country's economic development. This finding may be because the global trade networks can generate a virtuous cycle of urban aggregation and industrial growth, but the relation could be minimal within the urbanised countries and negative for resources exports countries. When it comes to the relevance of globalisation, the evidence for the role of international linkages on economic complexity has been found in both macro- and micro-level economies. By country, Antonietti and Franco (2021) find that an increase in inwards investment can raise economic complexity in countries at above-average development stages, and this increase is short-term and small for less developed countries. Hartmann et al. (2021) show that access to external knowledge helps middle-income countries escape the gravitational forces towards simple products and catch up by promoting the transformation towards and internal generation of more complex activities. By industry, Fritz and Manduca (2021) point out that the majority of traded industries in the United States are more complex than average, while most local industries are less complex than average. Whittle (2019) calculates the share of patenting activities of local and foreign firms in technology classes in Ireland and finds that foreign activities tend to be more active than local firms in generating the majority of complex knowledge.

2.2 Resilience

There are three main types of definition for resilience in previous studies. The first is an engineering-related definition, which construes resilience as the ability of an economy to 'bounce back' to its pre-shock state and path. The emphasis is placed on the recovery process. It is akin to the 'self-restoring equilibrium dynamics' in economics and market forces are assumed to the dominant mechanism in self-correction. The second definition refers to the 'ability to absorb' in the ecological literature. The stability of the system's structure and function is emphasised. When the shocks are too severe to absorb, the system may undergo an alternative equilibrium path. This resonates with multiple equilibria of an economy (Martin and Sunley 2015). Thirdly, from an evolutionary perspective, economies may experience shocks as an ongoing process instead of shifting from one equilibrium state to another. Resilience is thus regarded as an evolutionary process featured by constant changes and adaptions instead of an unchanging property of the regional economy. The creation and accumulation of knowledge forms the basis of the ever-changing economic landscapes (Simmie and Martin 2010). This last interpretation of 'resilience' also involves the enhancement of system's ability to cope with future shocks. This 'bounce forward' idea is close to the 'robustness' notion in complex adaptive system theory in the sense that both concepts stress that structural and organisational changes are necessary to restore and foster the system's core functions. The adaptive resilience also embodies the 'absorb' and 'bounce back' elements of the first two definitions.

To better illustrate the notion of resilience, Martin (2012) explores how resilience could be combined with the concept of 'hysteresis' in economics. He elaborates on four dimensions of resilience, i.e. resistance, recovery, reorientation, and renewal. The industrial 'portfolio' (i.e. manufacturing and construction industries, private service industries, and public sector services) seems to account for a large proportion of spatial variations in local resilience to recessionary shocks. Manufacturing seems to be the most vulnerable sector when it comes to resilience to challenges. In line with what hysteresis depicts, resilience as a dynamic process is always accompanied by continuous industrial structural changes. For example, when examining the employment changes of industries in recession, places would display strong resilience when the upturn of some industries could compensate the downturn of others. The successful transformation of industrial structures pays the way for reoriented long-run regional economic growth.

Resilience could not only be revealed in the time of a crisis but also be latent in the economy's development. This means the local ability to resist and recovery from a crisis can be built continuously. Nevertheless, resilience can also be eroded gradually, and then local economies become more vulnerable to shocks. The nature of shocks is not necessarily negative, as there are also positive shocks, such as technological breakthrough or infrastructure construction. Shocks themselves may not be a sudden phenomenon, as one shock may evolve before it reaches a tipping point. The impacts of shocks partly depend on the spatial analysis. A national shock could exert an influence that differs among localities. As there are different local reactions to shocks, one positive development in one region may become negative in another.

2.3 Complexity and resilience

The evidence on the relationship between resilience and industrial structural characteristics is mixed (Doran and Fingleton 2018; Evans and Karecha 2014; Martin et al. 2016). Although economic structures may still evolve without shocks, shocks may accelerate the evolution or change its direction or the way that economic structures evolve. As a quality measure of the industrial space, complexity is no exception with regard to its relationship between resilience. This part reviews the previous studies with respect to the mechanisms to achieve regional resilience and proposes their possible linkages with economic complexity.

Decline in productivity (Möller 2010). Labour hoarding is a necessary strategy for economic activities to bounce back after the shock. This is mainly because the increasing costs to recruit and nurture high-skilled workers in the long run. Labour hoarding can be achieved through a moderate reduction in productivity to absorb the shock. Productivity reduction is a compromise between employers and employees. For employers, they endure the high costs of maintaining their employees in the time of a shock to keep their competitiveness after the shock. For employees, they stop fighting for their welfare to avoid no work at all after the shock. But how is the productivity reduction during the crisis conditional on the complexity level of a city?

We assume that employers in lower-complexity cities are more likely to adopt the strategy of productivity reduction in the crisis, since they may be under more pressure to sustain their economic activities after the shock.

Deceleration in industrial dynamics (Wrobel 2015). In the time of a crisis, economic investment tends to favour the more profitable and stronger economies in the short term given its risk-aversion nature. In this sense, the shock can strengthen or even accelerate the previously 'right' trend. If complexity is the direction of city evolution, the industrial dynamics is more favourable for high-complexity cities. The industries in high-complexity cities are on average more complex compared with those in low-complexity ones, so high-complexity cities are more likely to maintain their pre-existing comparative advantages when faced with a demand shock. Meanwhile, the slowdown of economic growth can be associated with a less dynamic process of industry entry and exit.

We assume that the industrial dynamics in higher-complexity cities are more stable, given its more favourable business environment in the time of a recession.

Redistribution of comparative advantages (Martin and Sunley 2011). The development of comparative advantages or industrial clusters is one common strategy of local economies to influence resource allocation and boost economic growth. In this sense, the continuous accumulation of comparative advantages at the city level is a reinforcing cycle with economic prosperity. This process needs to slow down or even move backwards to some extent to make room for the built-up of resilience at least in the short term. This is due to the fact that, when it comes to the motivation for the development of new comparative advantages, the underlying logic during the bust time may be different from that during the boom time. The former tends to be driven by demand, whereas the latter is more likely to be stimulated by supply. Specifically, in the face of a shock, it is not the logic that diversity (relatedness) is beneficial for the development of new specialisations so that new comparative advantages are more likely to develop in locations presenting high diversity (relatedness). However, it is the logic that new comparative advantages tend to appear where the supply of new industries is more likely to meet the local demand to develop such new specialisations. The former logic may hardly apply to the shock period because their starting point for industrial location choice is to maximise capitalisation by reducing cost from a supply side. Hence, it may to a greater extent apply to the boom period when people are reluctant to challenge the norm if their basic demand seems to be satisfied at a lower cost. However, in the shock period, the pattern of comparative advantages should not be static but dynamic through redistribution when the demand to do so appears. From a demand side, the redistribution of comparative advantages may result from the need to reallocate resources among local industries, which can act as a strategy for the local economy to deal with the shock. Because resources can be reallocated to sectors of more growth potential with an attempt to buffer the influence of the shock on the economy as a whole. During the crisis, different sectors can be hit to different degrees, and less complex industries tend to cater for a broader market and can play an essential role in achieving growth. In this sense, the development of new specialisations as a mechanism of resilience tends to be found in cities which have a greater motivation to promote non-complex industries. Cities at different degrees of complexity may have different degrees of demand to redistribute comparative advantages. This strategy may work in the short run but can cause problems afterwards such as over-capacity issues for non-complex industries and damage for complex industries.

We assume that cities at a lower complexity level may have a stronger motivation to redistribute comparative advantages and to develop some new comparative advantages in industries with growth potential. This is because they have a greater demand to avoid a sudden breakdown caused by overwhelming dependence on previous comparative advantages that suffered during the shock. By contrast, since cities at a higher complexity level tend to develop comparative advantages from a supply side, they would prefer to keep their competitive edge of the boom period in the face of a shock.

These different ways of responding to the shock may apply to cities at different complexity levels. However, this point does not mean a specific mechanism may be exclusive to a specific level of complexity. Instead, these mechanisms of regional resilience are proposed in a relative term owing to their relative importance for corresponding cities at a particular level of complexity. Cities at every level of complexity are likely to present all these three kinds of responses to be resilient in the time of a shock.

3 Empirical design

We elaborate on the conceptualisation of the empirical design from several aspects, including the relationship between regional resilience and industrial structure, the concept of resilience, the baseline or control group of resilience, and the method of empirical work. We compare three representative studies on the relationship between regional resilience and industrial structure from these aspects (Holm and Østergaard 2015; Martin et al. 2016; Rocchetta and Mina 2019). We then build on these previous studies to explain what is new about this study accordingly.

3.1 Establishing the relationship between regional resilience and industrial structure

First, with respect to the relationship between regional resilience and industrial structure, several aspects of industrial structure have been investigated. Martin et al. (2016) demonstrate the existence of such a relationship that could vary among regions, which could result from the industrial mix effect and the region-specific competitive effect. Holm and Østergaard (2015) prove a non-linear relationship between regional resilience and industrial structure. They show resilient regions could present different types depending on which dimension of industrial structure (e.g. urbanisation, entrepreneurship, diversity) could help a region adapt in the time of a shock. Rocchetta and Mina (2019) find a linear relationship between regional resilience and technological coherence in that high technology proximity of regional economies could lead to superior performance under recessionary conditions. Although these three studies show the relevance of the industrial structural factors of interest for regional resilience, the examination of why this causal effect can exist is absent. Thus, the question remains as to through what mechanism the relationship between regional resilience and industrial structure should be acknowledged as a reasonable one, regardless of the aspect of industrial structure explored. To fill this gap, this study examines the mechanisms through which regional resilience differs among cities at different complexity levels in addition to exploring the patterns of the relationship between regional resilience and economic complexity.

3.2 Regional resilience

Second, with regard to the concept of resilience, different aspects of regional resilience have been highlighted. Martin et al. (2016) measure regional resistance and recoverability from recessionary shocks as two dimensions of resilience in terms of the actual level of drop and rebound compared with the expected one. Holm and Østergaard (2015) regard resilience as a population concept by comparing growth dynamics before and after the burst of a shock and place regional adaptability at the core of this concept by evaluating the extent to which regional sensitivity to the business cycle can create resilience. Rocchetta and Mina (2019) investigate adaptive resilience of a regional economy in terms of the ability to absorb the effects of an exogenous shock and examine whether drivers of regional growth are the same as those that drives resilience.

As shown by the three studies, the concept of resilience is established based on comparison of economic performance, which could take different forms in a spatial or dynamic dimension. For a spatial dimension of comparison, Martin et al. (2016) and Holm and Østergaard (2015) regard the national level as the baseline to indicate resilience at the regional level, whereas Rocchetta and Mina (2019) depend on regional differences as part of the measurement for resilience. For a dynamic dimension of comparison, Martin et al. (2016) measure different phases of resilience after the burst of shock, whereas Holm and Østergaard (2015) and Rocchetta and Mina (2019) capture resilience by comparing regional performance before and after the shock. In this sense, Martin et al. (2016) focus on resilience that is based more on a spatial comparison, Holm and Østergaard (2015) centre on resilience that exhibits more of a dynamic dimension of comparison, and Rocchetta and Mina (2019) consider resilience that accounted for both spatial and dynamic dimensions at the same time. To examine the non-linear relationship between complexity and resilience in terms of how complexity could moderate the effects of an exogenous shock during and after the shock, we draw inspiration from these studies to cover different aspects of resilience accordingly. Specifically, we apply the idea of Martin et al. (2016) to examine resistance and recovery as two stages of resilience, and follow Holm and Østergaard (2015) and Rocchetta and Mina (2019) to assume adaptive resilience as a population concept, and employ the mode of comparison developed by Rocchetta and Mina (2019) to acknowledge simultaneously spatial differences and dynamic changes in illustrating resilience.

3.3 The 'shock': the global financial crisis

Third, when exploring different aspects of regional resilience in the face of a common shock, three studies depend on different baselines or control groups to conduct their respective comparison work. In the study by Martin et al. (2016), to examine how different regions in the U.K. reacted to a common shock differently, the national-level reaction defined as the weighted sum of change rates at the regional level is adopted as the expected or 'counterfactual' level to measure different degrees of regional resilience. The study by Holm and Østergaard (2015) regard the national growth rate as a common business cycle indicator for all regions in the same country, which could act as an explanatory variable when evaluating regional performance before and after the burst of a shock. In both studies, the national fluctuations could act as the baseline to help explore how a common shock can influence different regions differently. When it comes to the difference between these two studies, in the former work in which the U.K. is segmented into twelve major regions, the national reaction could differ depending on different ways of segmentation of regions in the same country. In the latter work, however, the national growth pattern would not be different regardless of what way of segmentation of regions. The study by Rocchetta and Mina (2019) distinguishes itself from the first two studies in terms of the comparison work. They assume the shock to be the same treatment for all regions during the shock period by defining it as a dummy variable with the pre-crisis period acting as the control group when evaluating the effect of the shock. In other words, whereas the first two studies rely on annual changes in economic performance to show the shock, the third study replace annual fluctuations by using two aggregate trends for two subperiods. In this respect, for the same exogenous shock (i.e. the global financial crisis) to be examined, we follow the study by Rocchetta and Mina (2019) in terms of having a pre-crisis period as the control group, and make a step further by having two subperiods (i.e. resistance and recovery) after the burst of the crisis in accordance with the two phases of resilience like what Martin et al. (2016) do.

3.4 Method

Fourth, when examining the relevance of industrial structure for why different regions present different degrees of resilience, different methods of empirical work are conducted in these three studies. Although both Martin et al. (2016) and Holm and

Østergaard (2015) prove that industrial structure may have a non-linear relationship with regional responses to the shock, this relationship is examined in different manners in the two studies. The former adopts a decomposition method to identify the contribution of the industrial mix effect and regional competitive effect to regional resilience for individual regions. The latter evaluates the marginal effect of the business cycle indicator conditional on industrial structure to assess the pattern of how regional sensitivity changes as one dimension of industrial structure changes. Similar to the study by Holm and Østergaard (2015), Rocchetta and Mina (2019) also evaluate the coefficient of the interaction term between the moderator variable and the treatment variable or the business cycle indicator, although they assume that the relationship between moderator variables and regional resilience can be linear. This interaction term could also be regarded as a difference-in-difference estimator with its sign indicating regional resilience. By contrast, in the study by Holm and Østergaard (2015), the marginal effect of the shock-related variable conditional on the moderator variable could not directly prove regional resilience but regional sensitivity. This finding could help identify sources of resilience if the patterns of sensitivity are somewhat consistent with those of resilience for some regions presenting some common industrial structural characteristics. We start with illustrating the local industry composition from the perspective of economic complexity, which may have a non-linear relationship with regional resilience. Specifically, for the econometric model, we follow Holm and Østergaard (2015) and Rocchetta and Mina (2019) by interacting the treatment variable with its moderator in a difference-in-difference framework to evaluate the role of complexity in resilience. Further, we estimate the marginal effect in the same way as Holm and Østergaard (2015) to explore the extent to which the effect of the shock on the outcome variable varies depending on the regional complexity level (see Appendix A for a discussion of the potential limitation).

4 Data and variables

In this section, first, we outline the data for analysis. Then, we provide the broad picture of how the global financial crisis influenced the Chinese economy in the timeline of recent few decades. Next, we illustrate the nature of this exogenous crisis and its relevance for the change of several growth indicators in the face of a shock [1]. Subsequently, we elaborate on the calculation, implication, and patterns of economic complexity. Finally, we divide cities into low-, medium-, and high-complexity groups and explore how indices of growth and its sources change in different periods or among different city groups.

4.1 Data

The data for empirical analysis (e.g. employment, output, and exports) is obtained from the Annual Surveys of Industrial Firms maintained by the State Statistical Bureau in China. The data on goods transport is obtained from the China City Statistical Yearbooks. Industries are aggregated at the three-digit level. To make data comparable throughout the period, all industry codes are adjusted according to the China Industry Classification standard (GB/T 4754 2002). The dataset covers all 169 three-digit industries. The descriptive statistics and correlation matrix of the variables are presented in Tables B1-B2 in Appendix B.

4.2 The global financial crisis

The empirical work is conducted on the manufacturing industry in Chinese cities in the time of the 2007–2008 global financial crisis. The 2007–2008 global financial crisis is a demand-related economic shock. The weight of external demand in the Chinese economy can be reflected by the fact that the year 2007 could be one turning point in the fast economic growth trajectory for thirty years, during which the average annual

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[1] When it comes to the indicators to illustrate resilience, the limited potential of whatever indicators are chosen should be acknowledged, if indicators are necessary to shed light on the nature of resilience. To begin with, resilience cannot completely be reflected by the degree to which key indicators of interest bounce back, although resilience is widely measured in this way like a common sense. Moreover, the set of indicators used to indicate the state of the economy can be updated after a common shock, if a more reasonable set of indicators could be adopted. Specifically, key indicators are originally established to indicate the state of the economy from some aspect. The influence of a shock on the economy is thus interpreted as how these key indicators change in the face of a shock. However, the economy itself that these indicators are derived from can change after facing a shock. In this regard, indicators that are of less interest previously may be given more attention in the future due to their relevance for a shock-related resilience. This fact implies that the set of indicators for resilience could evolve over time after one shock and another.

rate of growth had been around 10% (see Figure 1). Every country has its own way of response, given their respective economic connection with external demand.

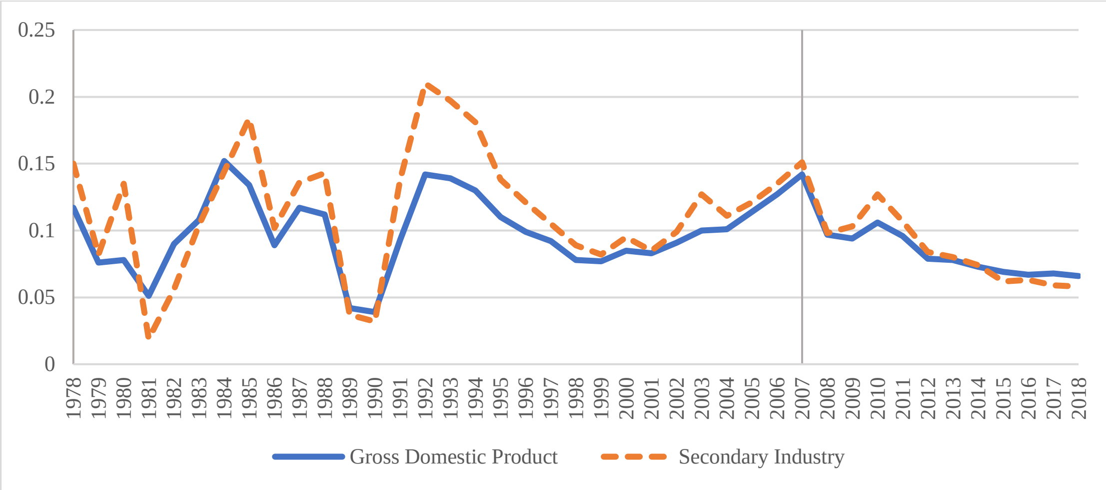

Figure 1. Growth rates of GDP in the total economy and secondary industry from 1978 to 2018
Source: Data is obtained from the China Statistical Yearbooks.

4.3 Growth indicators

To shed light on the nature of the shock and corresponding industrial behaviour to face it nationwide, Figure 2 shows the growth rates of exports, sales, output, and employment in manufacturing[2] before and after the 2007 crisis over the period 1999–2013. The exports one is the indicator directly associated with the financial crisis. The sales variable is a commonly used business cycle indicator (Holm and Østergaard 2015). Output growth is an indicator of particular interest to policy makers. Employment growth rate is widely used to indicate the degree of resilience (Rocchetta and Mina 2019). Before 2007, these indicators followed almost the same trends. The growth rate of exports was the fastest, sales and output rose at the same moderate pace, and employment grew at a relatively slow speed. The growth rate of exports dropped first in 2007 compared with other indicators, followed by those of sales and output in 2008, and then the employment figure fell in 2009. However, the growth rates of output and employment rebounded first in 2010, followed by those of exports and sales in 2011. In this sense, the degree of decline in the growth rates of output and employment may

[2] The data is obtained from the Annual Surveys of Industrial Firms. The sample of enterprises in the dataset accounts for more than 90% of the total industrial output. Data in Hunan Province was unavailable in 2011 and 2012, and its employment or output contribution to the total was less than 1% in 2010.

have been less severe than expected.

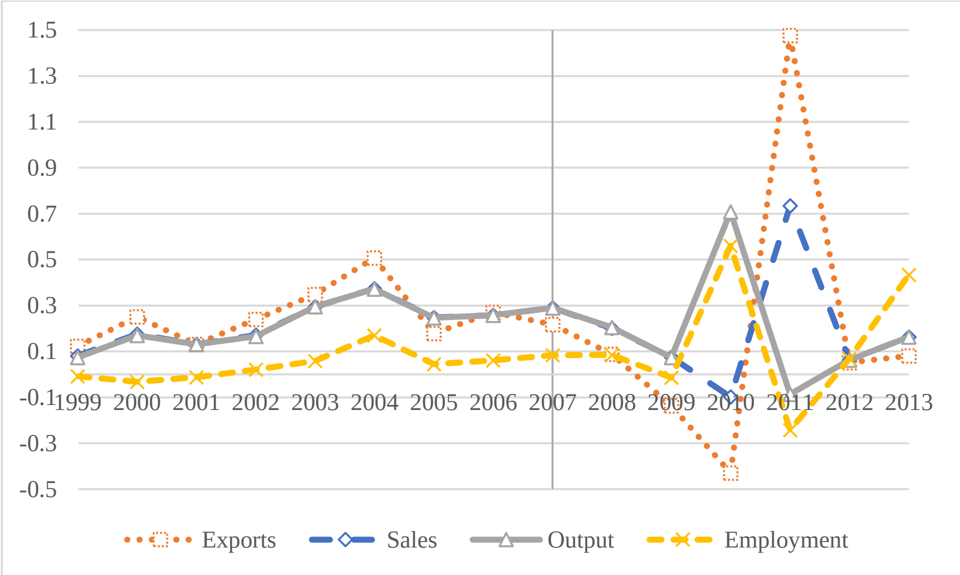

Figure 2. Growth rates of exports, sales, output, and employment in manufacturing

4.4 The measurement of economic complexity

The concept of complexity is calculated based on the meso industry level instead of the micro firm level or the macro whole-economy level. The level of complexity can be adopted to describe either an industry (i.e. a specific division of economic activities) or a city (i.e. the industrial composition in an economy). This study focuses on the latter[3]. The Economic Complexity Index (ECI) of a city's industry composition is calculated using the method of Hidalgo and Hausmann (2009) (for other complexity metrices, see Balland et al. 2022, Hidalgo 2021). Only industries that are significantly observed in the cities are considered in the calculation of ECI. In other words, an industry needs to be accounted for when a city has a comparative advantage in this industry. The first step is to calculate a city's Revealed Comparative Advantage (RCA) in each local industry:

$$RCA_{c,i,t} = \frac{Employment_{c,i,t}/Employment_{c,t}}{Employment_{i,t}/Employment_{t}} \quad (1)$$

[3] City-year pair is the unit of analysis in this study when it comes to measuring economic complexity and resilience from a spatial dynamic perspective. Regarding economic complexity at the city level, cities as the arena for agglomeration can provide capabilities (*e.g.*, human capital, production services and institutions) for incubating and accommodating sophisticated activities and cutting-edge technologies. Cities can be divided into different tiers based on a city's development level (Li et al. 2020). With respect to regional resilience, it is based on the changes in economic performance in the aftermath of the financial crisis compared with its pre-crisis one, given the causal effect of the crisis in aggregate time-series trends.

where the numerator measures the share of industry *i*'s employment in city *c*, and the denominator is the share of the same industry's employment in the whole country. That $RCA_{c,i,t}$ is above 1 implies that a city has a comparative advantage in this industry's production compared with the national average.

The next step is to analyse the connections between cities and the industries they are specialised in. A bipartite network *M* (*n*k* matrix) is constructed. $M_{c,i}$ takes value 1 if the city *c* exhibits a relative high RCA in industry *j* at year *t* (i.e. RCA is above 1) when compared with the national average; otherwise 0 (*c=1, ..., n; i=1, ...k*). ECI combines information on the two-mode degree distribution of cities and industries in the city-industry network *M*. The method of reflections is adopted to obtain the following two sets of observations in an iterative manner as measures of ECI:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_t M_{c,i}\, k_{i,N-1} \tag{2}$$

$$k_{i,N} = \frac{1}{k_{i,0}} \sum_t M_{c,i}\, k_{c,N-1} \tag{3}$$

where $k_{c,0}$ refers to the industrial diversity of city *c* (the number of industries in which a city has a comparative advantage) and $k_{i,0}$ measures the ubiquity of industry *i* (the number of cities where an industry's RCA is higher than one). The next iteration produces $k_{c,1}$ (the average ubiquity of industries located in city *c*) and $k_{i,1}$ (the average diversity of cities where industry *i* operates). In the following iteration, $k_{c,2}$ reflects the average diversity of cities specialised in industries that exist in city *c*, and $k_{i,2}$ reveals the average ubiquity of industries located in cities that has industry *i*. For each additional iteration, a more precise ECI can be estimated by incorporating feedback effects and eliminating noise, although the meanings of ECI get more complicated to interpret. Iterations terminate when the relative rankings of cities and industries are stable, thereby making the most of the city-industry network to generate a quality measure of economic composition.

As Figure 3 shows, economic complexity can give information on diversity and ubiquity in that the complexity indicator ($k_{c,n}$) has a positive correlation with diversity ($k_{c,0}$) and a negative one with ubiquity ($k_{c,1}$) for the period 1998–2013. Thus, complex economies tend to have an industry composition that other economies are unable to imitate. Figure 4 suggests the spatial variance of economic complexity across cities (a progressively declining pattern from coastal to inland areas and its increasing trend over time).

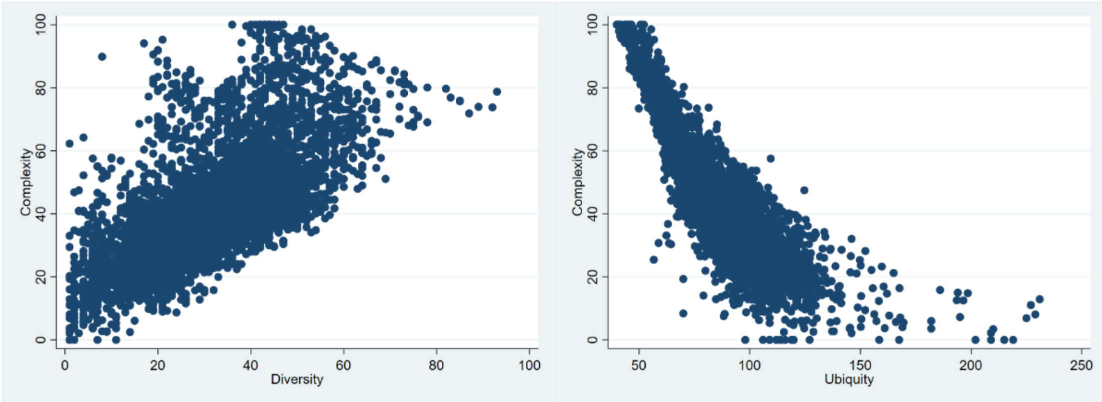

Figure 3. City diversity and complexity (left), and average ubiquity and complexity (right) (1998–2013)

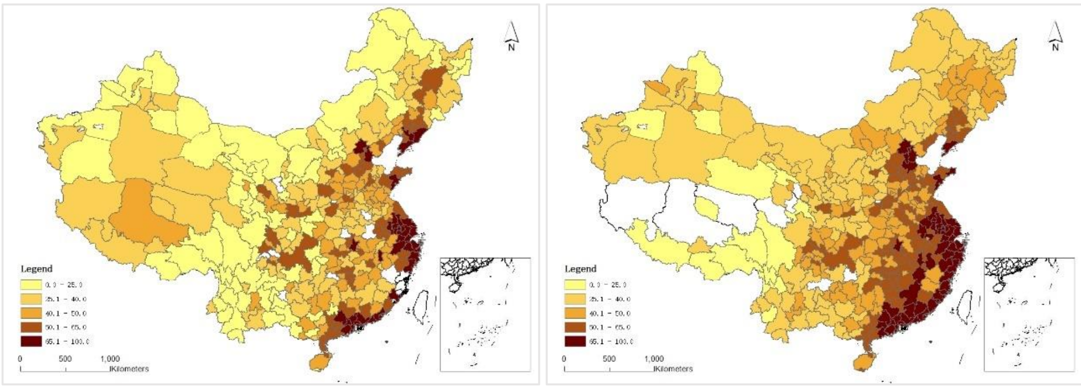

Figure 4. Economic complexity in 1998 (left) and 2013 (right)

4.5 Complexity and growth

Cities are divided into three groups every year based on their level of complexity (i.e. low, medium, and high) with each group consisting of approximately one third of the observations. Figure 5 shows the group averages of employment, output, and their growth rates. Cities of a higher complexity level tend to have more employment and output on average (top panels). In terms of their growth rates, before the crisis three groups almost fluctuated at the same pace. However, since 2007 the differences between their group averages may have widened (bottom panels). Medium-complexity cities might be the least volatile during this period. The employment growth in low-complexity cities and the output growth in high-complexity cities were exposed to a greater degree of instability[4].

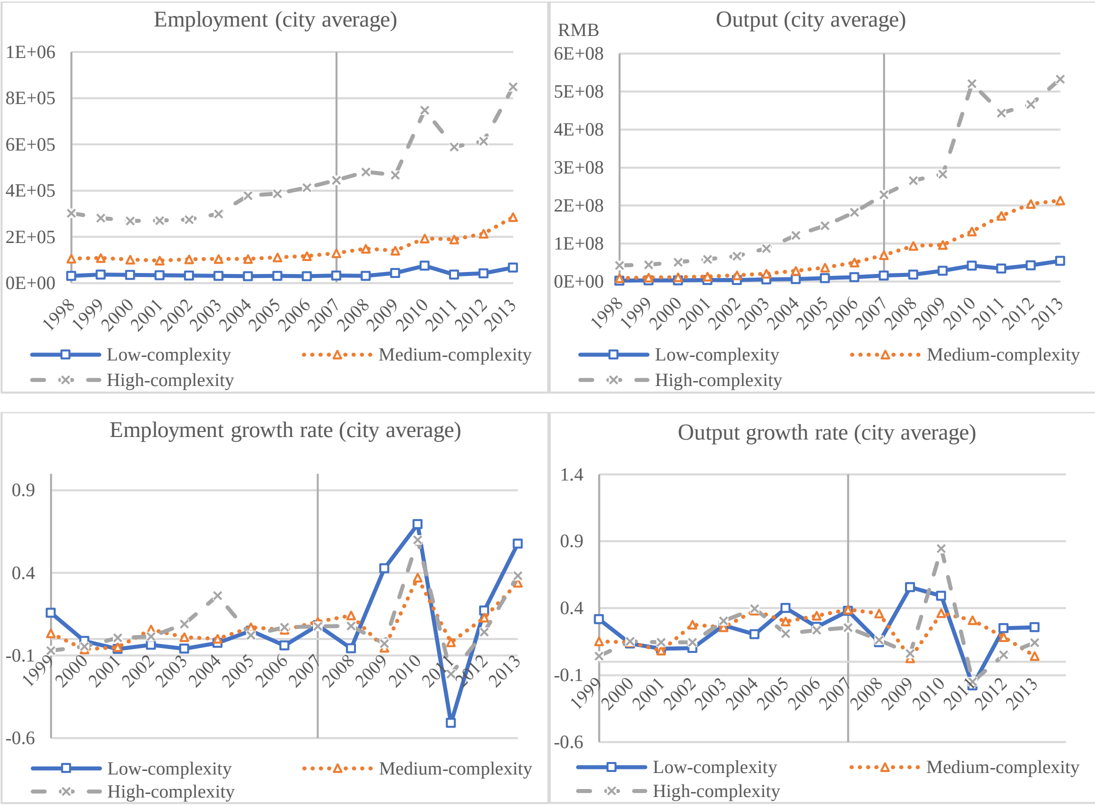

Figure 5. Employment, output and their growth rates for low-, medium-, and high-complexity cities

Further, sources of growth may interplay with the shock differently in cities with different complexity levels, if economic complexity matters for the influence of the shock on the local economy. Table B3 presents descriptive statistics of explanatory variables for economic growth in different time periods among different city groups. Three explanatory variables include the city complexity level, export share (i.e. the share of exports in total output), and goods transport growth (i.e. the growth rate of goods transport by road and railway). These variables may not only contribute to economic growth but also interplay with the crisis to influence the resilience

[4] An overall growing pattern of employment and output despite some decline in their growth rates after the recession could reflect the government's efforts to offset declining external demand and to cushion the global economic downturn by investing in revitalisation industries and infrastructure. However, an unprecedented result of such policy responses could be the over-capacity issue in some industries involved. A spike in the amount and growth rate of output or employment in the year 2010 may reveal the temporary overheating of some production activities due to stimulative strategies.

performance. Three periods refer to pre-crisis (2005–06), crisis (2007–10), and post-crisis (2011–13). Three city groups stand for low-, medium-, and high-complexity cities. We find that complexity tends to decrease from pre-crisis to crisis and increase from crisis to post-crisis. Export share shows a decreasing trend over time. Goods transport growth does not change markedly. Export share is likely to be higher in cities with higher complexity. Goods transport growth does not differ among cities with different complexity levels.

5 Econometric analysis and findings

We evaluate the moderating effect of economic complexity on regional resistance to and recovery from the crisis in a step-by-step manner. First, a growth model to explain regional employment and output growth is conducted to evaluate the effects of complexity and domestic and global demand on economic growth. Second, the determinants of regional resilience are examined by interacting the shock dummies with the key explanatory variables of economic growth. Third, the non-linear relationship between complexity and resilience is explored by evaluating the marginal effect of the shock conditional on city complexity. Fourth, different mechanisms of resilience are tested in terms of their relative applicability to different complexity levels. Fifth, we conduct the robustness check.

5.1 Relationship between complexity and growth

To begin with, we carry out the following regression of growth on complexity and other key explanatory variables:

$$Growth_{c,t} = \beta_0 + \beta_1\left(Complexity_{c,t-1}\right) + \beta_2\left(Export_{c,t-1}\right)$$
$$+\beta_3\left(Transport_{c,t-1}\right) + \mu_c + \varepsilon_{c,t} \qquad \text{(Model 1)}$$

where $Growth_{c,t}$ is either employment or output growth in the main analysis of resilience; $Export_{c,t-1}$ is the export share in the total regional output to measure the city dependence on global demand; $Transport_{c,t-1}$ is the growth rate of goods transport through road or railway to measure domestic demand. β_1 captures how economic growth differs with the city complexity level. β_2 denotes how the export share contributes to economic growth. β_3 measures the extent to which the goods transport growth could promote economic growth.

Table 1 presents the results obtained by fitting Model 1 with standard ordinary least squares (OLS). The model is conducted in the full panel from 2005 to 2013, which is further divided into different periods based on different aggregate trends of growth dynamics (i.e. the pre-crisis 2005–06, the crisis 2007–10, the post-crisis 2011–13). During the full period from 2005 to 2013, city complexity has a significant negative relationship with employment growth but a positive relationship with output growth. An increase in the export share can significantly promote both employment and output growth. The coefficient of goods transport growth is not significant.

Regarding how the relationship differs in different subperiods, the results show that the significant positive relationship between complexity and economic growth can become a negative one after the burst of the shock. The export share may not promote economic growth in the build-up and face of the shock but can play a positive role in the recovery period. Specifically, city complexity may significantly contribute to economic growth before 2007, when the export share has no significant effects. However, in the immediate aftermath of the shock from 2007 to 2010, cities with higher complexity may suffer more in their economic growth, and the export share continues to have no significant contribution. Subsequently, in the recovery period from 2011 to 2013, the export share has a significant positive effect on growth, and complexity significantly contributes to output growth but not employment growth.

Table 1. Results for Model 1: effects of complexity and domestic and global demand on economic growth

	Employment growth				Output growth			
	All years 2005–13 (1)	Pre-crisis 2005–06 (2)	Crisis 2007–10 (3)	Post-crisis 2011–13 (4)	All years 2005–13 (5)	Pre-crisis 2005–06 (6)	Crisis 2007–10 (7)	Post-crisis 2011–13 (8)
Complexity	–0.015***	0.005***	–0.046***	0.004	0.027***	0.007**	–0.018***	0.102***
	(0.004)	(0.002)	(0.005)	(0.014)	(0.008)	(0.003)	(0.006)	(0.026)
Export	3.044***	–0.253	–0.706	5.566***	10.241***	0.620	–0.942	11.414***
	(0.290)	(0.326)	(0.666)	(0.567)	(0.559)	(0.500)	(0.829)	(1.019)
Goods	–0.001	–0.003	–0.004	0.005	–0.004	–0.004	–0.008	–0.002
	(0.006)	(0.004)	(0.006)	(0.014)	(0.011)	(0.007)	(0.007)	(0.025)
City dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.596	–0.285*	3.380***	–0.898	–3.129***	–0.359	1.937***	–8.104***
	(0.383)	(0.157)	(0.408)	(1.145)	(0.739)	(0.240)	(0.507)	(2.058)
Observations	2,537	565	1,142	830	2,537	565	1,142	830
R-squared	0.111	0.572	0.250	0.444	0.206	0.643	0.207	0.638

Notes: Standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.2 Determinants of resilience

To examine how economic complexity acts as a moderating factor in the resistance to and recovery from the shock, a difference-in-difference method is adopted to evaluate the difference in regional resilience among cities of different complexity levels. Both the crisis and post-crisis dummies are then interacted with complexity and the export share. Examining how these key explanatory variables moderate the influence of the shock could then indicate the determinants of resistance and recovery as two phases of regional resilience. Hence, the model takes the form:

$$Growth_{c,t} = \alpha + \beta_1(Complexity_{c,t-1}) + \beta_2(Export_{c,t-1}) + \beta_3(Goods_{c,t-1}) + \beta_4(Shock_t) + \beta_5(Shock_t * Complexity_{c,t-1}) + \beta_6(Shock_t * Export_{c,t-1}) + \mu_c + \varepsilon_{c,t} \quad \text{(Model 2)}$$

where the coefficient β_1 on $Complexity_{c,t-1}$ indicates the effect of economic complexity on economic growth during the pre-crisis period. Similarly, the coefficient β_2 on $Export_{c,t-1}$ indicates the effect of global demand proxied by the export share on economic growth during the pre-crisis period. The coefficient β_3 on $Goods_{c,t-1}$ measures the average effect of domestic demand proxied by the goods transport growth on economic growth. $Shock_t$ is a dummy variable introduced as the treatment and has three categories. The base group is the pre-crisis period from 2005 to 2006. The years after the burst of the shock are divided into the crisis period 2007–2010 and the post-crisis period 2011–2013 to represent the resistance stage and recovery stage, respectively, based on the contraction and expansion of exports (see Figure 2). The pre-crisis years between 2005 and 2006 take the value of 0, crisis years from 2007 to 2010 are defined as 1, and post-crisis years from 2011 to 2013 are 2. The two coefficients β_4 on $Shock_t$ (denoted as $Crisis$ and $Post - crisis$ in the results table) refer to the difference in economic growth between crisis and pre-crisis years and the difference between post-crisis and pre-crisis years, respectively, when the city complexity level is zero, the export share is zero, and the goods transport growth is at its average level.

Two coefficients β_5 on the interaction term $Shock_t * Complexity_{c,t-1}$ (denoted as $Crisis * Complexity$ and $Post - crisis * Complexity$ in the results table) capture how the influence of the shock on economic growth depends on city complexity in crisis and post-crisis years, respectively. Cities of different levels of complexity may have different degrees of dependence on the global and domestic markets, which may moderate the influence of the shock at the city level. For example, the export-oriented manufacturing can play a critical role in the growth of high-complexity cities before the shock. Accordingly, the damage of this demand-related crisis can be higher for cities of a higher level of complexity. To control for the bias caused by the significant positive correlation between complexity and the export share, two coefficients β_6 for the interaction term $Shock_t * Export_{c,t-1}$ (denoted as $Crisis * Export$ and $Post - crisis * Export$ in the results table) are estimated as well to evaluate the moderating effect of the export share in regional resistance and recovery.

The interaction term between the shock and goods transport growth is not incorporated into the model. We do not think that domestic demand would interact with complexity to modify the influence of the shock due to the insignificant correlation between regional complexity and goods transport growth. Low-complexity cities tend to be located in inland areas and their goods may relatively depend on road and rail for transport, whereas high-complexity cities are mainly located in coastal areas and can rely on ocean shipping to a greater degree. However, different growth rates of goods transport at the city level may not moderate the influence the shock differently, given its indirect relationship with the nature of the crisis. However, there might exist a tricky relationship between the export share and goods transport growth, which may reflect the trade-off in demand between the domestic market and the global market. Therefore, the model should include the goods transport growth as an independent variable considering its association with the export share. Explanatory variables except for the treatment variable are lagged one period to control for the endogeneity issue[5]. μ_c is the fixed-effects error term. More details on model specification can be found in the corresponding analysis in Section 5.3 related to Tables 2 and 3.

Table C1 in Appendix C presents the results for Model 2 in a difference-in-difference framework to help us explore how cities can suffer from the shock differently depending on their different complexity levels. We not only conduct the regression in the full sample (columns 1 and 5) but also in low-, medium, and high-complexity cities, across which the influence of the shock is supposed to differ. However, the results obtained should be interpreted with caution. If we hypothesise that the influence of the shock can depend on the city complexity level, which is exactly the case and constitutes the reason for our choice to use an interaction model as the corresponding method, we analysts should not try to interpret the coefficients in an interaction model in terms of their magnitude and significance, due to the issues discussed in the study by Brambor et al. (2006). Instead, we should make a step further by calculating substantively meaningful marginal effects and standard errors, as what we do below.

5.3 Complexity and resilience

To examine the potential non-linear relationship between resilience and city complexity, the marginal effect of the shock conditional on complexity is evaluated in the form of:

$$\frac{\partial Growth_{c,t}}{\partial Shock_t} = \beta_1 + \beta_3 Complexity_{c,t-1} + \frac{\partial X_{c,t-1}}{\partial Shock_t}\Gamma \qquad \text{(Model 3)}$$

where β_3 is the coefficient on the estimated marginal effect and measures the extent to which economic growth in times of crisis can change in comparison to its pre-crisis counterpart and how such change is conditional on the complexity level of a city; $X_{c,t-1}$ is a vector of explanatory variables other than complexity and their interaction terms with the shock, and Γ is a vector of the corresponding coefficients. As the shock is

[5] See Figure B1 in Appendix B for how the variable for complexity changes year by year from 1998 to 2013 in terms of its average value across cities. The heterogeneity across years of this variable demonstrates dynamism in the industry in China.

divided into two periods (i.e. crisis and post-crisis), every interaction term with the shock would have two coefficients to indicate the effects of one moderator on resistance and recovery, respectively.

Particularly, the explanatory variables and the interaction terms are consecutively incorporated into the model. First, we examine the relationship between complexity and resilience by evaluating the marginal effect of the shock conditional on complexity without controlling for other explanatory variables. Second, we add the export share and the goods transport growth as an independent variable respectively to see how the relationship between complexity and resilience changes accordingly. Third, based on how the influence of the shock can change with the variation of the export share and goods transport growth respectively, we further incorporate their interaction terms with the shock into the model separately. Finally, we estimate the ultimate model to produce a more accurate and sensible estimate of the relationship between complexity and resilience after controlling for the effects of both global and domestic demand.

In each of these steps, to begin with, the results are shown in the typical results table for the interaction model (Tables 2–4). The figures are then presented to illustrate graphically the marginal effect of the shock and corresponding standard errors across the observed range of the moderating variable (Figures 6–11). In the figures, the line is the estimated marginal effect. The shaded area around the line is a 95% confidence interval to show the conditions under which the marginal effect is statistically significant, i.e. when the confidence interval is entirely above or below the zero line. Finally, we report the values and proportion of real-world observations that can fall within the range of significance at the 90% level[6]. Specifically, the typical results obtained from different model specifications for two outcome variables (i.e. employment and output growth) are displayed in Tables 2 and 3, respectively.

[6] See Figures C1–C3 in Appendix C for the distribution of moderating variables (i.e. complexity, export share, and goods transport growth) in different periods (i.e. pre-crisis, crisis, and post-crisis)

Table 2. The influence of the shock on employment growth based on different model specifications

	Dependent variable: Employment growth							
	Baseline	Export (average)	Goods (average)	Export	Complexity & export	Goods	Complexity & Goods	**Full Model**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crisis	0.317***	0.276***	0.330**	0.203***	0.396***	0.147***	0.335***	0.478***
	(0.106)	(0.102)	(0.129)	(0.048)	(0.124)	(0.043)	(0.130)	(0.158)
Post-crisis	0.231**	0.154	0.282**	0.294***	0.332***	0.270***	0.282**	0.380**
	(0.112)	(0.108)	(0.138)	(0.050)	(0.128)	(0.045)	(0.138)	(0.163)
Complexity	–0.005	–0.013***	–0.013***		–0.007*		–0.013***	–0.016***
	(0.004)	(0.004)	(0.005)		(0.004)		(0.005)	(0.005)
Crisis * Complexity	–0.004*	–0.002	–0.004		–0.006*		–0.004	–0.009**
	(0.002)	(0.002)	(0.003)		(0.003)		(0.003)	(0.004)
Post-crisis * Complexity	0.001	0.006**	0.000		–0.001		0.000	–0.001
	(0.002)	(0.002)	(0.003)		(0.003)		(0.003)	(0.004)
Export		3.969***		3.076***	2.902***			2.975***
		(0.282)		(0.369)	(0.503)			(0.553)
Crisis * Export				–0.066	0.786			1.086*
				(0.319)	(0.510)			(0.563)
Post-crisis * Export				1.131***	1.303***			1.033*
				(0.330)	(0.500)			(0.549)
Goods			–0.001			0.007	0.008	–0.001
			(0.006)			(0.027)	(0.027)	(0.005)
Crisis* Goods						–0.012	–0.013	
						(0.028)	(0.028)	
Post-crisis * Goods						–0.004	–0.006	
						(0.028)	(0.028)	
City dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.385	0.076	0.887**	–0.557**	–0.045	0.011	0.883**	0.479
	(0.362)	(0.350)	(0.408)	(0.267)	(0.354)	(0.276)	(0.408)	(0.400)
Observations	2,990	2,990	2,537	2,990	2,990	2,537	2,537	2,537
R-squared	0.083	0.147	0.086	0.145	0.149	0.079	0.086	0.153

Notes: Standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. The influence of the shock on output growth based on different model specifications

	Dependent variable: Output growth							
	Baseline	Export (average)	Goods (average)	Export	Complexity & Export	Goods	Complexity & Goods	**Full Model**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crisis	0.287	0.157	0.166	0.125	0.315	0.009	0.171	0.329
	(0.230)	(0.213)	(0.260)	(0.099)	(0.258)	(0.087)	(0.261)	(0.297)
Post-crisis	0.469*	0.231	0.554**	0.633***	0.804***	0.541***	0.558**	0.914***
	(0.244)	(0.226)	(0.277)	(0.106)	(0.267)	(0.091)	(0.278)	(0.308)
Complexity	0.052***	0.030***	0.024**		0.045***		0.024**	0.015
	(0.009)	(0.008)	(0.010)		(0.009)		(0.010)	(0.010)
Crisis *	–0.005	0.002	–0.003		–0.004		–0.003	–0.006
Complexity	(0.005)	(0.005)	(0.005)		(0.007)		(0.005)	(0.008)
Post-crisis *	0.002	0.017***	0.000		–0.005		0.000	–0.005
Complexity	(0.005)	(0.005)	(0.006)		(0.007)		(0.006)	(0.008)
Export		12.331***		9.734***	9.057***			9.485***
		(0.590)		(0.772)	(1.050)			(1.043)
Crisis * Export				0.650	0.713			1.503
				(0.667)	(1.063)			(1.062)
Post-crisis *				3.855***	4.347***			3.682***
Export				(0.691)	(1.043)			(1.034)
Goods			–0.005			0.010	0.010	–0.005
			(0.011)			(0.055)	(0.054)	(0.010)
Crisis* Goods						–0.016	–0.016	
						(0.057)	(0.056)	
Post-crisis *						–0.014	–0.014	
Goods						(0.057)	(0.057)	
City dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	–3.204***	–4.164***	–1.432*	–1.773***	–4.436***	0.091	–1.435*	–2.624***
	(0.788)	(0.732)	(0.820)	(0.558)	(0.738)	(0.558)	(0.821)	(0.755)
Observations	2,990	2,990	2,537	2,990	2,990	2,550	2,537	2,537
R-squared	0.128	0.252	0.113	0.249	0.258	0.093	0.113	0.278

Notes: Standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

First, we evaluate the marginal effect of the shock on employment and output growth in both crisis and post-crisis periods without controlling for explanatory variables other than complexity. We adopt the baseline model specifications in column (1) of Tables 2 and 3, with Figure 6 presenting how the influence of the shock is conditional on the city complexity level. The results show that there is a bifurcation in the patterns of resistance and recovery with regard to the relationship between the influence of the shock and the complexity level of the city. Specifically, during the resistance period in the immediate aftermath of the shock (2007–2010), the influence of the shock tends to be more damaging to cities of a higher complexity level. However, during the subsequent recovery period (2011–2013), high-complexity cities are more likely to recover better by presenting a higher growth rate compared with that during the pre-crisis period[7].

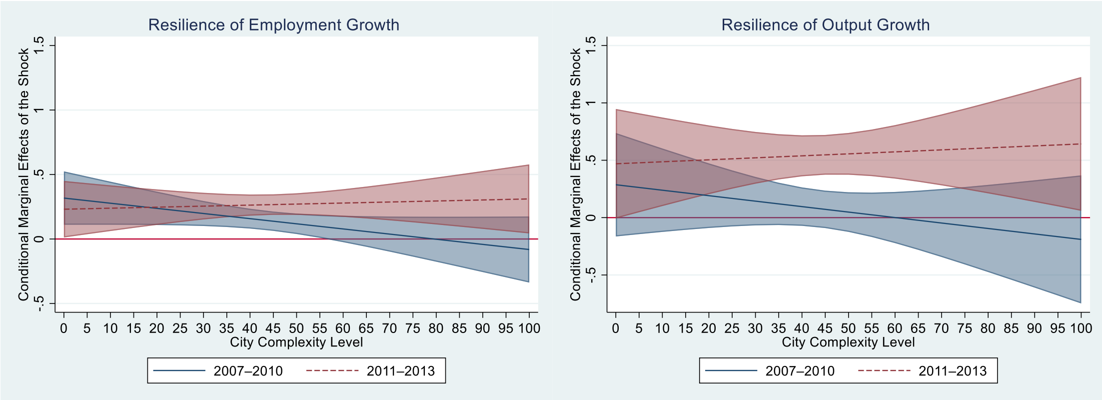

Figure 6. Marginal effect of the shock conditional on complexity in the baseline model

Second, we individually control for the average effects of the export share and the goods transport growth. We adopt the model specifications in columns (2)–(3) of Tables 2 and 3, and present the marginal effect of the shock conditional on complexity in Figure 7. After controlling for the export share as a proxy for global demand (top panel), during the crisis period, the resistance performance decreases (for employment growth) and improves (for output growth) with one-unit increase in the city complexity level. During the post-crisis period, cities with higher complexity tend to recover better[8]. By contrast, after controlling for the goods transport growth (bottom penal), the relationship between complexity and resilience does not change markedly in terms of

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[7] In terms of how many observations can fall into the range of significance at the 90% level, during the crisis period, cities with complexity no more than 55 show significant resistance in employment growth, which can account for 80% of the total observations in this period. Cities at all complexity levels do not present significant resistance in output growth. During the post-crisis period, recovery in employment and output growth is significant for cities at every complexity level.

[8] When it comes to the level of complexity having significant moderating effects, during the crisis period, complexity can significantly contribute to employment growth until the level of 80 and to output growth at a level from 25 to 85, accounting for 93.34% and 90.75% of the total observations, respectively. During the post-crisis period, almost all complexity levels can significantly lead to regional recovery in employment growth, and economic complexity no less than 10 can play a significant role in recovery of output growth, making up 97.75% of the total.

the magnitude and significance of the marginal effect. The sensitivity of resilience to complexity after controlling for the export share may reflect that the mechanisms of resilience may differ across cities with different complexity levels (see Section 5.4 for further discussion). This exogenous shock is directly related to global demand and can thus exert an influence on the local economy depending on the export share. Since the export share is significantly correlated with complexity, we feel the need to control for the modifying effect of the export share in the shock time as well[9], without which some bias for estimating the effect of complexity could occur.

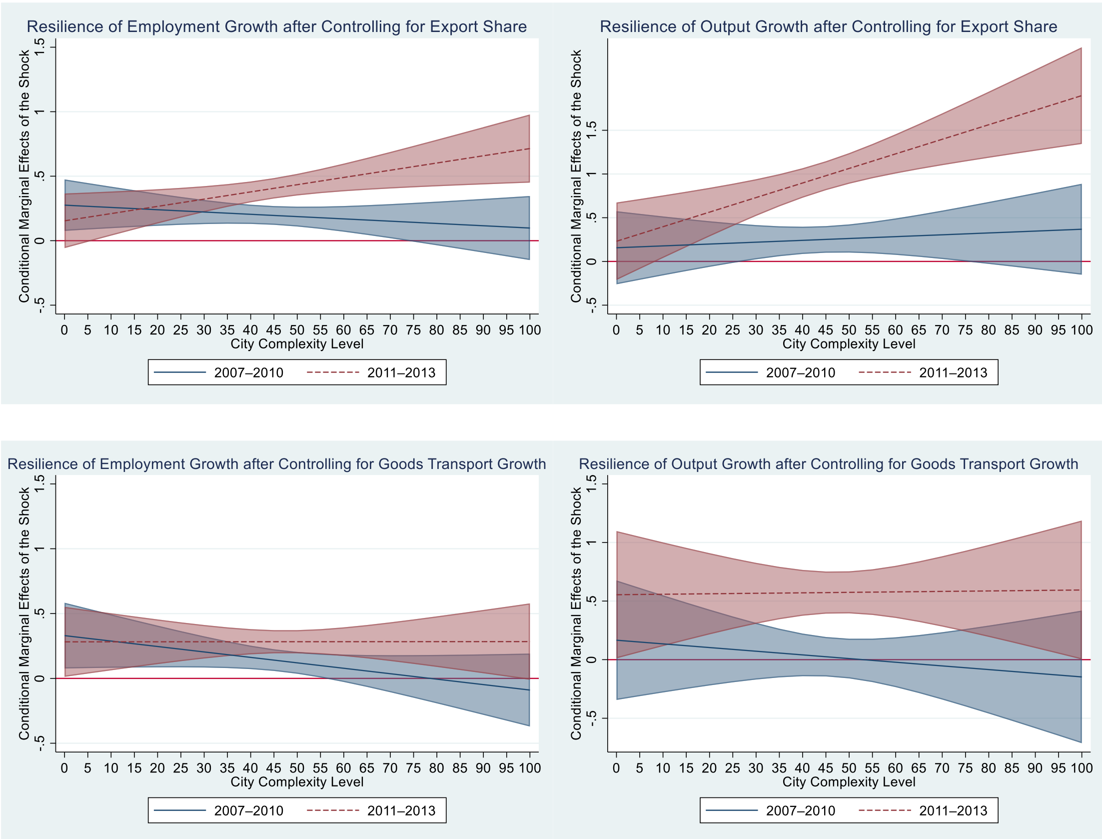

Figure 7. Marginal effect of the shock conditional on complexity after controlling for the average effects of domestic and global demand

Third, we examine the moderating effects of export share and goods transport growth on the influence of the shock, respectively. The results show that export share

[9] We do not further control for the change in the interplay between complexity and the export share after the burst of the shock, because of their linear relationship (Table B1), meaning that cities at a higher complexity level tend to have a higher export share.

can modify the influence of the shock, whereas goods transport growth cannot. For export share, we illustrate the extent to which the export share can modify the influence of the shock for a locality (Figure 8 top panel) based on the model specifications in column (4) of Tables 2 and 3. Employment growth in cities with a higher export share are more likely to be influenced by the burst of the crisis but may experience a greater extent of recovery subsequently in the post-crisis period. For output growth, the pattern of bifurcation also exists but differs in the way that both resistance and recovery is positively associated with complexity[10].

We further estimate the marginal effect of the shock conditional on complexity after controlling for the export share as a moderator of the influence of the shock. We adopt the model specifications in column (5) of Tables 2 and 3 and present the results in Figure 8 bottom panel. Regional resilience in both employment and output growth decreases as the complexity level increases during both crisis and post-crisis periods[11]. Thus, the effect of complexity on resilience without controlling for the interaction between the export share and the shock (Figure 6) may partly reflect the effect of the export share[12]. The results suggest that high-complexity cities may predominantly rely on the export share to rebound compared with cities with low complexity[13]. In other

[10] For the range of observations having significant results, in the crisis period, the positive moderating effect of the export share is significant until the level of 0.4 for employment growth and from 0.04 to 0.46 for output growth, accounting for 97.19% and 63.51% of the observations, respectively. In the post-crisis period, the marginal effect is significant positive at all levels of the export share.

[11] For the significant results of complexity as a moderator, in the crisis period, its positive effect for employment growth is significant until the level of 55 and for output growth from 20 to 50, corresponding to 80% and 65.72% of the observations; and in the post-crisis period, the effect is significant at every complexity level.

[12] Antonietti and Franco (2021) find that on average the effect of the inward foreign direct investment accumulation on economic complexity at the country level could be small and short-term. To test the nature of the positive correlation between complexity and the export share at the city level, we find that the statistical significance of the positive correlation between economic complexity and the export share disappears after controlling for city fixed effects. This finding means that the city dummies can effectively control for the underlying cause of their correlation and thus make it less of a problem to include both of them as explanatory variables because their correlation if any would not change the fact that they are fundamentally different concepts.

[13] Specifically, after controlling for Shock*Export, cities of a higher complexity level are less resilient now, particularly when it comes to recovery in the post-crisis period. This change is consistent with the

words, more complex cities are less likely to strengthen or develop substitutes for global demand as drivers for employment growth[14].

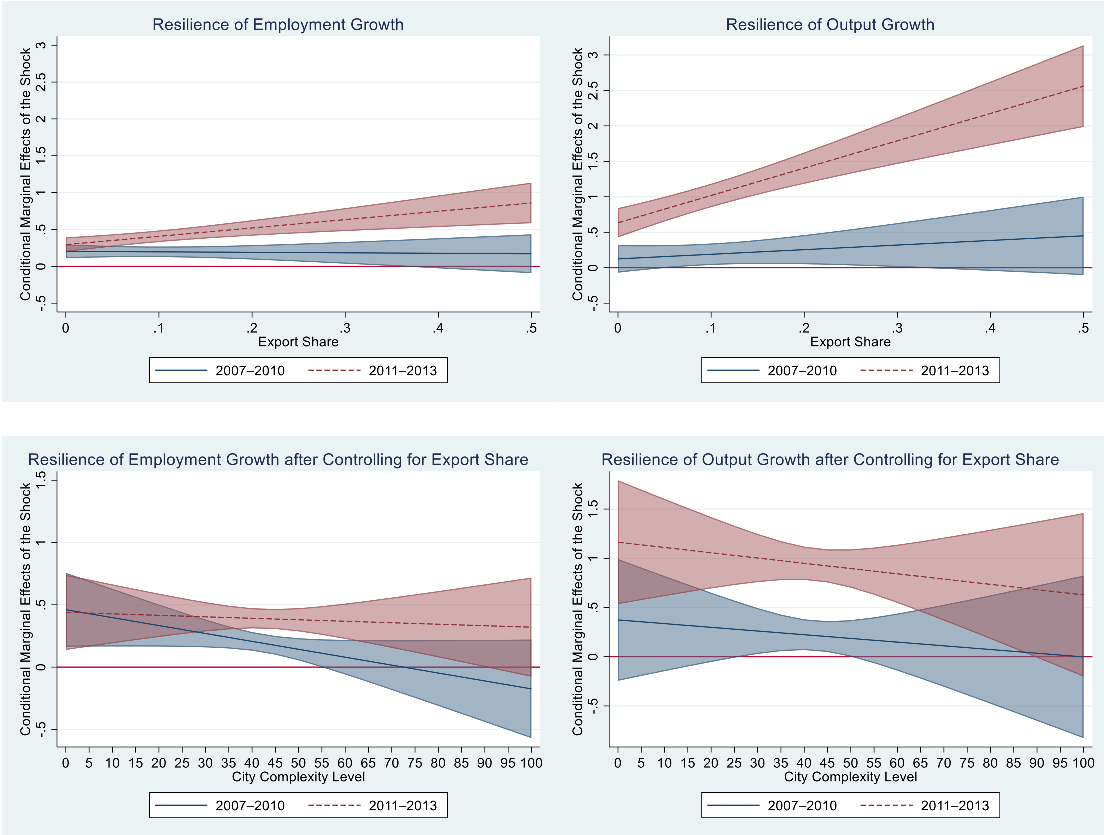

Figure 8. The relevance of the export share for the marginal effect of the shock

For goods transport growth, we investigate the relevance of domestic demand for the marginal effect of the shock (Figure 9) based on model specifications in column (6) of Tables 2 and 3. We find that the influence of the shock does not differ markedly in cities with different growth rates of goods transport (top panel), regardless of the period

fact that recovery strengthens as the export share increases. By contrast, cities with lower complexity tend to behave better in resilience, implying that these cities are more likely to develop other sources unrelated to the global market to increase their employment growth momentum.

[14] This fact does not contradict another fact that other factors (e.g. productivity and industrial dynamism) may still play a fundamental role in employment growth in high-complexity cities. The greater resilience in cities with lower complexity may reflect their efforts to develop other factors to boost employment growth, although it is another question as to whether the development of these factors could be better without the shock.

and the outcome variable[15]. Therefore, after including $Shock * Transport$ into the model in column (7) of Tables 2 and 3, the marginal effect of the shock conditional on complexity can remain the same (bottom panel), compared with that without $Shock * Transport$ (Figure 6). The domestic market may help employment growth resist to the shock and subsequently recover better as well (top-left panel) and help output growth recover after the crisis (top-right panel), but the modifying effect is not economically significant. The differences between different periods in terms of the marginal effects essentially reflect the influence of the shock during the crisis and post-crisis periods. Therefore, the variable for the goods transport growth without its interaction[16] with the crisis needs adding in the model.

[15] When it comes to the proportion of observations with significant results, in the crisis period, the goods transport growth until the level of 2.3 has a significant positive effect on employment growth, accounting for 97.72% of the observations. For output growth, it is insignificant for the whole observed range of goods transport growth. In the post-crisis period, the goods transport growth at every level has a significant positive effect on both employment and output growth (top panel).

[16] The interaction effect between goods transport growth and crisis does not change with goods transport growth, so there is no need to add this interaction effect when estimating the marginal effect of the crisis. But it is necessary to control for the average effects of the goods transport growth to generate a more accurate of the influence of the shock.

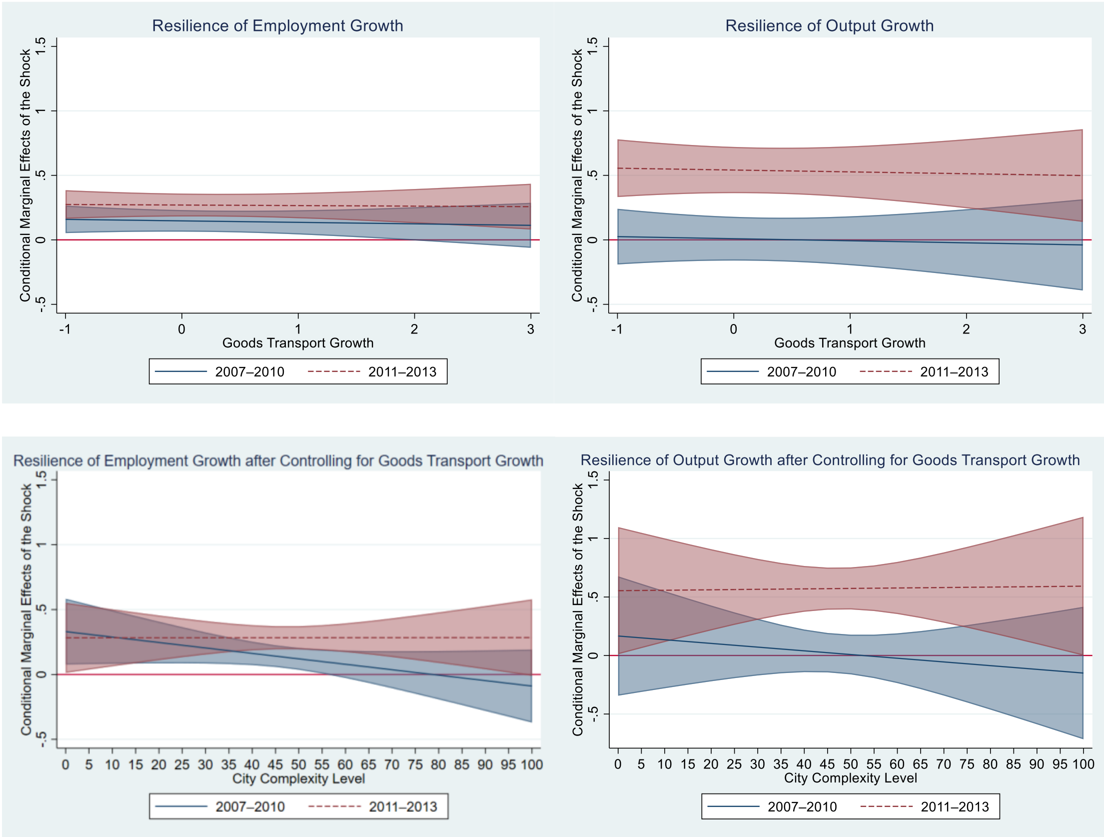

Figure 9. The relevance of the goods transport share for the marginal effect of the shock

Finally, we illustrate the relationship between complexity and resilience when controlling for the modifying effect of global demand and the average effect of domestic demand[17]. We adopt the full model specifications in column (8) of Tables 2 and present how the marginal effect of the shock on economic growth is conditional on the city complexity level in Figure 10. The results show that both resistance and recovery vary with complexity. During the crisis period, employment growth is resistant in less complex cities, whereas output growth is resistant in cities with medium complexity. During the post-crisis period, recovery is found at every complexity level

[17] Before adding the export share and goods transport growth into the model simultaneously, we estimate how the effect of the export share on growth can differ in cities with different levels of the goods transport growth (Table C2 and Figure C4 in the Appendix).

and tends to decrease as complexity increases, regardless of the growth indicator[18].

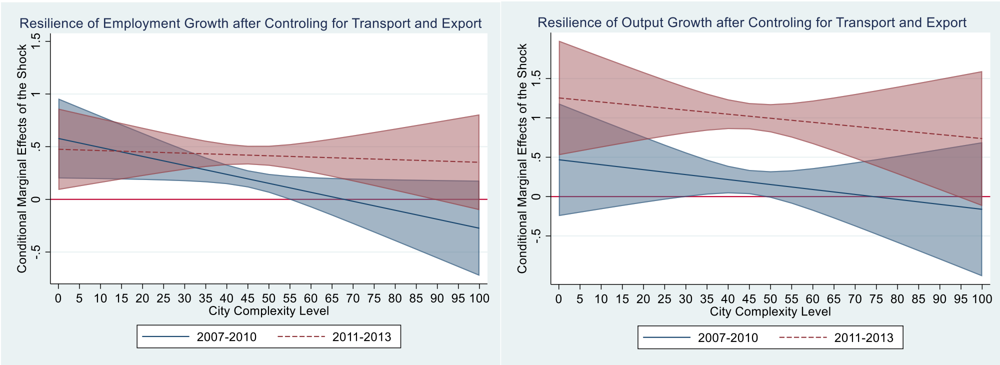

Figure 10. Marginal effect of the shock conditional on complexity in the full model

5.4 Mechanisms of resilience

Cities of different degrees of complexity can be resilient through various channels, i.e. reduction in productivity, deceleration in industrial dynamics, and redistribution of comparative advantages. We test how the influence of the shock on productivity growth, industrial dynamics and comparative advantages changes with the city complexity level. We adopt the model specifications in Table 4 and control for the export share and the goods transport growth in the same way as column (8) of Tables 2 and 3. Productivity is measured as output per employee. Industrial dynamics is divided into three components, i.e. the numbers of pre-existing industries, entry industries, and exit industries in an overlapping 5-year interval (Boschma et al. 2013; Cortinovis et al. 2017; Montresor and Quatraro 2017). Industry membership or industry specialisation counts if a city has a comparative advantage in an industry as Equation (1) shows. In other words, a pre-existing/entry/exit industry is defined as whether an industry maintains/acquires/loses its comparative advantage in a city in a 5-year interval. The number of comparative advantages, or the number of specialisations, refers to the number of industries whose RCA is above 1 in a city. Particularly, for the first channel, the complexity level is based on its value in a lagged year. For the last two channels,

[18] For the range of observations with significant marginal effects of the shock, during the crisis period, employment growth is resistant in cities with complexity below the level of 55, and the figure for output growth is from 25 to 50, accounting for 80.01% and 58.85% of the observations, respectively. During the post-crisis period, economic complexity can help recover employment growth until the level of 95 and output growth at every complexity level, accounting for 98.87% and all of the observations.

the complexity level is calculated based on its value in the first year for every 5-year interval. Figure 11 graphically presents the extent to which productivity growth, industrial dynamics, and comparative advantages can differ among cities at different complexity levels in times of crisis.

Table 4. Results for the relationship between complexity and different mechanisms of resilience

	(1)	(2)	(3)	(4)	(5)
Variables	Productivity growth	Entry industries	Exit industries	Pre-existing industries	Industrial specialisations
Complexity	0.025***	-0.013	0.158***	0.077***	0.084***
	(0.003)	(0.025)	(0.025)	(0.020)	(0.024)
Transport	0.605**	-1.960	12.368***	-2.079	-4.936*
	(0.266)	(2.775)	(2.807)	(2.296)	(2.675)
Goods	-0.004	0.002	-0.036	0.013	0.014
	(0.003)	(0.027)	(0.027)	(0.022)	(0.026)
Crisis	-0.199***	1.841***	0.232	1.728***	3.171***
	(0.075)	(0.706)	(0.722)	(0.584)	(0.680)
Crisis *	0.002	-0.098***	-0.086***	0.054***	-0.069***
Complexity	(0.002)	(0.020)	(0.020)	(0.016)	(0.019)
Crisis * Export	-0.076	10.619***	8.781***	-9.790***	3.330
	(0.269)	(2.728)	(2.782)	(2.255)	(2.627)
Post-crisis	0.089	4.188***	1.447*	4.991***	8.798***
	(0.078)	(0.734)	(0.748)	(0.607)	(0.707)
Post-crisis *	-0.004*	-0.078***	-0.064***	-0.018	-0.117***
Complexity	(0.002)	(0.020)	(0.021)	(0.017)	(0.020)
Post-crisis *	0.816***	4.705*	-0.203	-3.653	2.437
Export	(0.263)	(2.750)	(2.799)	(2.276)	(2.651)
City dummies	Yes	Yes	Yes	Yes	Yes
Constant	-1.556***	10.860***	2.556	46.128***	57.796***
	(0.191)	(1.856)	(1.887)	(1.536)	(1.790)
Observations	2,524	2,507	2,522	2,519	2,519
R-squared	0.158	0.458	0.456	0.917	0.920

Notes: Standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

To begin with, the reduction in productivity growth is more likely to occur in low-complexity cities during the crisis but in high-complexity cities after the crisis (top-left panel). Specifically, during the resistance period from 2007 to 2010, the burst of the crisis has a reductive effect on productivity growth when complexity is not large, but this reductive effect decreases as complexity increases. On the contrary, in the post-crisis or recovery period from 2011 to 2013, complexity at a low level can somewhat promote productivity growth, whereas complexity above a certain level can have a negative effect on productivity growth[19].

Next, deceleration in industrial dynamics as a mechanism to realise resilience in economic growth may always occur, especially for more complex cities. Specifically, (*i*) industry entry decelerates except for that in cities at a low complexity level (top-right panel), (*ii*) industry exit also slows down at almost every level of complexity (medium-left panel), and (*iii*) the maintenance of pre-existing industries tends to be strengthened in cities at all complexity levels (medium-right panel). During the crisis, cities with lower complexity level are more likely to increase the number of new industries, whereas cities with higher complexity tend to increase the number of pre-existing industries and decrease the number of exit industries, when explanatory variables other than complexity are fixed. The post-crisis period could see more industries to enter and exit compared with the crisis period at every complexity level, and less complex cities may have a stronger tendency to maintain pre-existing industries[20].

[19] When it comes to the proportion of observations falling into the range of significance, during the crisis, the influence of the shock is negative on productivity growth when complexity is no more than 60, accounting for 84.6% of the observations. After the crisis, productivity growth increases compared with that before the crisis when complexity is below 10 and decreases above 55, making up 2.25% and 23.67% of the observations, respectively.

[20] When it comes to the significant marginal effect, for industry entry, during the resistance period, complexity below 20 (roughly 6.37% of the observations) may have a positive effect on the number of entry industries and complexity above 35 (66.54%) has a negative effect. During the recovery period, the figures are complexity below 50 (about 66.39% of the observations) and complexity above 75 (7.58%), respectively. For industry exit, the number of exit industries decreases during the crisis when complexity is more than 25 and after the crisis when complexity is more than 35, accounting for 86.75% and 67.62% of the observations, respectively. For the maintenance of pre-existing industries, the shock from 2007 to 2010 has a positive effect on the number of pre-existing industries when complexity is above 5 (99.48% of the observations), and the effect is positive at every complexity level from 2011 to 2013.

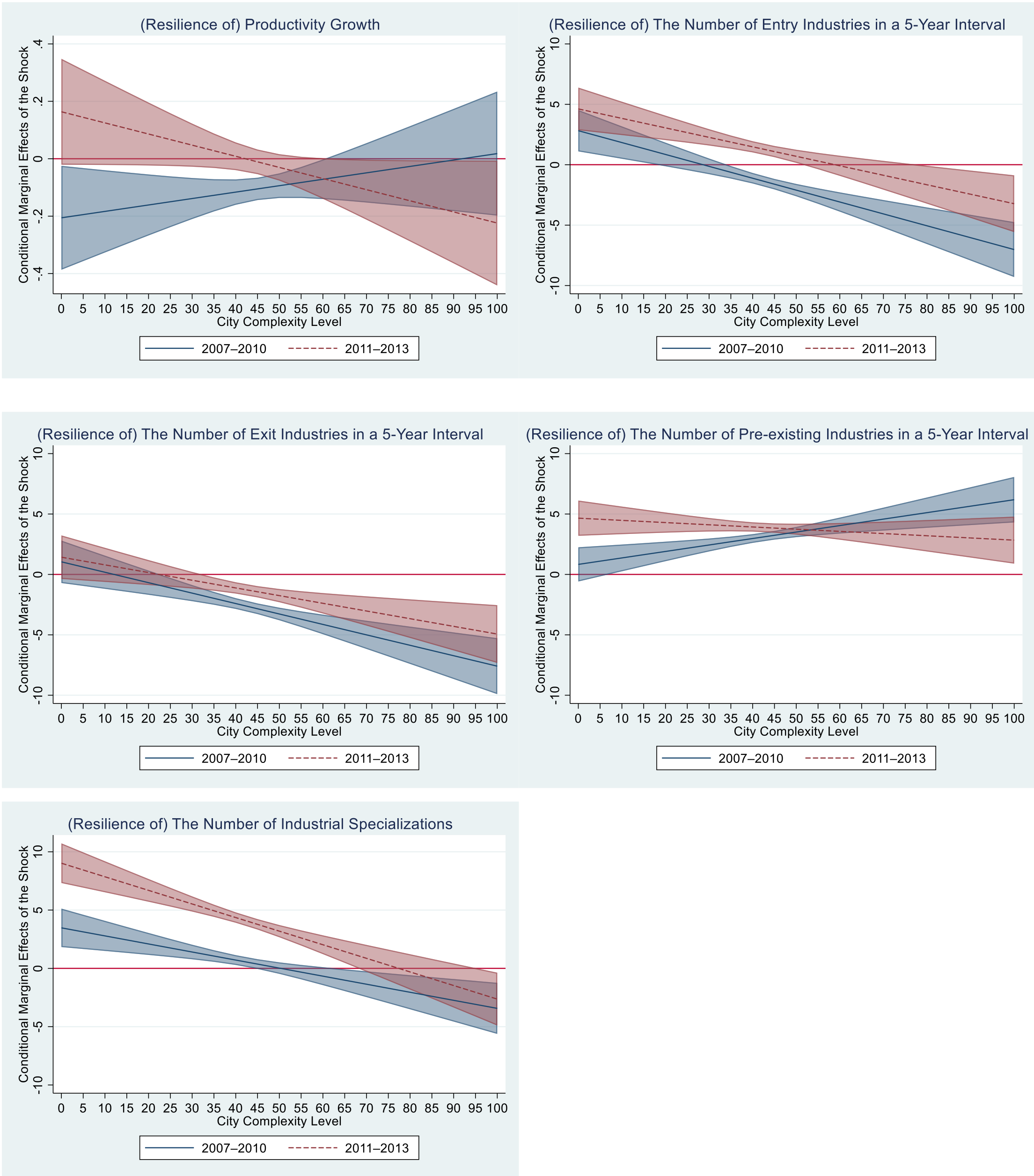

Figure 11. Marginal effect on different mechanisms of resilience conditional on complexity

Redistributing comparative advantages as a mechanism of resilience is more evident in less complex cities. Specifically, cities with lower complexity are more likely to develop new specialisations while stabilising industry exit and maintenance, thereby increasing their number of comparative advantages (bottom-left panel). On the contrary, highly complex cities tend to decrease industry entry and exit while increasing industry maintenance, which altogether has a reductive effect on the number of comparative advantages. During the crisis, the positive effect of complexity on keeping the number of comparative advantages can decrease with the level of complexity and even turn to a reductive one. During the post-crisis period, the number of specialisations can be larger than that during the crisis at every complexity level[21].

5.5 Robustness check

One issue is related to the validity of the argument that the pre-crisis period from 2005 to 2006 can be adopted as the control group when estimating the influence of the crisis in a difference-in-difference framework. The data on the explanatory variable goods transport growth is available from 2004 on, and for the availability of other variables, the start year could be as early as 1998. So, the question arises as to whether or the extent to which the unavailability of goods transport growth for the early years will influence the estimation results for the pre-crisis period, i.e. the control group in the difference-in-difference framework. The difference, if any, may be due to the fact that, during the build-up of the shock, the global linkages tend to decrease their contribution to the economic growth. Complementary analysis provides evidence for this argument in that, during the pre-crisis period from 2005 to 2006, the estimated effect of the export share is smaller for employment growth and the figure even becomes negative for output growth in comparison with the estimate during a longer period from 1999 to 2006. However, from 1999 to 2006 the national growth rates of the key indicators involved remain stable (see Figure 2), which might reflect the stability of the global market as a driving force for the domestic economy as a whole. Moreover, when evaluating the difference-in-difference model, the control group from 2005 to 2006 is more likely to generate consistent estimation results among different model specifications (e.g. Table 2) compared with that from 1999 to 2006. In this sense, 2005 to 2006 could represent the pre-crisis period effectively because the overall trend of economic growth was stable without remarkable change until 2007 and a relatively short pre-crisis period can help control idiosyncratic growth dynamics in the years of

[21] When it comes to the significant results, during the crisis period, complexity has a positive effect on the number of comparative advantages until the level of 45, but the effect becomes negative from the level of 60 on, accounting for 61.21% and 15.1% of the observations, respectively. During the post-crisis period, the number of comparative advantages tends to increase compared with its pre-crisis counterpart when the city complexity level is no more than 65 and can decrease from the level of 95 on, making up 85.45% and 1.13% of the observations, respectively.

boom.

6 Conclusion

This research aims at establishing the link between resilience and complexity. Following these two strands of literature, a conceptual framework is first constructed to shed light on the foundations to bridge these two concepts, and they are division, agglomeration, and connection. Comparative advantages (i.e. division) are bricks to build up the economy in the normal way. Complexity results from iterations of division and is an advanced spatial form of agglomeration. Connection makes it possible for division and agglomeration to exist together and update over time and across space. Shocks one after another are an inevitable movement of the symphony for development in company with growth. In this study, the complexity lens is adopted to examine the patterns, mechanisms, and necessities of resilience, in the context of the above-mentioned concepts. Empirically, we examine the influence of the shock proxied by the period dummies by estimating the extent to which the economic growth rate during and after the crisis changes compared with that before the crisis. Accordingly, the extent to which the influence of the shock varies depending on the city complexity level can be illustrated by the coefficient and standard error of the marginal effect of the shock conditional on each complexity level.

Three main findings are as follows. First, the influence of the shock on economic growth can vary depending on the city complexity level, when global and domestic demand are held fixed. The relationship between resilience and complexity can differ among resistance during the crisis and recovery after the crisis for employment and output growth. Low complexity can contribute to resistance in employment growth, while medium complexity can help resistance in output growth. Recovery can be found at every complexity level and can somewhat decrease with complexity. Second, global demand can have a positive correlation with complexity and can also modify the influence of the shock but not in the same way as complexity does. Domestic demand has no correlation with complexity and does not interact with the shock but its relationship with international linkages may be different in the face of a shock. Third, we find that temporary sacrifice of productivity growth alongside the redistribution of comparative advantages occurs in low-complexity cities in times of crisis. Cities with high complexity tend to sustain their pre-crisis sectoral strengths and decrease industry entry and exit. In this sense, policy makers can pay more attention to those cities at a lower complexity level to support them to arrange their building blocks to a reasonable pattern and to advance their industry composition as well.

This study contributes to the literature on the relationship between economic complexity and regional resilience by establishing a conceptual framework and empirical design and providing empirical evidence in a transitional economy such as China. A limitation in this study is the data unavailability for more recent years to examine a longer period of recovery. Future work could continue if researchers could get access to such informational data.

Appendix

A. Discussion of the potential limitation

Finally, to examine why regions present different degrees of resilience, the proposed baseline or control group has its own assumption and corresponding drawback, which could imply some limitation in a methodological sense. In the study by Martin et al. (2016), to assess how and why regions differ in their reactions to recessions, the change rate at the national level is adopted as the expected reaction, and then regional resilience is measured in terms of the difference between the actual and expected reactions. However, the underlying assumption of this baseline is that regions are assumed to react to this shock to the same degree, but the research question is to explore regional resilience at different degrees across space. Here comes the problem: the research question is supposed to deny the assumption no matter what the case is. In other words, either the assumption or the research question could act as the truth but both of them cannot be the truth at the same time. Nevertheless, the meaningful part of this chosen assumption and the corresponding research question is that the shock should be acknowledged as a common shock for different regions in the same country, although their reactions should not be assumed to be the same if the research question is to examine their different degrees of resilience, so a method in which regions are assumed to react differently from the very beginning is more reasonable if it is necessary to keep the assumption and corresponding research question compatible at the same time.

The study by Holm and Østergaard (2015) also examines regional industrial resilience when the business cycle turns and adopts the sales growth rate at the national level as the business cycle indicator common to all regions. This study assumes that the regional employment growth is faced with the same pressure derived from the national downward trend in the time of a shock, but regions differ in their industrial structure which could help them moderate the effect of the shock differently. Hence, this study may face the same problem as that in the first study because they both assume that different regions encountering a common shock of the same magnitude could react differently when the national level is adopted as the baseline. An endogeneity issue of this problem may lie in that the national reaction can actually vary with the reaction of every region involved, no matter how it is calculated. Another related issue in this study could be that the business cycle indicator (i.e. sales growth) as an explanatory variable can significantly correlate with the outcome variable of interest (i.e. employment growth), because they may follow roughly the same aggregate patterns when it comes to their ups and downs.

The study by Rocchetta and Mina (2019) explores how technological coherence can moderate the effect of a shock to a regional economy through a different-in-difference estimator. The assumption of the method adopted in this study is that resilience is defined based on the comparison of employment growth rates between the pre-crisis and the crisis periods. Continuation of the growth path thus serves as the foundation of resilience. In this sense, the exogenous shock for an economy may turn out to be something that acts as a coat for a person when this coat can be put on or taken off for this person without doing any good or harm. However, the difference between a coat and a crisis can be that, as it is believed, a coat is man-made and under the control of a human, but a crisis is exogenous and out of human control. If the method makes sense, this difference should not make sense. Hence, the results may be at the same reasonable level as this analogy, or in other words, a coat and a crisis are essentially the same thing and they are both man-made and under human control. But this actually may contradict with the assumption that the crisis is an exogenous one. This may constitute the inner contradiction of this method used to measure the causal effect of an exogenous shock in a difference-in-difference framework.

B. Descriptive statistics and correlation matrix

Table B1. Descriptive statistics

	Obs.	Mean	Std. Dev	Min	Max
Employment growth	2,990	0.207	0.790	-1	10.258
Output growth	3,004	0.488	1.764	-1	29.127
Shock dummy	3,042	1.111	0.737	0	2
City-level complexity	2,995	44.590	17.799	0	100
Export share	2,995	0.077	0.114	0	1.484
Goods transport growth	2,573	0.305	3.296	-0.995	103.931
Productivity growth	2,976	0.191	0.676	-0.919	19.668
Number of entry industries	2,923	10.064	5.212	1	37
Number of exit industries	2,997	9.009	5.555	1	55
Number of pre-existing industries	2,981	22.930	11.305	1	72
Number of specialisations	2,995	32.873	14.123	1	82

Table B2. Correlation matrix

	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*	*i*	*j*	*k*
a	1										
b	0.654*	1									
c	0.127*	0.106*	1								
d	0.020	-0.034	0.003	1							
e	-0.114*	-0.084*	-0.110*	0.684*	1						
f	0.000	0.003	0.010	-0.037	-0.028	1					
g	-0.016	0.340*	-0.008	-0.140*	-0.063*	0.033	1				
h	0.011	0.050*	0.090*	0.263*	0.046*	-0.010	0.044*	1			
i	-0.029	0.192*	-0.043*	0.412*	0.213*	0.004	0.016	0.331*	1		
j	0.030	-0.024	0.124*	0.660*	0.319*	-0.040*	-0.138*	0.288*	0.412*	1	
k	0.020	-0.010	0.108*	0.654*	0.289*	-0.038	-0.110*	0.614*	0.480*	0.931*	1

Notes: *a*: Employment growth. *b*: Output growth. *c*: City-level complexity. *d*: Shock dummy. *e*: Export share. *f*: Goods transport growth. *g*: Productivity growth. *h*: Number of entry industries. *i*: Number of exit industries. *j*: Number of pre-existing industries. *k*: Number of specialisations. * p<0.05.

Table B3. Descriptive statistics of sources of growth over time by complexity

		All years 2005–13				Pre-crisis 2005–06			
		Complexity level				Complexity level			
		All	Low	Medium	High	All	Low	Medium	High
Complexity	Mean	44.590	27.036	42.829	64.057	45.534	29.234	43.584	63.947
	S.D. [a]	17.799	8.001	4.323	13.359	16.768	7.035	3.055	13.342
	Obs. [b]	2995	1002	999	994	676	226	226	224
Global demand	Mean	0.114	0.025	0.047	0.162	0.096	0.035	0.058	0.195
	S.D.	0.077	0.037	0.047	0.157	0.118	0.042	0.041	0.154
	Obs.	2995	1002	999	994	676	226	226	224
Domestic demand	Mean	0.305	0.640	0.195	0.201	0.259	0.233	0.291	0.245
	S.D.	3.296	6.392	0.999	1.216	1.789	0.992	2.018	1.947
	Obs.	2573	624	933	986	570	139	209	222
		Crisis 2007–11				Post-crisis 2011–13			
		Complexity level				Complexity level			
		All	Low	Medium	High	All	Low	Medium	High
Complexity	Mean	43.55	26.224	41.756	62.837	45.383	26.634	43.801	65.830
	S.D.	17.745	7.737	4.403	13.837	18.499	8.710	4.629	12.510
	Obs.	1,351	452	451	448	968	324	322	322
Global demand	Mean	0.079	0.027	0.049	0.163	0.062	0.015	0.035	0.137
	S.D.	0.126	0.041	0.057	0.179	0.088	0.021	0.032	0.115
	Obs.	1,351	452	451	448	968	324	322	322
Domestic demand	Mean	0.296	0.578	0.197	0.210	0.347	1.001	0.125	0.159
	S.D.	3.175	6.258	0.405	1.039	4.122	8.385	0.179	0.664
	Obs.	1,142	280	420	442	861	205	304	322

Notes: [a] S.D. is short for standard deviation. [b] Obs. is short for observations.

On the one hand, we conduct t-test to examine whether the average values of each indicator are significantly different between different periods (at 5%) when the city group is fixed (Table B3). For complexity, the average value presents a U shape over time in each city group, although the increase from crisis to post-crisis is not significant in low-complexity cities and the decrease from pre-crisis to crisis is not significant in high-complexity cities. Regarding the export share, the average value significantly drops in the crisis period and even to a larger degree in the post-crisis period. For the goods transport growth, there are no significant changes in the average value over time in every city group except for medium-complexity cities experiencing a significant decrease in goods transport from crisis to post-crisis. On the other hand, we test whether the average values of each indicator are significantly different between cities at different complexity levels (at 5%) when the period is fixed. First, the average complexity is significantly different among three city groups. Second, cities at a higher complexity level tend to have a higher export share on average. Third, the growth of goods transport may not significantly differ with complexity.

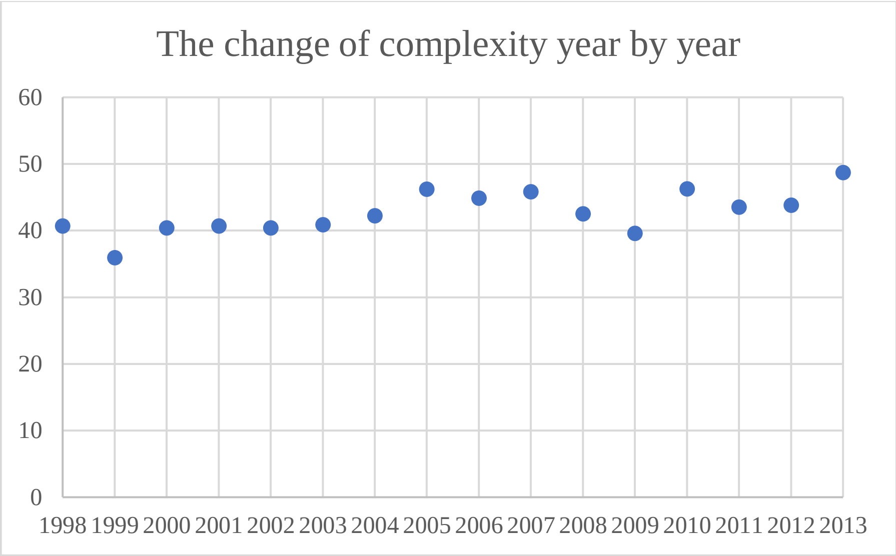

Figure B1. The change of complexity year by year in terms of its average value across cities

C. Complexity and resilience

Table C1. Results for Model 2: Difference-in-difference models to examine determinants of resilience

	Employment growth				Output growth			
	All complexity	Low complexity	Medium complexity	High complexity	All complexity	Low complexity	Medium complexity	High complexity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Complexity	–0.016***	–0.031***	–0.004	–0.027***	0.015	–0.012	0.027	–0.020
	(0.005)	(0.010)	(0.023)	(0.009)	(0.010)	(0.019)	(0.032)	(0.018)
Global demand	2.975***	–1.063	4.171**	2.244***	9.485***	0.727	13.235***	4.916***
	(0.553)	(1.236)	(2.103)	(0.645)	(1.043)	(2.295)	(2.976)	(1.266)
Domestic demand	–0.001	0.001	–0.005	–0.002	–0.005	–0.003	0.004	0.000
	(0.005)	(0.004)	(0.034)	(0.018)	(0.010)	(0.008)	(0.048)	(0.036)
Crisis	0.478***	1.027***	0.798	0.330	0.329	0.758	0.628	0.012
	(0.158)	(0.328)	(1.065)	(0.357)	(0.297)	(0.609)	(1.507)	(0.700)
Crisis * Complexity	–0.009**	–0.030***	–0.019	–0.004	–0.006	–0.022	–0.020	0.001
	(0.004)	(0.011)	(0.025)	(0.007)	(0.008)	(0.020)	(0.036)	(0.014
Crisis * Global demand	1.086*	–0.064	2.648	0.408	1.503	–1.005	6.339*	0.323
	(0.563)	(1.377)	(2.347)	(0.654)	(1.062)	(2.557)	(3.321)	(1.284)
Post-crisis	0.380**	0.441	–2.042*	1.410***	0.914***	–1.315*	–4.798***	3.327***
	(0.163)	(0.361)	(1.157)	(0.383)	(0.308)	(0.670)	(1.637)	(0.751)
Post-crisis * Complexity	–0.001	–0.018	0.054**	–0.017**	–0.005	0.041*	0.112***	–0.045***
	(0.004)	(0.012)	(0.027)	(0.007)	(0.008)	(0.022)	(0.038)	(0.015)
Post-crisis * Global demand	1.033*	5.316**	5.982***	0.904	3.682***	14.368***	33.340***	3.053**
	(0.549)	(2.150)	(2.270)	(0.631)	(1.034)	(3.994)	(3.212)	(1.238)
City dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.479	1.481**	–0.519	1.313**	–2.624***	0.040	–2.250	0.411
	(0.400)	(0.667)	(1.204)	(0.540)	(0.755)	(1.240)	(1.704)	(1.060)
Observations	2,537	617	934	986	2,537	617	934	986
R-squared	0.153	0.258	0.267	0.297	0.278	0.187	0.662	0.365

Notes: Standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

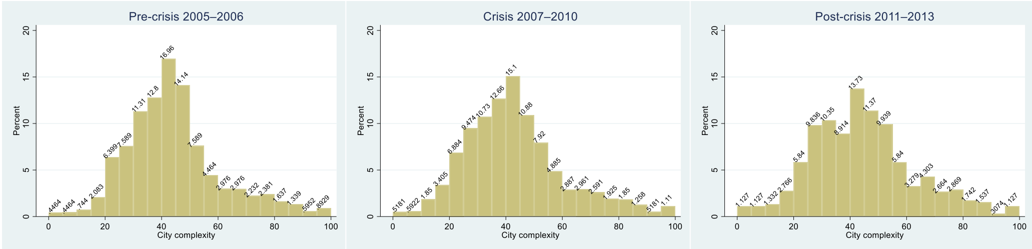

Figure C1. Distribution of city complexity as a moderating variable

Figure C2. Distribution of export share as a moderating variable

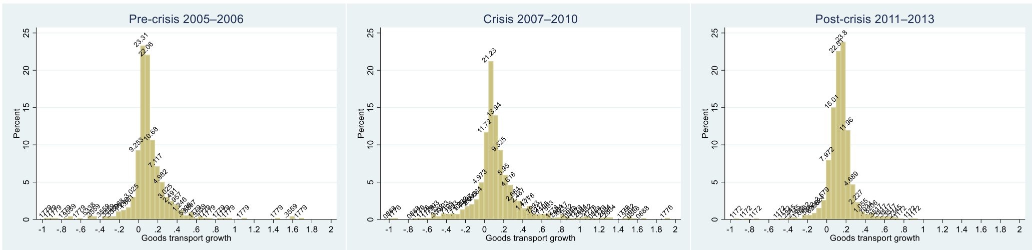

Figure C3. Distribution of goods transport growth as a moderating variable

Table C2. Results for the relationship between the export share and the goods transport growth

	Employment growth			Output growth		
	Pre-crisis	Crisis	Post-crisis	Pre-crisis	Crisis	Post-crisis
	(1)	(2)	(3)	(4)	(5)	(6)
Export	–0.385	–2.775***	6.605***	0.432	–1.731**	13.488***
	(0.325)	(0.658)	(0.695)	(0.498)	(0.785)	(1.267)
Goods	0.014	–0.006	0.057**	0.013	–0.011	0.090**
	(0.011)	(0.008)	(0.024)	(0.017)	(0.010)	(0.045)
Export * Goods	–0.164	0.028	–4.425**	–0.163	0.121	–8.316***
	(0.115)	(0.269)	(1.742)	(0.175)	(0.320)	(3.175)
City dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.072	0.974***	–0.743	0.119	1.010**	–1.587
	(0.091)	(0.330)	(0.651)	(0.139)	(0.394)	(1.186)
Observations	565	1,142	830	565	1,142	830
R–squared	0.563	0.174	0.451	0.636	0.199	0.632

Notes: Standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

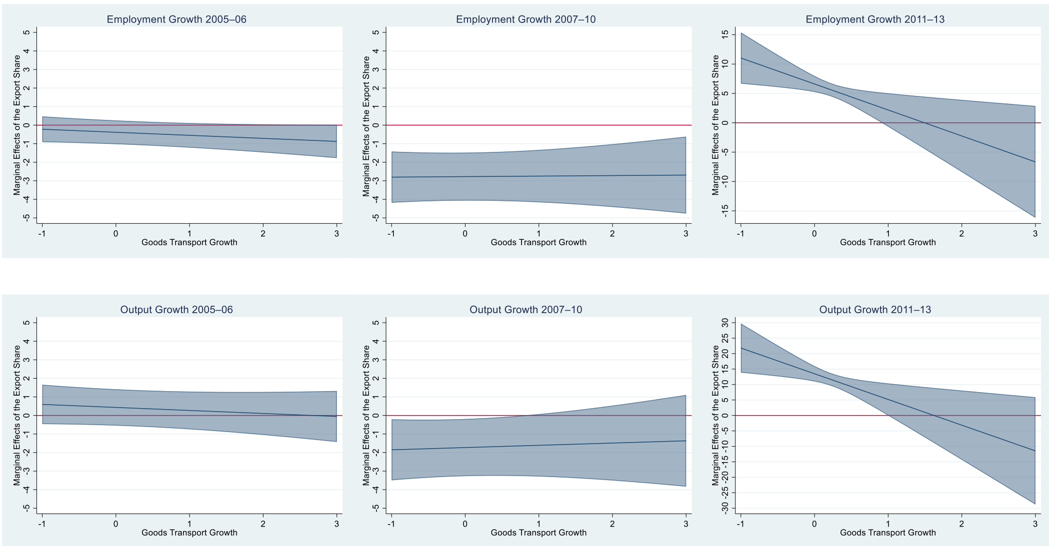

Figure C4. Marginal effect of the export share conditional on the goods transport growth

We evaluate the marginal effects of the export share on economic growth conditional on the goods transport growth during the pre-crisis, crisis, and post-crisis periods, respectively[1]. The results show that the role of the global market in regional

[1] Global and domestic demand can help regional resilience cope with a recession, particularly in the recovery period. Specifically, when the export share or the goods transport growth is controlled for, the

resilience could vary across space depending on a city's domestic demand. Based on the model specifications in Table C2, the results presented in Figure C4 show that the relevance of domestic demand for the influence of global demand on economic growth can vary across periods. Before the crisis from 2005 to 2006, the marginal effect of the export share on economic growth is almost zero regardless of goods transport growth[2]. During the resistance time in the aftermath of the crisis when the export share dropped from 2007 to 2010, the marginal effect of the export share is negative for both employment and output growth. However, an increase in the goods transport growth can lead to a decline in this reductive effect, which implies that the domestic market might more complement the global market[3]. In the subsequent recovery period from 2011 to 2013, the marginal effect of the global market on economic growth is positive but tends to decrease again as the goods transport growth increases[4]. Hence, the domestic and global market may constitute substitutes as sources of economic growth[5].

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contribution of complexity to resilience can decrease. The issue may lie in whether the domestic and global markets can act as substitutes or complements if they can interplay with each other to influence economic growth.

[2] When it comes to the percentage of observations falling within the range of significance, for employment growth, the marginal effect of the export share is significantly negative when the goods transport growth is larger than 1.1, making up 1.06% of the total observations. For output growth, the marginal effect is not significant for all observations.

[3] In terms of the significance of the marginal effect, it is significantly negative for employment growth at every level of goods transport growth and for output growth when the goods transport growth is below 1.5, constituting 85.89% of the observations.

[4] For significant results, the marginal effect on employment and output growth is significantly positive when the goods transport growth is no more than 0.9 and 1.0, accounting for 99.88% and all of the observations, respectively.

[5] When the global market performs well, a lower level of exploration by the domestic market means that the global market can face less competition and thus enjoy more development opportunities without much constraint. When the global market shrinks, goods transport growth may help the global market establish connections with the domestic market to recover.

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Study 3 Spatial disparities in state-granted land prices: The role of regional industrial relatedness and market-orientedness

Abstract Recent research shows that the importance of relatedness for regional diversification can be contingent on institutional arrangements at the country level. This chapter intends to explore the role of regional industrial relatedness in spatial disparities in state-granted land prices and the relevance of regional market-orientedness for such relatedness externalities in a transition economy like China. Parcel-level land transfer records matched with manufacturing firms above a designated size are applied in the empirical analysis. The results show that the relationship between land prices and relatedness is positive in highly market-oriented places and negative in low market-oriented places.

Keywords: State-granted land prices, regional industrial relatedness, city market-orientedness, industry complexity, agglomeration economies

1 Introduction

The importance of relatedness to regional diversification processes has been widely acknowledged in previous studies across a set of domains, ranging from products, to industries, skills, technologies, and exports (Hidalgo et al. 2007a; Neffke et al. 2011a; Neffke and Henning 2013; Petralia et al. 2017; Reinstaller and Reschenhofer 2019). In particular, how related diversification may unfold tend to present regional variations depending on various factors such as innovation capacity (Xiao et al. 2018b), interregional linkages (Balland and Boschma 2021a), development level (Pinheiro et al. 2022a), scientific capabilities (Balland and Boschma 2022). A recent strand of empirical work within this vast literature is interested in examining the relevance of institutions for related diversification (Antonietti and Boschma 2021; Boschma and Capone 2015a; Menzel and Kammer 2019; Santoalha and Boschma 2021). For instance, Boschma and Capone (2015) investigate how the form of market economy in the developed world can influence the direction of regional diversification into related or unrelated industries, and show that the probability to diversify into related industries is higher in coordinated market economies than in liberal market economies. An interesting case that could be studied in this context is the relevance of market-oriented institutional arrangements for related diversification in a transition economy like China. There have been a lot of discussions about how China transitions from a planned economy to a market-oriented economy (Wu 2002; Zhang and Wu 2019). Despite this national trend, certain regions can be more market-oriented than others (Jiang and Lin 2021; Liu et al. 2016). In this chapter, with a focus on spatial variance in land prices, we aim to explore how the importance of relatedness can be reflected in land values, and further test the relevance of regional market-orientedness for such relatedness externalities.

This chapter hypothesises that a firm operating in an industry more related to the local economic composition may invest in more valuable land resources, and this positive association can be stronger in highly market-oriented cities. The hypothesis rests on the premise that in a highly market-oriented place, where the local market is highly competitive, more related industries can make better use of the market offerings and thus may be willing to pay more to acquire land. We employ the dataset of Annual Survey of Industrial Firms (ASIF) covering all manufacturing firms above a designated size and match these firms with the parcel-level land transfer dataset obtained from the China land market website to get the information on which firms acquire land at what prices between 2011 to 2013. Regional industrial relatedness in terms of how related one industry is to the existing industries of a locality is calculated by adopting the same method as Hidalgo et al. (2007) on the basis of the co-occurrence patterns of industries at the city level. City market-orientedness is denoted by a comprehensive indicator to capture city-level innovation and entrepreneurship from a variety of aspects (i.e., new firm formation, inward investment, venture capital, invention patent, practical new-type patent, design patent, and brand), to which government institutions may be irrelevant. Relatedness can be subject to the diversity of the local industrial portfolio to come into being and thus deliver the information on the potential to establish linkages among previously unrelated industries by exploiting the benefits of geographical proximity. In this sense, relatedness is more likely to generate knowledge spillovers in highly market-oriented places, as relatedness externalities can capitalise on a high level of innovative and entrepreneurial capabilities in these areas to be more positive. One underlying mechanism can be that land prices in more market-oriented places can benefit more from the complementary relationship between complexity and relatedness, given that complex industries can be attached high economic values.

In order to address how relatedness can play a role in spatial disparities in land prices, we develop an empirical framework in the context of land marketisation in China, because the corresponding institutional background can enable the market mechanism to take effect in determining land prices and thus allow us to investigate relatedness externalities in terms of how relatedness can influence land prices. Previous research has delved into the determinants of industrial land expansion and efficiency in China from multiple angles, including but not limited to economic transition (Huang et al. 2015), local governments' supply behaviour (Huang and Du 2017), industrial economic structure (Yang et al. 2019), state strategy (Zhou et al. 2019), interaction between the state and market forces (Jiang and Lin 2021), and development zones (Xi and Mei 2022).

This paper can be positioned within the stream of literature on the local economic structure-land price relationship in that local economic structure may influence the formation of industrial land prices as a market force and thus act as one of the determinants of why land prices present spatial variations across cities (Lu and Wang 2020; Yuan et al. 2019). In particular, recent studies have demonstrated positive agglomeration externalities for land use efficiency, but agglomeration effects at the local level may differ when it comes to a specialised or diversified economy and present regional heterogeneity no matter the type of agglomerative forces (Peng et al. 2017; Zhang et al. 2022). Along this strand of literature on an agglomeration-land value relationship, what seems under-explored could be the role of regional industrial relatedness, which we argue as a form of agglomeration can generate a land price premium, and the degree of market-orientedness at the local level can affect the relationship between relatedness and land prices.

In the analysis, we test how relatedness at the city industry level is associated with land prices at the parcel level. To estimate relatedness externalities, we control for city-wide economic characteristics and firm-level attributes in a step-by-step manner to account for the relevance of regional socioeconomic levels and sorting effects in addition to a vector of government-related variables to reveal the presence of any supply pattern. We further examine the relationship between land prices and relatedness in cities at high and low market-orientedness levels separately to explore the relevance of market-orientedness for the relationship between land prices and relatedness. We find that a firm operating in a more related industry in a locality may be willing to pay a higher price to acquire land. Whereas this positive association between land prices and relatedness is stronger in highly market-oriented places, relatedness externalities tend to be negative in low market-oriented places.

The next section presents the conceptual framework for relatedness, land prices, and regional market-orientedness, followed by the third section, where we elaborate on the institutional background on how industrial land is granted to firms by the government in China. The fourth section outlines the calculations of regional industrial relatedness. In the fifth section, we explain the empirical design and findings concerning the relationship between relatedness and land rents and the role of market-orientedness in this relationship. The sixth section provides concluding remarks.

2 Conceptual framework: Relatedness, land prices, and regional market-orientedness

Since the land marketisation began, the market force has been playing an increasingly important role in shaping land prices. As a result, both the supply of and demand for industrial land can be related to how land prices display spatial disparities in terms of the land granted by the government to firms (Yuan et al. 2019). In other words, how land is granted can not only reveal the land supply scheme adopted the government in terms of its expansionary or contractionary nature (i.e., whether the government intends to increase or decrease the land supplied) but also signal the demand for the land in the market from the firms' side in terms of their investment decision (e.g., location, relocation, new projects). To examine how the demand side influences spatial variations in industrial land prices, previous studies have mainly focused on city-level driving forces (e.g., population density, economic structure, GDP per capita, outside capital) to account for between-city variations in land values (Lu and Wang 2020; Song et al. 2022; Yuan et al. 2019). However, it may be under-explored in terms of how demand-related factors can account for within-city variances in land prices. In this regard, we make an attempt to fill this knowledge gap by delving into the role of relatedness at the city industry level in spatial disparities in land prices. In the following three subsections, we argue that the relationship between regional industrial relatedness and land prices essentially reflects the existence of agglomeration economies and that relatedness externalities can vary across cities with different degrees of market-orientedness. Specifically, we first explore the concept of regional industrial relatedness, then probe into the relationship between relatedness and land prices, and finally illuminate the relevance of market-orientedness for such relationship.

2.1 Relatedness

The exploration of agglomeration economies as a source of economic growth and prosperity has stemmed from the seminal work Principle of Economics by Alfred Marshall in the late 19th century (Marshall 1890). From then on, a growing number of studies on agglomeration economies have ranged from magnitudes of different externalities (e.g. localisation economies, urbanisation economies), microlevel driving forces to the role of institutions (Duranton and Puga 2004; Farole et al. 2011; Puga 2010). Particularly, the past two decades have witnessed the promising developments of evolutionary economic geography, which aims to explain the spatial evolution of firms, industries and cities from a firm-location perspective (Boschma and Frenken 2011). One key assumption of how economies evolve over time is the principle of path dependence, which highlights the significance of historical processes in determining the location choice of new economic activities. Accordingly, related variety has been investigated by a large body of literature as a means of agglomeration externalities in addition to specialisation and diversification (Asheim et al. 2011; Boschma and Iammarino 2009; Castaldi et al. 2015; Content et al. 2019; Frenken et al. 2007), when these agglomeration externalities are all rooted in the existing industrial landscape. An institutional turn in economics and a spatial emphasis placed on the interplay between institutions and economic geography highlight the emergence of place-based policies for regional development (Barca et al. 2012). Pre-existing capabilities need to be better leveraged to help shape future development paths, and related variety can be one key notion in understanding regional assets (Balland et al. 2019a).

Regional industrial development is more likely to benefit from co-location with economic activities related to existing businesses, as knowledge spillovers between them could happen given their close cognitive proximity. This claim about related variety has been widely confirmed in the developed world and could be regarded as a rule that applies to the market economy (Essletzbichler 2015; Kogler et al. 2013; Neffke et al. 2011b; Neffke and Henning 2013). Particularly, evidence for the positive effects of related variety is more common compared with the relatively contradictory findings in terms of agglomeration economies derived from specialisation and unrelated variety

(Frenken and Boschma 2015). Cainelli and Ganau (2019) hypothesise that knowledge spillovers measured by related variety positively influences firms' short-run employment growth by analysing Italian manufacturing micro-level data. Duschl et al. (2015) examine the effects on firms' growth prospects of proximity to related economic activities and find that the positive association depends on the kind and age of industry. Specifically, proximity to knowledge-generating activities is more likely to be beneficial for firms' growth compared with intra-industry geographical concentration, especially for those firms at the early stage of industrial life cycle. When it comes to the relationship between new and existing industries, Neffke et al. (2011) find that new industries that are technologically related to pre-existing industries are more likely to enter the local market. This is because related businesses can have stronger absorptive capability to identify and exploit knowledge (Mueller 2007).

Previous studies distinguish *a co-occurrence concept of relatedness* from an *entropy-based measure of (related or unrelated) variety* (Content and Frenken 2016; Whittle and Kogler 2020). A recent study by Rocchetta et al. (2022) highlights that the regional technological coherence index for relatedness may exert an opposing effect on regional productivity compared with an entropy-based measure of variety, and the effect of entropy-variety on productivity is driven by related variety, although unrelated variety may exhibit the same shape as relatedness. Related variety and unrelated variety are two distinct measures captured by within-industry entropy and between-industry entropy, respectively (Frenken et al. 2007). They can constitute two components of industry variety at the local level. These two indicators are essentially subject to industrial hierarchy based on industry classification at different aggregation levels. However, the notion of co-occurrence relatedness is subject to a geographical hierarchy and is derived from proximity values between different industries based on their co-location patterns (Hidalgo et al. 2007a). That a place has a comparative advantage in an industry can be adopted as a proxy for the occurrence of an industry in a place. The co-occurrence matrices of industries count how often a pair of industries co-occur in the same geographical space, so that if two industries are related, they are more likely to be produced together, or vice versa. The proximity values derived from co-occurrence matrices can indicate the degree to which industries require similar factors of production (e.g., labour, land, capital, skills, technologies, or institutions) regardless of whether they as subsectors belong to the same sector or not. Clusters of industries based on their pairwise proximities are found to show agreement with how industries can be classified according to relative factor intensity (Leamer 1984). The relatedness level of a particular industry to the local industrial portfolio tends to be higher in a more diversified economy, which may possess a more diverse set of capabilities and can provide a larger portion of requisite capabilities for an industry to develop. Hence, related industries defined by relatedness are more likely to develop in a more diversified environment. In contrast, in an entropy-variety logic, related variety can resemble specialisation around some sectoral domains in terms of their similarities in a specific type of knowledge, whereas unrelated variety can make for a diversified economy with dissimilar knowledge (Grillitsch et al. 2018a). Therefore, it can have different meanings when it comes to relatedness as the driver of related diversification compared with related variety.

2.2 Relatedness and land prices

The local economic structure as a market force in China may influence the formation of industrial land prices and act as one of the determinants of why land prices present spatial variations across cities, although the findings may not necessarily display a consistent pattern in terms of the direction of the influence. For example, Lu and Wang (2020) show that higher dependence of local economy on oversea capital can lead to lower industrial land prices due to governments' behaviour in regional competition to attract investment; in contrast, Yuan et al. (2019) find that more capital inflows from outside China at the local level may result in a land price premium through increasing the demand for land. These contradictory findings may lie in how the relative importance of supply and demand in the land market may change over time, as evidenced by Huang and Wei (2016), who point out that agglomeration effects resulting from localisation and urbanisation economies may play an increasingly important role in the spatial distribution of foreign direct investment compared with government-related institutional factors (e.g., special economic zones, coastal open cities, provincial capital cities, and development zones).

With respect to the importance of agglomeration for land values, industrial agglomeration may stimulate land use efficiency, but the effects may differ when it comes to a specialised or diversified economy, and regional characteristics can be one factor to account for such different effects. For example, Peng et al. (2017) distinguish two main types of urban economic structure (i.e., the diversified and specialised economies), and observe that only a diversified economy can significantly improve intensive land use, and further reveal the existence of a larger minimum city-population-size threshold for diversified agglomerations to bring about positive technology externalities than that for specialised agglomerations. Another example from Zhang et al. (2022) highlights that with regard to the underlying mechanism (i.e., labour market externalities, technology externalities, and capital externalities) for agglomeration effects, specialised and diversified agglomerations can promote urban land use efficiency in different ways, and notes that the impact of industrial agglomeration in local and neighbouring regions may present regional heterogeneity no matter the type of agglomeration.

Due to the existence of agglomeration economies, a land price premium can result from industrial agglomeration at the local level. Relatedness refers to how one industry is related to the industrial portfolio of a city. When the relatedness is higher, the city can have a comparative advantage in more industries related to the industry. In this sense, relatedness can be regarded as one aspect of agglomeration in terms of the availability of regional capabilities that an industry requires. Hence, we argue that for industries presenting a higher level of relatedness at the local level, the land prices tend to be higher.

In the case of agglomeration, the relationship between agglomeration and individual-level economic performance can be derived from not only the existence of agglomeration externalities but also the sorting of well-performing firms towards dense agglomerations (Combes et al. 2012; Puga 2010). In other words, firm-level competition in regional industries at a higher relatedness level may be stronger. Accordingly, highly productive firms presenting higher relatedness to the local economy may end up in investing in places regarded as more valuable land resources. Hence, we argue that firm heterogeneity can act as one factor to drive up land prices.

2.3 Market-orientedness

Researchers seem to reach a consensus that the economic domains more related to existing local sectoral strengths can show greater diversification or growth potential than those less related (Content and Frenken 2016; Whittle and Kogler 2020). However, emerging evidence in recent literature shows that the role of relatedness in regional diversification may differ in different geographical contexts (Balland et al. 2019a; Petralia et al. 2017; Pinheiro et al. 2022a). The reliance on relatedness for new growth trajectories may also vary among industries. (Balland and Boschma 2021b; Feldman et al. 2015; Moreno and Ocampo-Corrales 2022).

One geographical dimension that recent papers focus on is about the place-specific institutional arrangements, which may influence the ability of regions or countries to diversify (Boschma 2017; Boschma et al. 2017). Boschma and Capone (2015) investigate how different forms of market economies in the developed world impact the direction of diversification into related or unrelated industries. The results show that relatedness as a driver of diversification is stronger in coordinated market economies than in liberal market economies, which can be characterised by incremental and radical innovations, respectively. They base their argument on the assumption that institutional frameworks can directly influence the sectors in which countries specialise and subsequently the type of innovations in each country. The arguments for a link between diversification and market conditions may rest on whether there exists easier access to credit on financial markets, a less specialised and more mobile workforce, market-based inter-firm relations, and weakly regulated product markets. Empirical evidence for the relationship between diversification and market-orientedness is found at the country level, however, we have limited evidence at the regional level.

Relatedness can be nurtured in a diversified environment in that co-located economic activities are more likely to be related over time (Juhász et al. 2021). Based on the co-location benefits, relatedness can be established between previously unrelated industries through building new connections between each other. And the foundation for such relatedness can lie in their similarities in capital, skills, inputs or outputs, technologies, institutions, and among others (Hidalgo et al. 2007a). The process of developing relatedness itself is a type of inter-industry cross-boundary innovation subject to a geographical hierarchy in terms of the diversity of the local industrial portfolio. Relatedness may spread from more diversified to less diversified areas to create new diversification opportunities for the latter[6], which may contribute to

[6] The relatedness of one industry with the industrial structure of one city can have positive values in most cases regardless of whether the industry actually exists in the city or not, but specialisation is only not null when the industry is indeed located in the city. Hence, compared with specialisation, relatedness can

nurturing relatedness to a lesser extent due to lack of diversity. However, following this principle of relatedness may imply a lock-in situation for less developed areas based on their relatively narrow range of existing capabilities. One underlying cause of this phenomenon may lie in a virtuous circle of relatedness accumulation and innovation enhancement on the basis of their feedback into each other: relatedness can act as a regional driver of innovation (Miguelez and Moreno 2018b; Moreno and Ocampo-Corrales 2022), and in turn an innovative and entrepreneurial platform may help transform and update the system's existing capabilities (McCann and Ortega-Argilés 2016; Rocchetta et al. 2022b). For example, Feldman et al. (2015) find that the absorptive capacity in larger, more inventive cities may hinge on a knowledge base with related technologies to develop target technologies in a significant manner but the influence of cognitive proximity in small cities is not significant. Plunket and Starosta de Waldemar (2022) show that relatedness can promote incremental innovations that reuse existing technological combinations and that small and novel players are more likely to build on local relatedness to produce innovations than universities and large organisations.

More recent studies have investigated relatedness as a driver of diversification in a complexity-framework context. Complex industries that are difficult to produce and imitate are regarded as economically valuable and thus generate both high rents and comparative advantages (Balland and Rigby 2017; Rigby et al. 2022). The capacity to develop complex industries can enhance the region's competitiveness by creating high values (Rigby et al. 2022). Balland et al. (2019) highlight the importance of relatedness for regions to diversity into complex industries, that is, regions need to rely on related capabilities to develop new specialisations in complex activities. In this sense, spatial variations in diversification processes towards complex industries can be to some extent attributed to how the relatedness to complex industries is geographically uneven distributed. Specifically, the relatedness to complex industries is found to be higher in economically advanced economies than in lagging areas, in accordance with a positive correlation between relatedness and development levels (e.g., GDP per capita, population density) at both the national and regional levels (Pinheiro et al. 2022a, 2022b). Again as Balland et al. (2019) show, a region with a more diversified portfolio

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provide information on a much wider range of industries particularly when it comes to the relationship between a new industry and pre-existing industries at the local level.

is more likely to provide a large set of capabilities for a rich number of related high-complex and low-complex technologies to develop at low risk. Moreover, Davies and Maré (2021) stress a city-scale dependence for the interaction between relatedness and complexity and only observe such interaction benefits for local employment growth in larger cities, where a sufficiently large labour market may enable knowledge spillovers among related activities.

3 State Land Granting to Industries in China

3.1 Land marketisation

Year 2007 marked a milestone in the marketisation process of industrial land in China. On the one hand, according to the Circular of the State Council on issues related to Strengthening Land Regulation and Control (State Council of China 2006), the use right of the state-owned construction land has to be transferred to industries through market-oriented tender, auction, and listing methods with the land price no smaller than the issued least standard price. This practice can improve the efficient utilisation of land and optimise the distribution of land resources by avoiding local governments' supplying extremely low land prices or even free land to firms and thus allowing the market mechanism to take effect in resource allocation. For example, Yuan et al. (2019) employ parcel-level urban land transaction records for 2008 and 2015 to investigate the relative importance of the market and the government in determining the heterogeneous pattern of urban land prices in China and show that market forces are playing an increasingly important role in land prices, although local governments can still exert an influence on industrial land markets through land supply decisions. On the other hand, the Outline of National General Land Use Plan in China (2006–2020) (State Council of China 2008) is released as a long-term guidance for the protection and utilisation of land resources, which provides national- and provincial-level control indicators for different land-use types (e.g., the quota for construction land supplied before 2010 and 2020, particularly urban land for industry and mining purpose); however, the 15-year land use planning quota in terms of the binding target of newly increased construction land was exhausted within 7 years (Wang et al. 2020), although the planning implementation can have a certain effect on curbing the expansion of construction land (Zhou et al. 2017b). In this sense, how to resolve the contradiction between the growing scarcity of land resources and the increasing demand for urban land can be no less serious than ever.

Figure 1 illustrates the dynamics of the state-owned land supplied for construction use from 2003 to 2017 at the national level. First, the total land supplied, the land supplied for industry, mining and warehousing, and the land granted to manufacturing showed roughly the same temporal trend no matter when it comes to their amount or growth rate. Second, there exhibited an inverted-U shape in terms of how the figures of amount fluctuated over time, particularly during the period from 2008 to 2016. Third, a sudden drop in the growth rate of land supply was observed in 2007 and 2008, which may result from the decline in the global demand in the context of the Global Financial Crisis at that time. Our further calculation shows that the share of the land supplied to industry, mining and warehousing as a major land-use type in construction land saw a decrease from 40.63% in 2003 to 23.17% in 2017, ranking the highest before 2011 and then being surpassed by that for other uses (e.g., transport, public management and public services) but still exceeding those for residential uses and commercial and service uses. Moreover, the proportion of the land granted to manufacturing in both the total land supplied and the land supplied for industry, mining and warehousing rose from 2007 to 2010 and then fell gradually to 8.40% and 36.24% in 2016. Overall, the dynamics of land supply is closely connected with the aggregate economic landscape, and the share of the land granted to manufacturing signals its importance in the economy, but the stylised fact of its amount growing more slowly over time or even shrinking to some extent may warrant attention to help understand the demand side of the industrial land market.

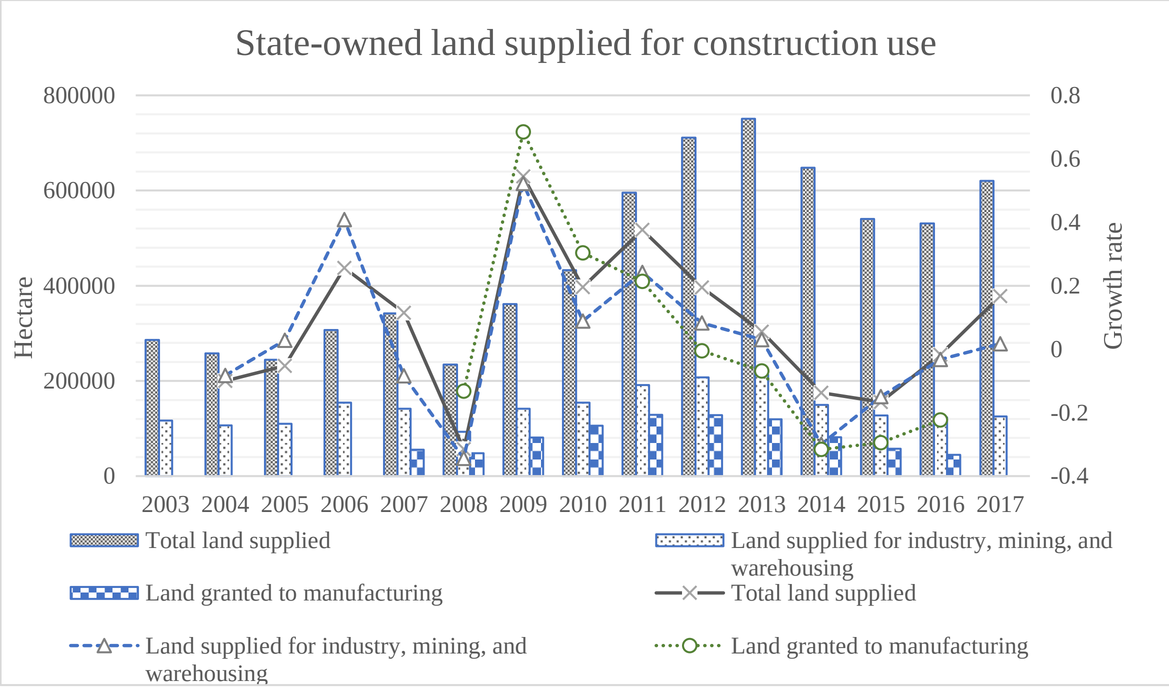

Figure 1. Supply of state-owned construction land 2003–2017

Source: The data for total land supplied and land supplied for industry, mining, and warehousing from 2003 to 2017 are collected from the China Land and Resources Statistical Yearbooks, and the data for land granted to manufacturing from 2007 to 2016 are obtained from the China land market website.

Figure 2 presents how the quantity and price of the land granted to manufacturing changes from 2007 to 2016 in the context of land marketisation. The amount of land granted presents an inverted-U shape over time, reaching its peak in year 2011 and 2012 and then declining. The land price per hectare first increased from 2007 to 2009, then decreased until 2012, and increased again continuously before 2016. In this sense, the fluctuations in the land market can to some extent be attributed to the land supply side given the divergence in the changes in quantity and price. Specifically, from 2009 to 2012, an increasing amount and a decreasing price are consistent with the expansionary land policy which aims at boosting investment due to the economic downturn pressure in the face of the Global Financial Crisis (Zhou et al. 2017b), whereas between 2012 to 2016, the decrease in amount and the increase in price may result from the tightening of land supply, as the scarcity of land resources requires the government to supply land more wisely to make better use of this limited resource (Liu et al. 2016). Overall, the relationship between quantity and price in the land granted to manufacturing somewhat reveals an increasing supply constraint faced by the land demand side, thereby posing a challenge for the supply side to meet in reality in term of how to better satisfy the land demand.

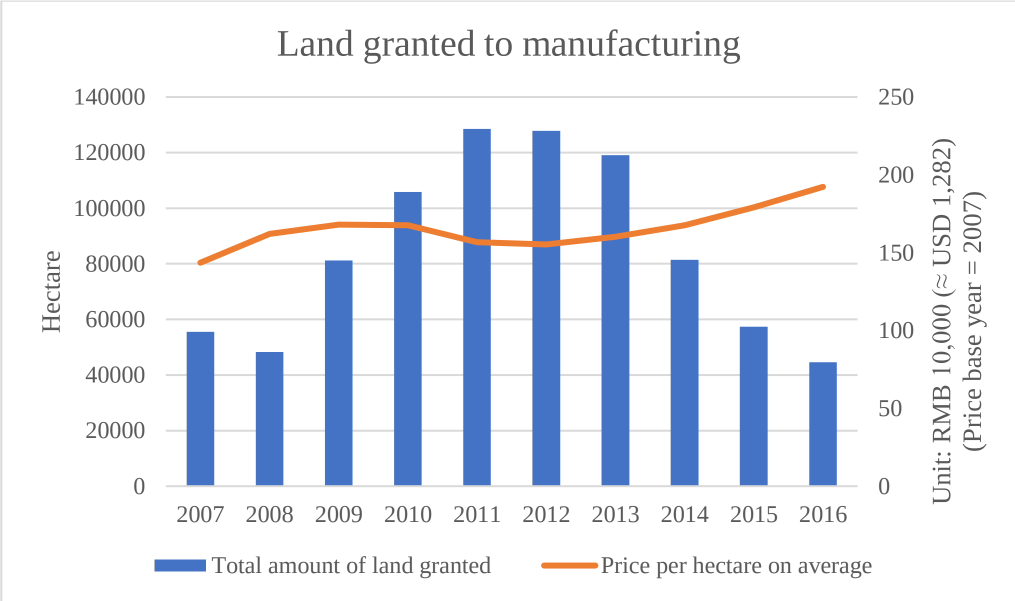

Figure 2. Quantity and price of land granted to manufacturing

3.2 The primary land market and the state

Land is either state-owned or collective-owned in China, and the land ownership cannot be transferred but land-use rights can be transferred on the market (Tian and Ma 2009; Yuan et al. 2019). There exist two tiers of land markets in China (i.e., the primary land market and the secondary market) depending on whether the land is provided by the government or firms when a firm requires land (Jiang and Lin 2021). The government provides land for granting in the primary land market, whereas firms transfer the use rights of land between each other in the secondary land market. The secondary land market is operating under the government regulation to make sure that the land prices in transferring is no less than the standard land prices set by the government to avoid inefficient transections. In this sense, during the economic boom period, the industrial land in the primary market is normally cheaper than that in the secondary market so that firms tend to acquire land from the government; however, in slump times, the land prices in the secondary market tend to be lower than those in the primary market, so that the secondary market where firms transfer land among each other may be active at that time. Around year 2013, when the increase in the industrial land supply was relatively high and the land market was at its boom period, the majority of land parcels for industrial use were granted by the government through the primary land market. Actually, so far, the secondary market for industrial land may be only active in more market-oriented areas and not universal nationwide, meaning that industrial land is predominantly provided by the government.

Land marketisation enables the combination of the state and market powers in shaping the geography of industrial land prices (Jiang and Lin 2021). The central government as the owner of urban construction land empowers the local governments as its agents to regulate the granting of industrial land, in which local authorities can make the best of market mechanisms (e.g., market-oriented land transfer methods, including auction, tender, and listing) (Liu et al. 2016). That a land parcel is granted by the government to a firm is the result of not only the decision of the firm over whether to invest in the land but also the decision of the government over whether to provide land or not. In this sense, one local government can be regarded as a company for granting industrial land, so that all local governments can constitute the supply side of the land market. This enables us to investigate the relevance of the government's supply behaviour for land prices in a systematic manner. Specifically, it is found that parcel-level industrial land prices tend to be negatively associated with per capita area of granted land at the city level (Yuan et al. 2019), implying that the government's land supply behaviour can influence between-city variations in land prices through determining the quantity of land for granting, so that places faced with a more severe industrial land supply constraint can have higher land prices.

Land marketisation does not necessarily mean that a steadily rising industrial land prices as a result of the switch from a government-dominated land pricing system to a market-oriented pricing mechanism can influence land demand or supply patterns substantially. On the demand side, Zhao et al. (2022) explore how the increase in land prices as a result of the land pricing reform in 2007 can reduce land demand and curb industrial land expansion by increasing the substitution between land and other inputs (capital and labour), and the results show that substitution is only observed between land and capital but the degree of substitutability is very low. In this sense, the effect of land prices on curbing urban industrial expansion, if any, can be very limited. On the supply side, the fees of granting industrial land as a source of local revenues are being attached diminishing importance as incentives for local governments to expand land supply, due to its relatively small share in local revenues in relation to the limited demand for industrial land. For example, in 2013, the transaction price value for land granted to industry, mining and warehousing only accounts for 6.8% of the public finance income nationwide, and the portion tends to decrease when the regional development level increases. Hence, we may expect that land prices can affect governments' land supply behaviour in a limited manner as well.

With respect to the role of multi-scalar governments in land supply, the land use planning system is implemented in China to regulate land use in a top-down and quota-based way (Zhou et al. 2017b). In this top-down system, the land use planning at the higher-level government is the guideline for that at the lower level, when five levels are covered and consist of nation, province, prefecture, county and township. The quota-based model indicates that the national land use planning provides the maximum amount quota of construction land, particularly its subcategory of land for industry, mining and warehousing, for a period of usually 15 years. On the one hand, the quotas determined by the central government are allocated between province-level governments and gradually delineated to the township level. On the other hand, the land use planning is implemented through the annual land use plan, which assigns annual land use quotas. In this sense, both the central government and local governments are involved through making short-term and long-term plans about land use before granting industrial land. In addition to land use planning, urban planning is another dominant government tool of territorial development guidance to accommodate industrial projects into areas planned for industrial land use (Gao et al. 2014; Zhang et al. 2018).

The role of the state in land supply may also lie in how economic zones as an essential source of industrial land can influence industrial landscapes (Wei et al. 2009; Zheng and Shi 2018). The construction of industrial zones may be dominated by the government aiming at establishing land markets subject to institutional regulation and control (Ding 2003; Gao et al. 2014). The industrial zone programme as a place-based policy is found to have positive effects on capital investment, employment, output, productivity, wages and the number of local firms (Lu et al. 2019; Wang 2013). In practice, development zones can be initiated by governments at different hierarchical administrative levels, and national-level zones originate from the state's will and operate under national supervision (Zhuang and Ye 2020). National zones may set higher entry threshold (e.g., investment intensity and tax revenue) to filter industrial enterprises and projects that apply for industrial land than the criteria imposed by the local governments (Zhang et al. 2018). Xi and Mei (2022) show that the establishment of a development zone at a provincial level or above can encourage the local government to expand the scale of industrial land transfers and adopt the approach of listing for land transfers, which may reduce the land allocation efficiency for the manufacturing industry.

Last but not least, industrial policies to guide local governments' land-supply behaviour may co-evolve with the actual demand from the industrial side. Chen and Naughton (2016) observe that China's technology and innovation policies may involve more government interventions targeted at specific industrial sectors after 2003, which somewhat mirrors the needs of high-quality development in China (Cheng et al. 2022). Yang et al. (2019) show that the allocation of land resources can be closely aligned with the industrial composition, and that the evolution of land use structure not only follows the law of upgrading from labour-intensive to capital-intensive and then to knowledge-intensive industries but also presents spatial variations in accordance with different upgrading stages at the regional level. Zhou et al. (2019) find that, as a response to the national strategies to promote economic transformation and industrial upgrading, local governments may be encouraged to attract more investment from high-tech industries in the process of land supply. Dong et al. (2021) show that higher land subsidies can increase the likelihood of a region to develop specialisations into new industries, and this degree of increase is greater for new industries with a higher level of complexity in comparison with the existing local industrial base.

3.3 Process of granting industrial land

In practice, although the process of granting land to industries may differ by city in detail, in general the way through which land is granted by local governments to firms can be described in the following five steps applicable nationwide, as Figure 3 shows.

First, guided by the urban planning and land use planning, a plan is determined as a top-down process (from province to city, from city to county) to control for the amount of industrial land that can be allocated to industries at the local level. Specifically, the indicator (i.e., the amount of land) is allocated among lower-level governments (e.g., cities) by the higher-level government (e.g., province). Although every year there is an overall control for the total amount of land for allocation at the national level, the plan is proposed based on the conditions (e.g., population, location, economic development situation) of a locality. For example, the province normally takes into consideration the situation of land granting in previous years in different cities to allocate this indicator.

The amount of land for granting at the local level is inelastic overall but can be flexible depending on the specific case.

Second, based on the annual land supply indicator in terms of the total amount of industrial land planned for granting at the local level, the local authorities need to come up with a relatively detailed plan to decide on the concrete implementation measures from several aspects, including basic principles, policy guidance, land parcels, supply plans (e.g., amount, structure, distribution, timetable, methods), guarantee measures (Ministry of Land and Resources 2010). This plan needs be made and published by the administrative departments of land and resources at the municipal or county level, which directly take charge of the work related to the granting of industrial land.

Third, the buyer would normally contact and communicate with the local government for information about the industrial land to be granted (e.g., the availability of a land parcel in a particular location for a particular investment purpose) in advance from the very first. Meanwhile, the government would generally set out to grant a land parcel when they know there exist potential buyers. In this case, if the land is available and buyers also exist, the buyers would be informed of the time when the granting announcement for auction will be published by the government, and then the buyers would take part in the auction, for example. Although the overall plan for the whole year in the whole region needs to be determined at the outset, the exact information about land parcels for granting cannot be completely certain at the beginning of the year due to various uncertain factors at the subregion or firm level (e.g., economic development, local plans, the progress of talks, the situation of projects). Sometimes other stakeholders or property owners (e.g., factories, urban villages) may be involved in a land parcel. The procedure of state-owned land collection and storage then needs performing through the operation of land conversion (e.g., relocation, demolition, compensation), which can make the whole process more complex. In most cases, the existing land parcels, particularly those located in industrial zones, would be given priority for granting.

Fourth, the local government is required to make a draft about the granting plan scientifically, prepare granting documents reasonably, and carry out tender/auction/listing for industrial land effectively. When making a draft about the plan for granting industrial land, the local administrative department of land and resources should consider not only the planning conditions (e.g., land use general planning, annual land use plan, urban planning) to grant land but also the local industrial characteristics (e.g., surrounding industrial distribution, environment requirements, land pre-application situation) by collecting clear comments made by different divisions of the local government (e.g., land and resources, development and reform, planning, environment and protection) in order to make a draft from various aspects (e.g., the parcel amount, concrete usage, land use conditions, industrial requirements) (Ministry of Land and Resource 2008a, 2008b). Moreover, local authorities should make industrial characteristics of the land parcel clear when preparing the documents to grant industrial land by providing investment intensity, industrial requirements, concrete industrial land grade and the like accordingly in addition to the general planning conditions (Ministry of Land and Resources 2007a). The first-time official announcement will provide the information and instructions of land granting, including starting time for tender/auction/listing, location, land area, land usage, planning indicator requirements, time span for land use, opening price, granting documents, granting procedures. In particular, the opening price is estimated by the third party based on the land market situation and can hardly be influenced by the government.

Fifth, the land granting notice will be released online by the local land and resources administrative department to allow for market-oriented transfer methods (i.e., tender, auction, listing) applied in the process of granting land. Taking the format of listing this common mechanism as an example, after passing a preliminary examination of qualifications, bidders attend the listing process, and the bidder offering the highest price which is no less than the opening price will be the final buyer. In this process, the bidder and their bidding price will be updated online in time. After the buyer is determined, within the assigned period of time, the content and the contract for granting need to be signed between the buyer and the seller, and a result announcement for granting needs to be published online later to make the information on land parcel and the deal public. Nevertheless, if there is no bidder during the process of listing, the initial announcement for granting will be cancelled. In particular, the local government is prohibited from setting exclusive qualifications and conditions for applicants (Ministry of Land and Resources 2007a).

Overall, the whole process is made public in terms of the granting plan, granting announcement, granting procedure, group determination of the opening price, bidding process, and granting result, and when the information is transparent as much as possible for people who need to know, the result of tender/auction/listing is market-oriented due to complete competition (Ministry of Land and Resources 2007a). The competitive nature of land granting has nothing to do with the number of participants in bidding (Ministry of Land and Resources 2007b).

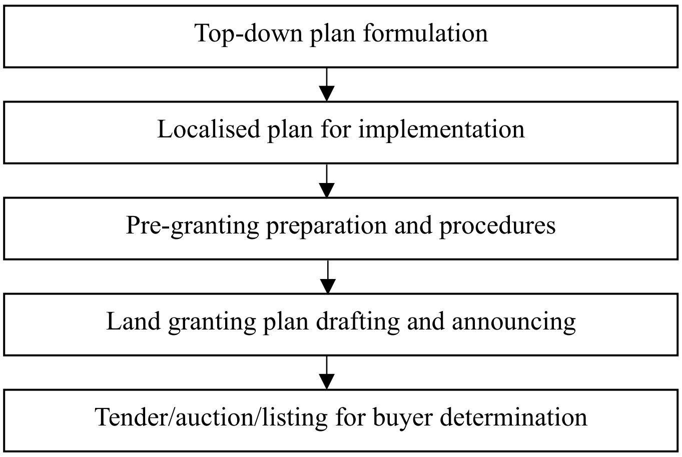

Figure 3. Elaboration on the process of granting industrial land

4 Measurement of regional industrial relatedness

4.1 Proximity

We calculate the regional industrial relatedness by applying the co-occurrence approach to portray the industrial space (Hidalgo et al. 2007a). The first step of measuring relatedness is to examine how related every pair of industries is by calculating proximity between them. Proximity is captured by the minimum of the pairwise conditional probabilities of a city having a comparative advantage in one sector given that the city also presents a comparative advantage in another sector. It is computed as follows:

$$\phi_{jkt} = min\{P(RCA_{jit} > 1|RCA_{kit} > 1),\ P(RCA_{kit} > 1|RCA_{jit} > 1)\} \quad (1)$$

where ϕ_{jkt} represents proximity between industry j and industry k at year *t*; RCA_{jit} stands for revealed comparative advantage for industry *j* in city *i* at year *t*, and takes the form:

$$RCA_{jit} = \frac{Employment_{jit}/\sum_j Employment_{jit}}{\sum_i Employment_{jit}/\sum_{i,j} Employment_{jit}} \quad (2)$$

where $Employment_{jit}$ is the number of employees working within sector *j* of city *i* at year *t*; $\sum_j Employment_{jit}$ is the total number of workers in all sectors of city *i* at year *t*; $\sum_i Employment_{jit}$ is the total number of employees in sector *j* nationwide at year *t*;

$\sum_{i,j} Employment_{jit}$ refers to the total employment of all sectors nationwide at year t. RCA_{jit} measures whether the industry j's production in city i is more than the average level in Chinese cities at year t (RCA_{jit}>1), indicating the level of specialisation of that industry j in city i.

Based on the equations above, to take industries in 2013 for an example, a 30-by-30 matrix of proximity values between every pair of 2-digit industries, a 165-by-165 matrix for 3-digit industries, and a 470-by-470 matrix for 4-digit industries, are calculated[7]. Each column or row in a matrix refers to one industry, and each element in a matrix refers to the proximity value between a pair of industries. Figure 4 shows the proximity matrices in 1998 and 2013 at different aggregation levels. Columns in proximity matrices are sorted by a complete linkage clustering algorithm, and elements with higher values are marked in brighter colours. Hierarchically clustered matrix presentation reveals a modular structure. The clustering of industries is shown to the left of a matrix with each colour representing a cluster. Compared with those in 1998, industries in 2013 can form fewer clusters at each aggregation level. More specifically, there are five distinct 2-digit clusters in 1998 but three in 2013, six 3-digit industries in 1998 but four in 2013, and five 4-digit industries in 1998 in contrast with four in 2013. This might reflect a higher level of relatedness among industries in 2013, when the likelihood of co-occurrence had increased with more linkages established among industries since 1998. This pattern corresponds with the finding that the average level of relatedness among 4-digit industries in 1998 is 0.137 and the figure for 2013 is higher at 0.159; the figure for 3-digit industries in 1998 is 0.186 and the figure for 2013 is 0.189. But with regard to 2-digit industries, the figure in 1998 is larger at 0.246 (0.238 in 2013), which might result from a higher level of homogeneity in terms of 2-digit industrial composition among places, but the real linkages might not have been established yet (as indicated by lower relatedness among 3-digit and 4-digit sectors than that among 2-digit sectors).

[7] Industries are categorised according to the China Industry Classification standard (GB/T 4754 2002). An industry is a collection of units that carry out similar economic activities. Such standardised industry classification system can give external validity to the empirical work in China by ensuring international compatibility. But we are limiting the way we can deal with the heterogeneity of industries, as certain types of economic activities cannot be classified in detail given the three tiers of industrial aggregation.

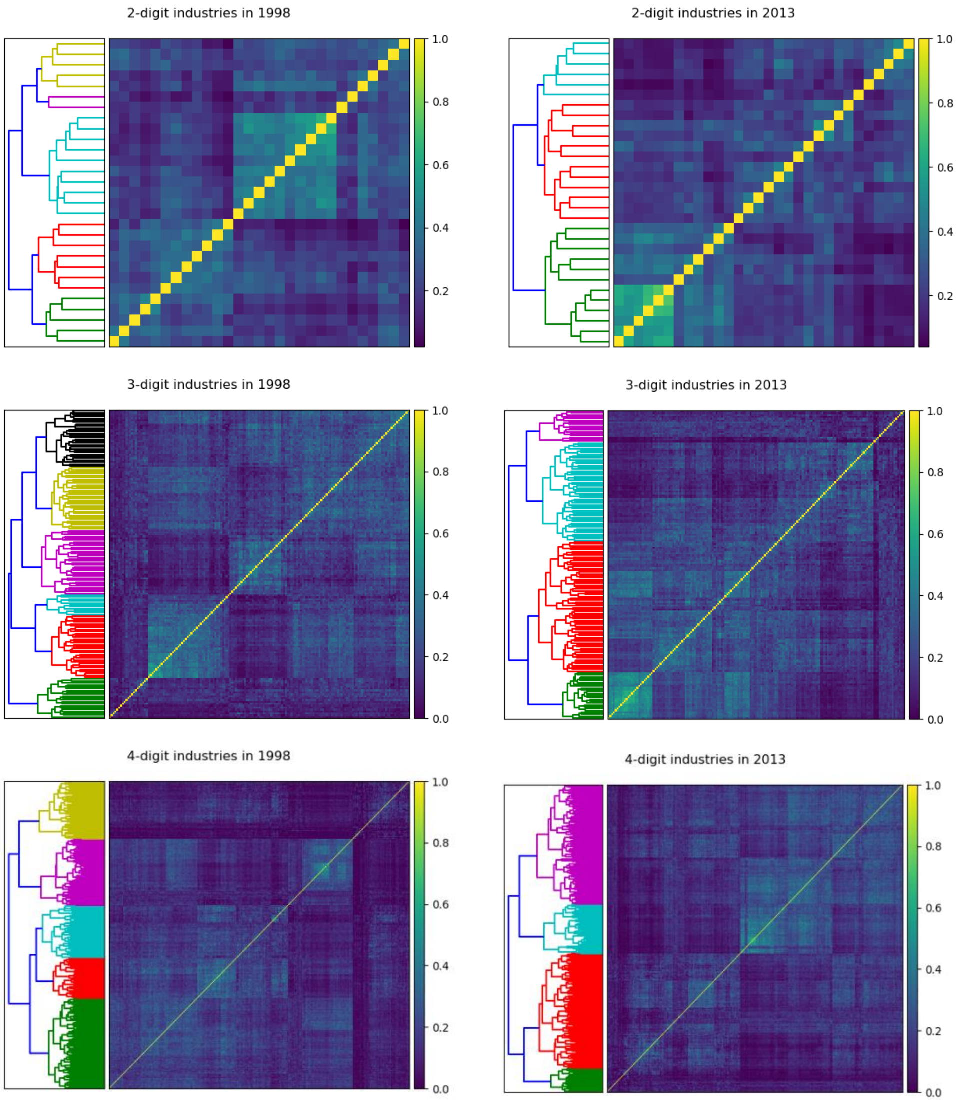

Figure 4. Hierarchically clustered proximity (ϕ) matrix in 1998 and 2013 for 2-, 3-, and 4-digit industries

Figure 5 compares the differences among 2-digit, 3-digit, 4-digit industries in terms of the cumulative distribution and frequency distribution of proximity values. It appears that the figures for 4-digit industries tend to be smaller compared with those for 3-digit and 2-digit industries. So as the industrial aggregation level increases, the co-location patterns tend to be more evident among industries. For example, with regard to 2-digit industries, the proximity between "Processing of Food from Agricultural Product" and "Manufacture of Foods" is relatively high at 0.63 in 2013, well above the average level among all 2-digit industries (0.24). This may result from their shared production capabilities, similar requirement for natural resource endowments and similar targeted consumer markets. However, when it comes to the proximity between 4-digit subsectors within these two sectors, situations vary widely among different pairs of subsectors, with proximity values ranging from 0 to 0.52 and at an average level of 0.21, which is still above the average level among all 4-digit industries (0.16). For instance, the proximity between "Grain Grinding" (a subsector of "Processing of Food from Agricultural Product") and "Rice and Powder Manufacturing" (a subsector of "Manufacture of Foods") takes the value of 0.52, while the proximity between "Fish Oil Extraction and Product Manufacturing" (a subsector of "Processing of Food from Agricultural Product") and "MSG (monosodium glutamate) Manufacturing" (a subsector of "Manufacture of Foods") is zero. Lower proximity values among 4-digit subsectors thus reflect variances in subsectors that belong to the same sector as well as the difference between 2-digit sectors. In this sense, proximity measured at a more disaggregated level may capture the degree of relatedness more accurately.

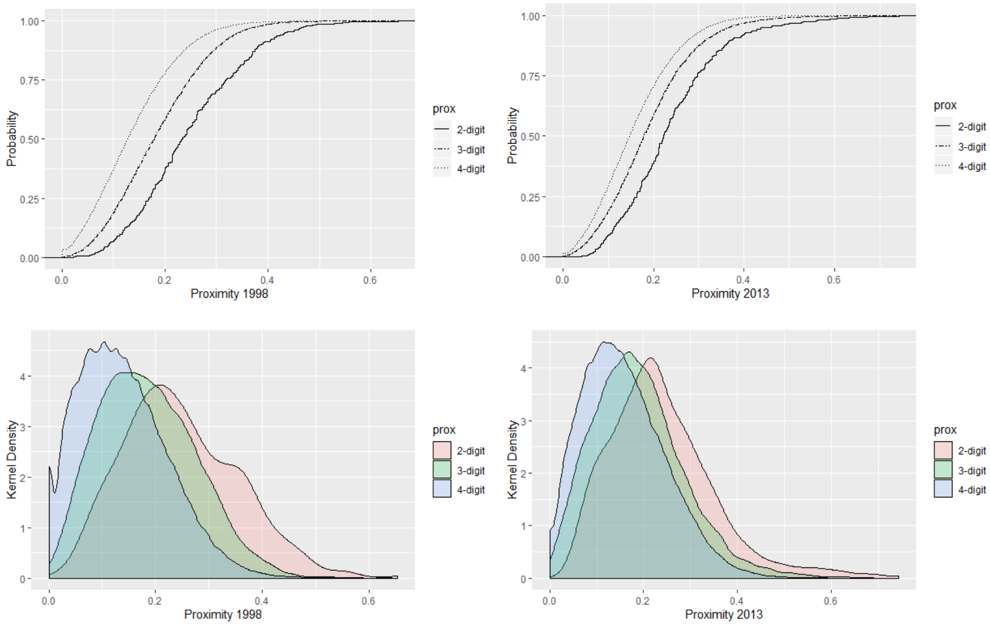

Figure 5. Cumulative distribution and frequency distribution for proximity values in 1998 and 2003 for 2-, 3-, and 4-digit industries

When two-digit, three-digit, or four-digit industries are all included, the network with all nodes reached is drawn by calculating the maximum spanning tree (see Figure 6), whose links maximise the tree's added proximity. Every code refers to a different industry and every link has the value of proximity between a pair of industries connected by this link. This representation provides the "skeleton" of the production space. One colour denotes one two-digit industry, or three-digit and four-digit industries that belong to this two-digit industry. The distributions of some analogous colours tend to be located adjacent to each other while others tend to be scattered, so the core-periphery structure appears not very evident. This indicates that industrial composition might result from both path-dependent and path-breaking processes. As previous studies show, the role of relatedness in industrial evolution and firm performance is evident in more market-oriented places, but less market-oriented places tend to break the path-dependent evolutionary trajectory through transitioning into less related industries (Guo et al. 2018; Guo and He 2017). The importance of relatedness for regional diversification can increase over time with the improvement of market institutions in early 2000s (Guo and He 2017), but decrease around late 2000s when Chinese regions can become more path-breaking and less reliant on relatedness (Zhu et al. 2017a). The state involvement can not only take good use of relatedness to attract and sustain industries (He et al. 2018), but also help encourage path-breaking regional development (Zhu et al. 2019c).

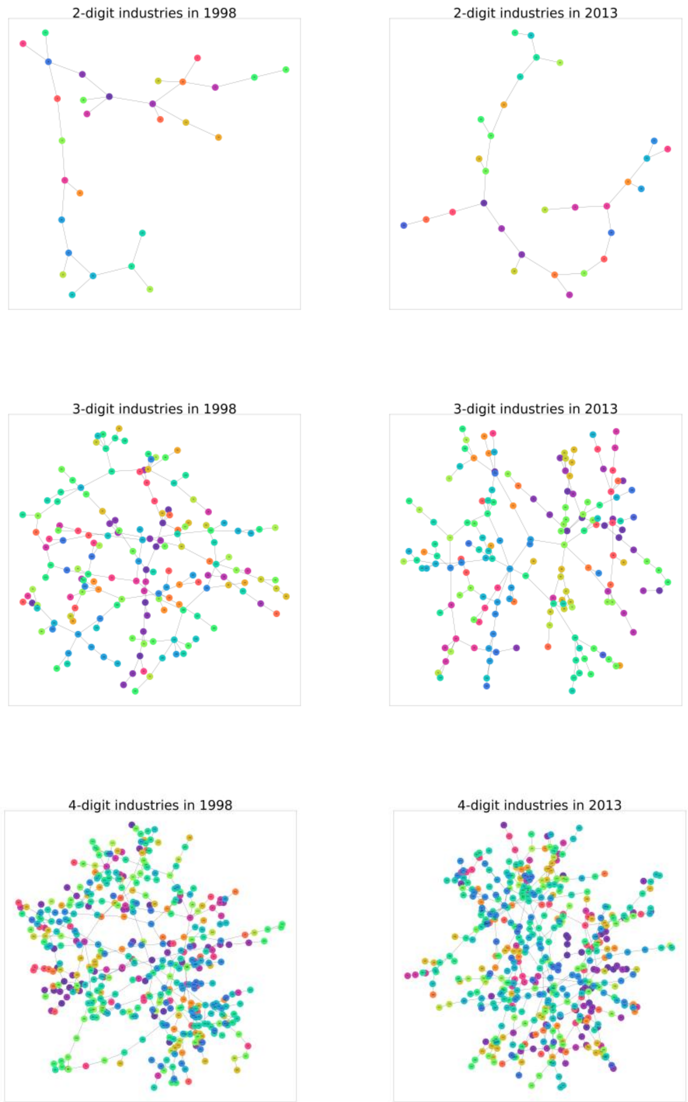

Figure 6. “Skeleton” representation of the production space in 1998 and 2013 for 2-, 3-, and 4-digit industries

4.2 Relatedness

The second step of measuring relatedness is to calculate how related one industry is to the industrial composition in a locality, which is defined as $Relatedness_{jit}$. This indicator captures the added proximity values between industry *j* with all advantage industries in city *i* at year *t*, divided by the sum of proximity values between this industry *j* with all industries, as Equation (3) shows:

$$Relatedness_{jit} = \frac{\sum_k x_{kit} \emptyset_{jkt}}{\sum_k \emptyset_{jkt}} \quad (3)$$

where $\emptyset_{jk}$ refers to the proximity between industry *j* and industry *k* at year *t*; $x_{kit} = 1$

if industry k has a comparative advantage in city i at year t ($RCA_{kit} > 1$) or 0 otherwise.

The concept of regional industrial relatedness essentially reflects the position of a particular industry in a local industrial space, and its formation may lie in the agglomeration patterns of industries at the local level. When it comes to the relationship between *relatedness* and *specialisation* or *diversity*, we find that a diversified place may have an advantage to present a high relatedness level to more industries than a specialised area. In contrast, the correlation between relatedness and specialisation is much smaller and can be negative. Specifically, when we employ entropy and location quotient indicators as proxies for diversity and specialisation respectively, it is found that relatedness is much more positively correlated with diversity than with specialisation. For example, in 2013 at a 4-digit industry level, when the data on output is used, regional industrial relatedness has a correlation with diversity at 0.811 but specialisation –0.042, and the coefficients at a 3-digit level are 0.779 and 0.006, and 2-digit level 0.620 and 0.241. The pattern holds when the data on employment is used with the figures at 0.769 and –0.098, 0.592 and –0.016, 0.322 and 0.218 respectively[8]. As this pattern shows, when the disaggregation level increases from 2 digit to 4 digit, the correlation between relatedness and diversity becomes stronger, and the correlation with specialisation is smaller, so that the relatedness moves closer to diversity but further away from specialisation.

5 Empirical analysis

5.1 Data

The land granting data is obtained from the China land market website (http://www.landchina.com/) maintained by the Ministry of Natural Resources. This dataset has released land granting records nationwide since 2007. Every observation in the dataset means a granting contract signed between a local government and a buyer. Compared with the widely used data from China Land and Resources Statistical Yearbooks at the aggregate level (Tian and Ma 2009; Zheng and Shi 2018), the dataset adopted in this research could provide micro-level information on a land granting event from several aspects, including land parcel characteristics, land use requirements, terms

[8] That output-based figures tend to be larger than employment-based ones may be due to the fact that output can capture the information on all types of inputs not limited to employment when it comes to the proximity between economic activities.

of the contract and the like (Yuan et al. 2019; Zhou et al. 2019). Specifically, every observation can cover details of the land parcel, such as land price, area, land grade, land source, transfer method, location, industry type, floor-to-area ratio, local authorities that grant the land, buyer name, signed date, construction date, production date, length of usage. Firm-level micro data is collected from ASIF maintained by National Bureau of Statistics. This dataset provides highly reliable annual survey data about industrial firms and includes information of all firms above a designated size in sectors including manufacturing, mining, energy production, and among others (Brandt et al. 2014). This research only focuses on firms in the manufacturing industry, as other sectors are largely dependent on natural resources in terms of production.

We focus on land parcels that can be matched with manufacturing firms above a designated size from 2011 to 2013. There are 7859, 9150, and 9494 matched land parcels, accounting for 25% (31424), 28% (32061), and 29% (32932) of the total number of land parcels granted for industrial use in year 2011, 2012, and 2013, respectively. Specifically, to take year 2013 as an elaboration of the data, 32932 land parcels are granted to manufacturing in 2013. After matching the names or project names in land granting with the firm names in the dataset of ASIF, we find that 9494 parcels are granted to the firms maintained in ASIF, and 8156 firms are involved in total, in which 887 firms are matched with more than one parcel of land and they are linked with 2225 parcels of land altogether as Table 1 shows. When matching the location of land parcels with that of the firms in ASIF, we find that 9416 land parcels are exactly located in the same city as where their corresponding buyer is located, and they are invested by 8092 firms, in which 876 firms invested in more than one land parcels in their home city. And the remaining 78 land parcels are granted to firms that are not located in the same city, and 68 firms are involved and 8 of them invested in more than one city.

Table 1. Number of firms to which industrial land is granted

	All land parcels		Parcels invested by local firms		Parcels invested by non-local firms	
	Number of land parcels	Number of firms involved	Number of land parcels	Number of firms involved	Number of land parcels	Number of firms involved
Total	9494	8156	9416	8092	78	68
One land parcel in a city by a firm	7269	7269	7216	7216	60	60
More than one land parcel in a city by a firm	2225	887	2200	876	18	8

To test if the names of other buyers in land transaction records are unmatched with the firms in ASIF due to their inaccurate name information, we randomly select 100 unmatched land parcels and rematch their corresponding buyer names with those in ASIF based on the core information in the names and other ascribed information, including city code, county code and industry category. We indeed find that 3 of these buyers are actually maintained by ASIF but fail to be matched due to their inconsistent name information in the land granting dataset and ASIF dataset, accounting for 3% of the sample. Specifically, these buyers are unmatched because some locational information is missed from (e.g., the province information) or added to (e.g., the city or county information) the original name. Based on the rate of matching failure (i.e., 3%), the total number of unmatched parcels as a result of inaccurate name information can be around 715, so that the matched sample (i.e., the 9494 land parcels) can account for around 93% of the real number in terms of the land buyers maintained by ASIF.

We choose the data in years 2011 to 2013 to carry out the empirical work for two main reasons. On the one hand, since the land marketisation for industrial use started in 2007, the degree of market-orientedness has reached to a relatively high level in 2011. For example, in 2007, 32% land parcels for manufacturing use were granted by the government through market-based transfer methods (i.e., tender, auction, and listing), but this figured rose to 94% in 2011, implying a substantial improvement in the role played by the market in granting industrial land. On the other hand, we avoid the years in the immediate aftermath of the Global Financial Crisis, which can help rule out the possibility of the global shock influencing the land supply and demand. In terms of the land granting sample of manufacturing firms above a designated size in the empirical work, more than 90% of the land parcels are granted to local firms, which may apply for land to set up new projects, implying that the existence of requirements for land applicants may be less of a problem since these firms must have passed the local government's examination of requirements once.

5.2 Model specification

We use the following equation (4) to estimate how various factors are associated with the spatial disparities in parcel-level land prices p_{if}:

$$p_{if} = \alpha + \theta_0 * X_{if} + \theta_1 * XI_{if} + \theta_2 * XII_{if} + \theta_3 * XIII_{if} + \gamma \tag{4}$$

where p_{if} is the price of an industrial land parcel granted by a city-level government i to a firm f, X_{if} indicates regional industrial relatedness; XI_{if} is a vector of variables to proxy government involvement, such as per capita area of granted land, a city's administrative level, national zones, high-tech industries (Huang et al. 2015; Yuan et al. 2019; Zhou et al. 2019); XII_{if} denotes city-wide economic characteristics, such as GDP per cap, population density, and manufacturing share (Song et al. 2022; Yuan et al. 2019); $XIII_{if}$ represents firm-level characteristics to account for sorting effects, such as ownership, age, and input intensity (Yang and Tsou 2020); and γ stand for the year dummies. Table 2 shows the measurement and sources for the variables used in the empirical work. Tables A1 and A2 in the Appendix present variables' descriptive statistics and correlation matrix.

The baseline model is to estimate the association between land prices and relatedness. We then examine how the coefficient of relatedness changes after controlling for government-related variables, and particularly the relevance of city and firm characteristics to separate relatedness externalities from city and firm heterogeneity effects.

Table 2. Data and variables

Variable	Measurement	Source [a]
Outcome variable at the parcel level		
Land price	The unit price of a piece of land granted to an economic agent (10,000 RMB per hectare)	CLMW
Explanatory variables at multiple levels		
City-industry-level characteristics		
Relatedness	The relatedness between one industry with the industrial profile of a city by using the co-occurrence method developed by Hidalgo et al. (2007) as described in Section 4	ASIF
Government involvement		
Land supply per capita	The amount of industrial land granted per capita in a city	CLMW
Higher administrative level	A dummy which is 1 if a city is ranked at the higher level of the administrative hierarchy (i.e., a capital city of a province, a sub-provincial city, or a directly controlled city), or zero otherwise	CCSY
National zone	A dummy which is 1 if a city has at least one national-level economic and technological development zone or high-tech development zone, or zero otherwise	CDZAAC
High-tech industry	A dummy which is 1 if an industry is listed as one of the high-tech industries (manufacturing) in the categorisation standard published by the national government	CSYHTI
City-level characteristics		
Population density	The number of people per square kilometre	CCSY, CSYRE
GDP per capita	Gross domestic product (GDP) per capita in a city	CCSY, CSYRE
Manufacturing share	The market share of manufacturing firms above a designated size in local GDP	ASIF, CCSY, CSYRE
Firm-level characteristics		
Labour	The number of employees in a firm	ASIF
Capital	The amount of fixed assets of a firm (1,000 RMB)	ASIF
Patent[9]	The number of authorised patents	CNIPA
Age	The number of years that a firm has existed	ASIF
Ownership	A dummy which is taken 0 if a firm is regarded as a private-owned enterprise, 1 as a state-owned enterprise, or 2 as a foreign-owned enterprise	ASIF

[a] Abbreviations: CLMW, China land market website; CNIPA, China National Intellectual Property Administration; CCSY, China City Statistical Yearbooks; CSYRE, China Statistical Yearbooks for

Regional Economy; CSYHTI, China Statistics Yearbook on High Technology Industry; CDZAAC, China Development Zone Audit Announcement Catalogue (2018 edition).

5.3 Results

The results in Table 3 show that there is a positive correlation between regional industrial relatedness and land prices, and the coefficient decreases to a certain degree when government involvement, city-wide economic characteristics, and firm-level characteristics are controlled for in a step-by-step manner, although the difference between model (3) and (4) is not statistically significant at the 10% level according to t-test results. How the coefficient of relatedness changes after adding control variables shows that relatedness externalities may interact with city and firm characteristics to develop and take effect. When it comes to the government-related variables, per capita area of land granted, a high administrative level, the existence of at least one national-level economic and technological development zone or high-tech development zone can have a significantly negative association with land prices. At the industry level, compared with traditional industries, high-tech industries (i.e., those industries with a relatively high share of R&D expenditure in the main business income) are more likely to afford higher land prices. At the city level, land prices are higher in places with higher GDP per capita, higher population density, or a smaller manufacturing share. At the firm level, firms with greater labour and innovation intensity, weaker capital intensity, older in age, a state or a foreign ownership may select land parcels with higher prices.

Table 3. The relationship between regional industrial relatedness and land prices

		(1)	(2)	(3)	(4)
	Variable	Price (ln)	Price (ln)	Price (ln)	Price (ln)
	Relatedness (four-digit)	1.226***	0.788***	0.412***	0.399***
		(0.047)	(0.047)	(0.048)	(0.048)
Firm	Labour (ln)				0.006*
					(0.004)
	Capital (ln)				–0.012***
					(0.002)
	Patent (ln)				0.023***
					(0.002)
	Age				0.004***
					(0.000)
	State ownership				0.066***
					(0.023)
	Foreign ownership				0.129***
					(0.014)
City	Pop. density (ln)			0.216***	0.204***
				(0.006)	(0.006)
	GDP per capita (ln)			0.586***	0.559***
				(0.009)	(0.009)
	Manu. share			–0.101***	–0.089***
				(0.011)	(0.012)
Government involvement	Land supply per capita (ln)		–0.057***	–0.164***	–0.162***
			(0.005)	(0.006)	(0.006)
	Higher admin. level (dummy)		0.305***	–0.095***	–0.099***
			(0.010)	(0.011)	(0.011)
	National zone (dummy)		0.227***	–0.040***	–0.043***
			(0.010)	(0.010)	(0.010)
	High-tech industry (dummy)		0.061***	0.065***	0.046***
			(0.012)	(0.011)	(0.011)
	Year dummies	Yes	Yes	Yes	Yes
	Constant	4.921***	4.783***	–2.236***	–1.757***
		(0.014)	(0.014)	(0.092)	(0.098)
	Observations	26,492	26,467	26,132	25,120
	R-squared	0.027	0.097	0.286	0.303

Notes: Standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

We then divide the sample into two subsamples in terms of the indicator for innovation and entrepreneurship at the city level, which is a comprehensive indicator based on the weighted sum of new firm formation, inward investment, venture capital, invention patent, practical new-type patent, design patent, and brand (Dai et al. 2021). As the results in Tables 4 and 5 show, the coefficients of relatedness in less innovative and entrepreneurial cities are negative and change slightly when city and firm characteristics are controlled for gradually, but in more innovative and entrepreneurial cities the coefficients are positive and change remarkably. This indicates that more related industries may have a higher demand for land in highly market-oriented places, but more unrelated industries may demand land more in low market-oriented places, implying a strong internal motivation for low market-oriented places to achieve path breaking in an industrial space defined by co-occurrence relatedness. This result is in line with the finding in previous studies in that relatedness can have a larger positive effect on developing new industries (Guo and He 2017), sustaining large firms (He et al. 2017a), and new firm survival (Guo et al. 2018) in more market-oriented places in China. In contrast, the finding in the developed world shows that relatedness as a driver of regional diversification is stronger in coordinated market economies than in liberal market economies (Boschma and Capone 2015a).

We conduct t-test to compare the coefficients in different regressions. In Table 4, the difference of the coefficients of relatedness is significant between Columns (1) and (2), (2) and (3), (3) and (4), and in Table 5, it is only significant between Columns (1) and (2). The relationship between relatedness and land values can be partly attributed to city-wide effects and individual sorting effects. Hence, relatedness externalities can be smaller after controlling for city-wide economic characteristics and then firm-level observable characteristics. And this pattern of how the relatedness coefficient decreases holds no matter for cities at a relatively high or low level of innovation and entrepreneurship, but to a lesser extent for the latter. That there are only significant differences between Columns (2) and (3), and (3) and (4) in cities with stronger innovation and entrepreneurship implies that how relatedness externalities may be sensitive to firm and city heterogeneity effects may depend on local market circumstances.

The positive relationship between a high-tech industry dummy and land prices can be stronger in highly market-oriented cities, where the demand for high-tech industries is likely to be higher, although the positive relationship between land prices and the high-tech industry dummy is not significant in low market-oriented places. This finding is in line with the fact that the transitional period from 2012 on featured by two state strategies (i.e., the "New-type Urbanisation" and "Innovation-driven Development") witnesses an increase in the amount of land granted to high-tech industries (Zhou et al., 2019), which may result from a demand-related motivation for high-tech industries to acquire land. Meanwhile, due to the quite low correlation between relatedness and the high-tech industry category, meaning that the relatedness of high-tech industries to the local industrial structure may not be significantly different from that of traditional industries too much, the bias in the estimation of relatedness externalities caused by the government's land supply preference for high-tech industries can be quite limited.

In terms of the government's land supply behaviour, the coefficient of land supply per capita is negative, in line with the finding in previous work (Yuan et al. 2019). That is to say, no matter the level of local market-orientedness, the existence of land supply constraint is something that cities can have in common. The result also shows that after controlling for land supply constraint proxied by the amount of land granted per capita, the coefficient of relatedness becomes weaker in both highly and low market-oriented places, when the local demand captured by GDP per capita, population density, and the manufacturing share is fixed (see Table A3 in the Appendix). One reason could be that, through posing a land supply constraint, local governments can intensify competition and increase land use efficiency, which can push land prices higher and lead to larger relatedness externalities[10].

[10] Since the data on other firms or organisations that get land but are not maintained in our firm dataset is not available, we cannot calculate the total amount of land granted to every industry, let alone related or unrelated industries, but due to the fact that every granting event for the firms maintained in our dataset is an outcome of the market competition involved all firms and organisations regardless of whether they are maintained in our dataset or not, how local governments' supply behaviour matters for relatedness externalities can be reflected in terms of how the relationship between land prices in our sample and relatedness changes after controlling for the total amount of land granted to all industries.

Table 4. The relationship between regional industrial relatedness and land prices in cities with high innovation and entrepreneurship

	Variable	(1) Price (ln)	(2) Price (ln)	(3) Price (ln)	(4) Price (ln)
	Relatedness (four-digit)	1.423***	1.205***	0.819***	0.785***
		(0.063)	(0.064)	(0.061)	(0.061)
Firm	Labour (ln)				0.009**
					(0.004)
	Capital (ln)				–0.008***
					(0.003)
	Patent (ln)				0.019***
					(0.002)
	Age				0.004***
					(0.000)
	State ownership				0.025
					(0.031)
	Foreign ownership				0.104***
					(0.016)
City	Pop. density (ln)			0.240***	0.225***
				(0.008)	(0.008)
	GDP per capita (ln)			0.631***	0.598***
				(0.012)	(0.012)
	Manu. share			–0.126***	–0.109***
				(0.015)	(0.015)
Government involvement	Land supply per capita (ln)		–0.104***	–0.165***	–0.163***
			(0.008)	(0.009)	(0.009)
	Higher admin. level (dummy)		0.174***	–0.157***	–0.150***
			(0.011)	(0.012)	(0.012)
	National zone (dummy)		0.101***	–0.251***	–0.232***
			(0.021)	(0.020)	(0.020)
	High-tech industry (dummy)		0.099***	0.085***	0.064***
			(0.016)	(0.014)	(0.014)
	Year dummies	Yes	Yes	Yes	Yes
	Constant	5.022***	4.939***	–2.711***	–2.227***
		(0.019)	(0.025)	(0.120)	(0.127)
	Observations	16,390	16,368	16,283	15,794
	R-squared	0.030	0.068	0.286	0.298

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. The relationship between regional industrial relatedness and land prices in cities with low innovation and entrepreneurship

		(1)	(2)	(3)	(4)
	Variable	Price (ln)	Price (ln)	Price (ln)	Price (ln)
	Relatedness (four-digit)	–0.431***	–0.399***	–0.441***	–0.445***
		(0.066)	(0.065)	(0.077)	(0.080)
Firm	Labour (ln)				–0.005
					(0.006)
	Capital (ln)				–0.014***
					(0.004)
	Patent (ln)				0.024***
					(0.003)
	Age				0.003***
					(0.001)
	State ownership				0.136***
					(0.035)
	Foreign ownership				0.124***
					(0.030)
City	Pop. density (ln)			0.156***	0.155***
				(0.008)	(0.008)
	GDP per capita (ln)			0.324***	0.324***
				(0.016)	(0.016)
	Manu. share			–0.046**	–0.044**
				(0.019)	(0.019)
Government involvement	Land supply per capita (ln)		–0.091***	–0.137***	–0.135***
			(0.008)	(0.009)	(0.009)
	Higher admin. level (dummy)		–0.287***	–0.321***	–0.309***
			(0.097)	(0.095)	(0.094)
	National zone (dummy)		0.075***	0.005	–0.009
			(0.011)	(0.011)	(0.011)
	High-tech industry (dummy)		0.016	0.029	0.021
			(0.018)	(0.018)	(0.018)
	Year dummies	Yes	Yes	Yes	Yes
	Constant	5.056***	4.995***	0.877***	1.122***
		(0.018)	(0.019)	(0.176)	(0.184)
	Observations	10,102	10,099	9,849	9,326
	R-squared	0.008	0.027	0.089	0.105

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Finally, we test how the complementarity role of complexity and relatedness can act as one underlying mechanism of the relevance of city market-orientedness for relatedness externalities. Industrial complexity is calculated by adopting the same method as the study by Hidalgo and Hausmann (2009). Three levels of complexity are defined with the mean – 0.5 times the standard deviation and + 0.5 times the standard deviation used as demarcation values. We estimate how the marginal effects of each complexity level (i.e., low, medium, and high) on land prices are conditional on relatedness in highly and low market-oriented cities respectively. As shown in Figure 7, the result shows that, no matter for industries at what complexity level, industrial complexity can produce a land price premium, and relatedness can moderate the effect of complexity on land prices, but the moderating effect of relatedness is positive in highly market-oriented places, but negative in low market-oriented places. Specifically, in highly market-oriented cities, the positive effect of complexity on land prices can be stronger when the level of relatedness increases, and more complex industries are more likely to exploit relatedness to create high values. Conversely, in low market-oriented cities, an increase in relatedness can lead to a decrease in the land price premium generated by complexity, and the degree of such decrease can be greater for more complex industries. This finding suggests that the complementarity role of relatedness and complexity can only be found in highly market-oriented places, thereby contributing to a positive relationship between relatedness and land prices in these areas[11]. Such interdependence of complexity and relatedness and the reliance of their complementarity on city markets are in line with what previous studies have found (Balland et al. 2019a; Davies and Maré 2021; Rigby et al. 2022).

[11] The reverse causality is also possible—the relevance of market-orientedness for relatedness externalities can contribute to the complementarity of relatedness and complexity, that is, only in highly market-oriented places where the relatedness externalities are positive, can the complementarity of relatedness and complexity exist. Thus, the empirical evidence for the complementarity of relatedness and complexity as an underlying mechanism for the relevance of market-orientedness for relatedness externalities may need to be accepted with caution without fully accounting for the endogeneity.

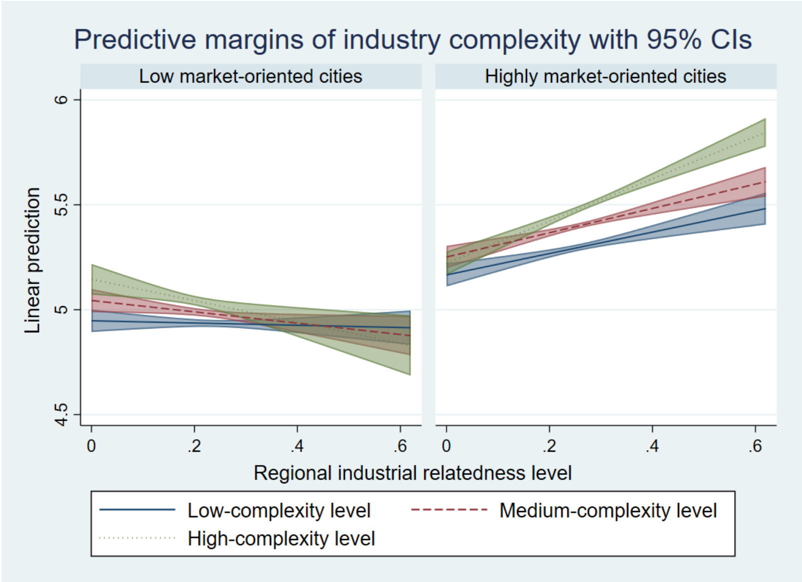

Figure 7. The marginal effects of complexity on land prices conditional on relatedness in cities at a high- and low-level of market-orientedness

6 Conclusions

Wide-ranging empirical evidence in previous research proves that regions are more likely to diversify into or develop new specialisations in economic activities that are more related to the local industrial composition. This chapter intends to investigate how regional industrial relatedness can contribute to a land price premium. To address this question, we examine the association between relatedness and spatial disparities in state-granted land prices in China.

Our measure of relatedness derived from geographical co-location patterns among different industries is subject to geographical hierarchy in terms of the regional capacity to accommodate a diverse set of sectoral strengths. This notion is fundamentally distinguished from the concepts of related and unrelated varieties which are captured by within-industry and between-industry entropies respectively based on industrial hierarchy at different aggregation levels. Relatedness in our definition can be higher in a diversified environment, whereas related industries in the form of related variety tend to reside in more specialised areas. Ignoring this basic fact can cause a measurement bias when comparing the effects of relatedness calculated by different approaches.

We develop our empirical framework in the context of land marketisation in China and match parcel-level land transection records with firm-level buyer information for the sample of manufacturing firms above a designated size. This institutional setting allows the market mechanism from a demand side to play a role in land values in terms of whether a firm operating in an industry more related to the local economy would like to pay more to acquire land. Along this line of enquiry, we further test whether the relationship between land prices and relatedness may differ in highly and low market-oriented cities, with market-orientedness measured by a comprehensive indicator for innovation and entrepreneurship at the local level. To tease out relatedness externalities on land values, we also control for government involvement, city socioeconomic characteristics and firm-level attributes. The results show that a firm in an industry more related to the local industrial portfolio tends to invest in more valuable resources. But positive relatedness externalities are only evident in highly market-oriented places. In contrast, in low market-oriented areas, relatedness is negatively associated with land prices. One underlying mechanism of the relevance of market-orientedness for relatedness externalities could rest on a positive (negative) moderating effect of relatedness on the association between complexity and land prices in highly (low) market-oriented cities.

This chapter can enrich the literature on the agglomeration-land value framework by providing empirical evidence on how industrial characteristics at the local level can account for spatial disparities in land prices through the lens of regional industrial relatedness. This chapter can also contribute to the literature on the relevance of institutions for related diversification by investigating the role of regional market-orientedness in relatedness externalities in a transitional economy like China. Policy implications can be drawn to formulate place-specific land use strategies and industrial development plans by incorporating a demand perspective.

Appendix

Table A1. Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Land price per unit (ln)	26,492	5.247	0.635	–0.317	9.903
Relatedness	26,503	0.249	0.082	0	0.536
Land supply per capita (ln)	26,478	0.096	0.703	–5.975	3.667
Higher administrative level (dummy)	26,503	0.193	0.395	0	1
National zone (dummy)	26,503	0.793	0.405	0	1
High-tech industry (dummy)	26,503	0.101	0.301	0	1
Population density (ln)	26,442	6.098	0.739	–0.379	7.812
GDP per capita (ln)	26,481	10.697	0.540	8.842	12.190
Manufacturing share	26,185	1.159	0.436	0.065	2.645
Labour (ln)	25,659	5.638	1.119	0	11.806
Capital (ln)	25,737	10.331	1.837	0.693	17.861
Patent (ln)	26,503	–3.669	2.247	–4.605	6.815
Age	26,202	10.298	11.008	1	196
State ownership (dummy)	26,503	0.022	0.147	0	1
Foreign ownership (dummy)	26,503	0.063	0.243	0	2

Table A2. Correlation matrix

	v1	*v2*	*v3*	*v4*	*v5*	*v6*	*v7*	*v8*	*v9*	*v10*	*v11*	*v12*	*v13*	*v14*	*v15*
v1	1														
v2	0.160*	1													
v3	–0.031*	0.072*	1												
v4	0.245*	0.183*	–0.021*	1											
v5	0.197*	0.185*	0.217*	0.25*	1										
v6	0.042*	0.020*	–0.039*	0.025*	0.026*	1									
v7	0.354*	0.376*	–0.097*	0.240*	0.267*	0.014*	1								
v8	0.422*	0.148*	0.423*	0.446*	0.443*	0.001	0.229*	1							
v9	0.150*	0.287*	0.447*	–0.167*	0.327*	–0.021*	0.405*	0.372*	1						
v10	0.093*	0.009	0.001	0.042*	0.013*	0.008	0.050*	0.080*	0.012	1					
v11	0.049*	–0.036*	0.036*	0.032*	0.013*	0.003	–0.001	0.086*	0.029*	0.513*	1				
v12	0.178*	0.062*	0.024*	0.090*	0.066*	0.089*	0.111*	0.152*	0.051*	0.259*	0.264*	1			
v13	0.144*	0.000	–0.003	0.079*	0.062*	0.036*	0.052*	0.117*	0.015*	0.330*	0.279*	0.231*	1		
v14	0.015*	–0.048*	–0.002	0.026*	–0.020*	0.001	–0.048*	–0.002	–0.054*	0.122*	0.172*	0.070*	0.150*	1	
v15	0.124*	0.085*	0.019*	0.090*	0.069*	0.026*	0.104*	0.131*	0.045*	0.108*	0.125*	0.023*	0.006	–0.039*	1

Note: v1: Land price per unit (ln). *v2*: Relatedness. *v3*: Land supply per capita (ln). *v4*: Higher administrative level (dummy). *v5*: National zone (dummy). *v6*: High-tech industry (dummy). *v7*: Population density (ln). *v8*: GDP per capita (ln). *v9*: Manufacturing share. *v10*: Labour (ln). *v11*: Capital (ln). *v12*: Patent (ln). *v13*: Age. *v14*: State ownership (dummy). *v15*: Foreign ownership (dummy). * $p<0.05$.

Table A3. The model results with and without the inclusion of land supply per capita

	All cities		Highly market-oriented cities		Low market-oriented cities	
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Price (ln)	Price (ln)	Price (ln)	Price (ln)	Price (ln)	Price (ln)
Relatedness	0.335***	0.325***	0.632***	0.615***	–0.451***	–0.428***
	(0.048)	(0.047)	(0.061)	(0.061)	(0.078)	(0.077)
Land supply per capita (ln)		–0.165***		–0.170***		–0.140***
		(0.006)		(0.009)		(0.009)
Pop. density (ln)	0.258***	0.201***	0.280***	0.203***	0.182***	0.154***
	(0.005)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
GDP per capita (ln)	0.465***	0.537***	0.469***	0.536***	0.240***	0.323***
	(0.007)	(0.007)	(0.010)	(0.010)	(0.015)	(0.015)
Manu. share	–0.188***	–0.062***	–0.178***	–0.048***	–0.132***	–0.040**
	(0.009)	(0.010)	(0.011)	(0.012)	(0.018)	(0.019)
Constant	–1.158***	–1.688***	–1.415***	–1.763***	1.679***	0.888***
	(0.072)	(0.074)	(0.104)	(0.105)	(0.168)	(0.174)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,135	26,132	16,283	16,283	9,852	9,849
R-squared	0.262	0.282	0.250	0.268	0.064	0.088

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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Concluding Remarks

1 Summary of the thesis

The first study examines how the sources for regional industrial path development are associated with productivity. Specifically, we adopt a conceptual framework based on the multiplicity of regional industrial path development and its mechanism (Grillitsch et al. 2018a). We identify six key sources for path development using a multi-actor and multi-scalar approach (Hassink et al. 2019). We examine the relative importance of each key source for path development and productivity as two complementary aspects of economic structural change at the regional industry level, compared with creativity and efficiency at the regional level in previous studies (Saviotti et al. 2020). We employ data on manufacturing industries at different aggregation levels in Chinese cities between 1998 and 2013. The results show that contributors to path development are not necessarily those to productivity. Related variety stimulates new sector emergence but not its efficiency, whereas unrelated variety promotes productivity but not new sector development. Specialisation has a stronger positive relationship with productivity at a higher aggregation level. Institutions are positively associated with new sector emergence but not productivity and sustainability. Innovation and external linkages moderately boost path development and efficiency.

The second study explores the relationship between city-level economic complexity and regional resilience during an exogenous shock. Specifically, with an evolutionary dimension of complexity and resilience adopted (Martin and Sunley 2007), we provide a framework for the role of complexity in times of crisis from an industrial development perspective. We construct an empirical design following previous studies in terms of exploring the relevance of industrial structure for resilience (Holm and Østergaard 2015; Martin et al. 2016; Rocchetta and Mina 2019). We use the method of Hidalgo and Hausmann (2009) to measure the city complexity level. Based on the Annual Survey of Industrial Firms dataset in China, we examine to extent to which the 2007–08 global financial crisis influenced economic growth in Chinese cities depending on their complexity level. We focus on how the marginal effect of the shock on employment and output growth is conditional on the city complexity level in crisis and post-crisis periods after controlling for domestic and global demand. The results show that both resistance and recovery vary with complexity. Employment growth is resistant in less complex cities, whereas output growth is resistant in medium complexity cities. Recovery is found at every complexity level and tends to decrease as complexity increases.

The third study explores the role of regional industrial relatedness in spatial disparities in state-granted land prices and the relevance of market-orientedness for relatedness externalities in a transition economy such as China. Previous research shows that the importance of relatedness as a driver of diversification can be contingent on a country's market-orientednss (Boschma and Capone 2015a). The market economy is increasingly characterised by high capabilities of innovation and entrepreneurship to drive the evolution of knowledge (Martin and Simmie 2008). We adopt a co-occurrence measure of relatedness (Hidalgo et al. 2007a), compared with an entropy notion of related variety (Rocchetta et al. 2022b). Parcel-level land transfer records matched with manufacturing firms above a designated size are applied in the empirical analysis. The results show that the relationship between land prices and relatedness is positive in highly market-oriented cities and negative in low market-oriented cities. The complementarity of relatedness and complexity in creating land values is evident only in highly market-oriented cities, in line with the findings of previous studies (Balland et al. 2019a; Davies and Maré 2021).

2 Main results

The overarching goal of this thesis is to understand the role of complexity in economic performance within an evolutionary framework. One underlying mechanism through which complexity matters is how regional industries follow a path-dependent evolutionary trajectory. The specificity of the Chinese case can help shed light on the generality of such principle of complexity from three aspects. First, the evolution of manufacturing industries in China is characterised by both path dependence and path breaking. Second, the growth of the Chinese economy can be influenced after the burst of an external shock. Third, market conditions in terms of innovative and entrepreneurial capabilities of a locality can vary across space. Accordingly, we ask three questions to understand the principle of complexity underpinned by relatedness through exploring how it operates in China:

- Are there multi-scalar and multi-agent driving forces of economic growth and development in the context of regional industrial evolution?

- Can economic complexity moderate the impact of an exogenous shock on regional economic growth?

- Do local market conditions influence the role of relatedness and the complementarity of relatedness and complexity?

Three studies answered these three questions in the affirmative, respectively. The first study demonstrates that sources of path development may not necessarily foster productivity, and that the six key sources (i.e. specialisation, related variety, unrelated variety, institutions, external linkages, and innovation) can behave in different manners. The second study highlights that regional economic growth's resistance to and recovery from a crisis can vary with city complexity, and that industrial dynamics in the face of a shock can differ across cities at different complexity levels. The third study concludes that the land price premium associated with regional industrial relatedness can be stronger in highly market-oriented cities, where the complementary role of complexity and relatedness in creating land values is also evident.

This thesis contributes to the literature by proposing a research framework to investigate the role of complexity in economic performance in the context of regional industrial evolution from three aspects, i.e. multiplicity of mechanisms, the role of complexity in times of crisis, and the role of relatedness in relation to local institutional arrangements. This thesis also formulates a conceptual framework for complexity and relatedness by identifying their links with industrialisation, urbanisation, and globalisation. Through empirically focusing on complexity and relatedness as explanatory variables, we examine their effects on various indicators of economic performance, including productivity, economic growth, and land values.

3 Policy implications

Firstly, the results imply that when one factor is good for regional industrial path development, it does not mean that this factor can be good for productivity, as the factor can have its internal balance when it comes to its effects on these two outcomes. Hence, the same factor can play differentiated roles in path development and productivity, which can thus be driven by different sets of factors. For example, the involvement of state-owned enterprises can effectively promote cities to develop specialisations in new sectors, but an increasing share of state-owned enterprises in a local industry can hamper the improvement of productivity. In this sense, the 'lock-in' issue related to the state involvement needs warranting close attention of policy makers.

Secondly, cities with different complexity levels may require different mechanisms to be resilient in times of crisis. Low-complexity cities reduce their productivity during the crisis. Cities with higher complexity are less likely to keep their momentum in industry entry and exit in both crisis and post-crisis periods. The ability to maintain comparative advantages in existing industries strengthens in the face of the shock, particularly for high-complexity cities. Low-complexity cities tend to increase their number of specialisations after the burst of crisis. It is necessary to make efforts to be resilient for the economy as a whole in the shock time.

Thirdly, the importance of one factor can vary across space depending on market conditions, as this factor can be contingent on specific market conditions to take effect. Cities can differ in terms of their development stages and corresponding market circumstances, which means that some cities can be more developed with more advanced market forces in place than others. Our results imply that relatedness is particularly a market-based product, so that more advanced economies can exhibit a higher level of relatedness and exploit positive externalities of relatedness in generating economic values to a greater degree due to their high capacity for innovation and entrepreneurship. In this sense, relatedness should not be the only factor that matters for development, particularly for less developed areas with a low level of market-orientedness, where a differentiated or even the opposite development logic should be emphasised. It is also noteworthy that relatedness captured by different measurements can have different meanings to a degree that results derived from different measurements may not be directly comparable.

4 Limitations and future research

One limitation is related to the data used in this thesis in that only firms above a designated size are covered in our main data source, i.e. the Annual Survey of Industrial Firms. Firms in this dataset can account for more than 90 percent of gross industrial output, and multiple official statistics mainly rely on this dataset to reveal dynamic industrial landscapes. As the data did not include all small- and micro-sized enterprises, our analysis paid limited attention to this type of enterprises, which, however, have experienced fast development in recent years with increasing importance in innovation, employment, and economic growth. This thesis can provide a basis for future studies which intend to enrich relevant research areas by incorporating analysis on enterprises of a small or micro size. For example, in the third study, the share of small- and micro-sized enterprises at the local level can be one critical dimension of market-orientedness worthy of future research.

Another limitation of this thesis is relevant to our predominant use of quantitative methods in the empirical work. Despite the reliance on econometric methods for the empirical design, we would like to highlight the value of qualitative research in formulating the conceptual framework and verifying the data analysis in the thesis at hand. To fully capture the complex picture of how regional industries evolve, future work could adopt qualitative methods to support, complement, and expand the quantitative associations found in this thesis. For example, based on the first study, case studies can help illustrate how different industries in the same region may follow different types of evolutionary trajectories, how a local industry may change its development path over time, how one driver of evolution may play differentiated roles in multiple forms of path development, and how the sources of productivity and path development may differ by a place-specific context.

There is also a limitation relating to the external validity of the findings in this thesis. During the studied period, the speed of economic growth can be remarkable in China in line with an ongoing process of industrialisation, urbanisation, and globalisation in this transitional economy. And the role of the state in new sector emergence and land supply in China can be distinguishable. The findings are thus rooted in this specific historical context and institutional background. However, the theoretical or conceptual framework in each study is established by drawing enormous inspiration from previous studies conducted globally, particularly those from the western countries. Hence, this thesis can inject fresh blood into the research agenda on complexity by telling a Chinese story from various aspects, such as the multiplicity of mechanisms for evolution, the role of complexity in times of crisis, and the relevance of regional market-orientedness for the role of relatedness. In terms of the future direction in this respect, on the one hand, to give empirical evidence across a spectrum of geographical contexts, it could be examined and discussed how the key findings obtained from the Chinese case can be distinguished from or consistent with those sought elsewhere. Specifically, the same empirical design in each study can be reapplied in other countries, although the measurements of some variables need to accord with the country-specific context and can be flexible depending on the data availability. For example, the methods to measure external linkages, institutions, and innovation are not limited to those used in this thesis, as the calculation of each variable can take various forms while delivering similar meanings. On the other hand, further research could continue to focus on the Chinese case by taking a step forward based on the current study to update the research framework for understanding the Chinese economy through a complexity lens. For example, the present study can be extended by considering (*i*) other contributors to path development, such as human capital, (*ii*) the influence of a shock of a different nature, such as the recent pandemic, and (*iii*) other sectoral domains such as scientific activities[1].

[1] Looking at manufacturing alone may not be sufficient to capture some new trends in industrial development, such as the development of clean, digital, and health industries, which all cover some industrial sectors beyond the scope of manufacturing.

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