Reaching Net Zero: Three Essays on Energy Conservation in Commercial Real Estate

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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.

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Abstract

Today, the building sector is one of the largest contributors to global emissions, making it a key priority in the race towards net zero. The climate agenda is also beginning to play a major role in driving the value of commercial assets, incentivising businesses that occupy, manage and own real estate to engage in energy conservation. In three papers, this work assesses the effectiveness of a suite of voluntary and regulatory strategies in steering the market towards increased energy efficiency and lower energy demand. The first article explores the effect of the UK's Minimum Energy Efficiency Standards (MEES) regulation on rental premiums of the London office market. The findings suggest that this policy has led to a significant decline in the rental value of office spaces directly affected by the regulation, as well as units with an energy performance certificate band closest to the compliance threshold. The second article examines the impact of energy management and productivity-enhancing measures embedded in a green certification label that assesses sustainable operations and maintenance practices of existing buildings. Using data on four major US markets, the results indicate that while there are energy management features that decrease energy consumption, savings emerging from these measures are more than offset by certain indoor environment features. The third paper analyses the effectiveness of sub-metering in eradicating energy losses due to the split incentive problem by applying data on office buildings from seven US markets. The findings suggest that this feedback technology reduces inefficiencies arising from usage split incentives, while pointing to adverse energy consumption outcomes in contractual agreements where the tenant is responsible for energy payments. Nevertheless, a reduction in the variability of energy consumption and an increase in the rent premium are uncovered for this type of lease arrangement, suggesting that sub-metering may offer significant risk-reduction benefits in the eyes of the tenant.

Dedication

I would like to dedicate this thesis to my family.

Preface

The following material from the research conducted for this thesis has been published:

Akhtyrska, Y., & Fuerst, F. (2021). People or Systems: Does Productivity Enhancement Matter More than Energy Management in LEED Certified Buildings? *Sustainability*, *13*(24), 13863. https://doi.org/10.3390/su132413863

The following material from the research presented in this thesis was submitted for publication to the *Energy Policy* journal on the 9th of July 2022 and is currently undergoing a peer review:

Akhtyrska, Y., & Fuerst, F. (2022). The Effectiveness of Climate Change Regulations in the Commercial Real Estate Market.

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Introduction

Climate change is recognised as one of the most significant issues facing modern society (Carbon Trust, 2005), posing a threat to the natural, economic and social systems on which it depends (Grantham Institute, 2022). The industrial, building, transport, and agricultural sectors are among the leading contributors to global greenhouse gas emissions (UN, 2022). To avoid the catastrophic effects of climate change, at the UN Climate Change Conference (COP21) in Paris, government leaders from 195 countries reached a breakthrough agreement to engage actively in mitigation activities to restrict the global temperature rise to 1.5°C above pre-industrial levels (UNFCCC, 2022). According to IPCC (2018), limiting global emissions in line with 1.5°C pathways requires "rapid, far-reaching and unprecedented changes in all aspects of society", as global net anthropogenic emissions of carbon dioxide would need to see a 45% reduction from their 2010 levels by 2030, and reach "net zero" by 2050.

The commercial real estate sector is a key source of CO2 emissions, driven by the materials and energy used in construction and, more significantly, energy demand from companies who own, manage and occupy existing real estate (Janda et al., 2021). Non-residential energy consumption from commercial and industrial organisations, government agencies and non-profit firms is estimated to amount to 60% of energy use worldwide (EIA, 2013). However, emissions of commercial buildings have historically been flat, with little evidence of widespread proliferation of cost-effective energy-saving opportunities (CCC, 2013; Cohen & Bordass, 2015). Most policy and voluntary initiatives promote energy efficient design, rarely targeting the operational energy performance of existing buildings (ibid). As a result, researchers report a wide discrepancy between the technical potential of commercial buildings and their existing energy utilisation (de Wilde, 2014). Closing the investment and performance gap is a complex and multi-layered challenge requiring both technical and social solutions (Janda, 2014).

The commercial real estate sector faces a major challenge to decarbonise while retaining profitability and productivity (Janda et al., 2021). The COP26 summit has highlighted a global desire among the real estate investment community for energy-saving opportunities in order to reap financial returns and protect assets against obsolescence (Mitchell, 2021). Fuelled by changes in corporate attitudes towards environmental issues, there is an emerging demand for sustainable offices by corporate occupiers (Dixon et al., 2009) seeking to engage in corporate social responsibility (Janda, 2014). Despite the apparent economic advantages of promoting energy efficiency throughout a building's life cycle, there are barriers preventing commercial owners and occupants from realising these cost-effective opportunities. In the rented sector, which accounts for approximately 38% of total occupied commercial space in the US (EIA, 2018) and 57% in the UK (Keane, 2015), the split incentive problem in the landlord-tenant relationship is one major reason for the commercial sector's lacklustre decarbonisation progress. Another concern is that, for a typical office tenant, a one percent improvement in staff productivity can generate a much greater increase in the bottom line compared to an equivalent percentage gain in energy savings. On the basis of higher expected financial gains, office occupants are therefore likely to favour buildings with energy-demanding services associated with greater productivity, such as high ventilation rates, improved air quality and narrower temperature set points. This means market signals cannot always be relied on and, in certain cases, adequate government intervention may be necessary to address environmental externalities associated with high energy consumption.

This research is organised into three papers, each exploring a distinct energy-saving initiative in the context of the commercial property market in two countries, the United Kingdom and the United States. The introduction outlines key concepts related to sources of greenhouse gas emissions in this sector, presenting the case and options for reducing operational energy usage. This section juxtaposes the existing policy and market initiatives of the UK and US in order to gain perspective on the solutions that address barriers to energy reduction. The research aims, scope and contribution to knowledge are presented against the backdrop of these themes.

Paper 1 focuses on the impact of the UK's Minimum Energy Efficiency Standards regulations on rents of commercial buildings in London. For the purposes of this research, lease data from Radius Data Exchange, CoStar's hedonic characteristics, and the EPC database of the Ministry of Housing, Communities and Local Government are combined using machine learning in Python. In answering the research questions, this paper applies Difference-in-Differences and Fixed Effects econometric approaches.

Paper 2 assesses the impact of operational energy management and productivity-enhancing measures on energy consumption and rental premium using a sample of green certified buildings in the US commercial market. This study combines information embedded in LEED Existing Buildings Operations and Management certification, CompStak's rental data, CoStar's hedonic characteristics and publicly disclosed energy consumption datasets from four major US commercial markets: San Francisco, New York, Boston, and Chicago. This study employs a multilevel modelling approach to uncover the contribution of these characteristics to rents and energy consumption.

Paper 3 investigates the energy-reduction potential and rental impact of a feedback technology, sub-metering, which enables tenants to monitor their individual energy usage in near real-time. This paper utilises information on the presence of tenant sub-metering from LEED Core and Shell and LEED Commercial Interiors certifications, energy disclosure data, CompStak's lease transactions, and CoStar's hedonic characteristics collected from seven US markets: Washington DC, Chicago, New York City, San Francisco, Los Angeles, Seattle, and Cambridge. The impact of sub-metering on the mean and dispersion of energy consumption and rents is investigated using a multilevel model approach with adjustment for the propensity of a net lease.

The final section of the thesis summarises the key findings of this work, presents limitations, and makes recommendations for future studies.

Origins of Greenhouse Gas Emissions in Commercial Real Estate

Emissions are generally categorised by their "scope", a classification which helps establish the emission sources for which a company is directly responsible and those outside its control (National Grid, 2022). Real estate owners have the greatest control of Scope 1 or direct emissions, which are emitted directly at the site and typically associated with gas combustion, whether in a boiler, furnace, or cooking equipment (Building Innovation Hub, 2022). Scope 2 emissions stem from purchased grid-level electricity and other centralised energy sources generated indirectly by natural gas, biomass, solar, nuclear, and so on (ibid). Finally, Scope 3 emissions are attributed to an organisation's supply chain and business operations, such as travel and embodied carbon. Since Scope 3 emissions are difficult to quantify, most greenhouse gas reporting protocols of buildings only include Scope 1 and Scope 2 types in their inventory (AHA, 2015). The US Environmental Protection Agency recommends using source energy use intensity (EUI) to calculate these emissions, which, unlike site energy use intensity, considers not only heat and electricity consumed on the premises but also the efficiency factors of the entire fuel mix required to operate a building (EPA, 2022).

According to IEA (2022), rising demand for energy services in real estate is outpacing energy efficiency and decarbonisation gains, leading to a net increase of emissions in buildings. More precisely, indirect (Scope 2) emissions from electricity use, estimated to account for two-thirds of operating emissions in buildings (Lucon et al., 2014), grew five times faster than improvements in the carbon intensity of power generation since 2000 (IEA, 2019). In contrast, direct (Scope 1) emissions of buildings have remained roughly the same during the past 40 years (Lucon et al., 2014). Considering the widening gap between energy demand and the potential of grid electricity to match it with green sources of energy, reliance on fossil fuels is set to increase (Trabish, 2021).

Although in the past much research has sought to reduce the energy consumption of residential buildings, the commercial realisation of this objective is no less important from a climate change mitigation perspective. Considering that commercial buildings account for 30% of final energy demand and only 20% of global floor area (IEA, 2019), their energy use intensity is higher compared to residential buildings. Given that commercial buildings account for 40% of all building emissions, their marginal emissions from a unit of consumed energy are also higher than in the residential sector. This is because a significant proportion of this sector's energy demand comes from electricity consumption required for services such as space cooling, equipment and connected devices (IEA, 2019). The commercial sector's high dependence on electricity is problematic not only due to the largely fossil-fuel-based power supply but also the additional emissions associated with the generation and distribution of electricity.

Building owners and occupiers cannot control the emission factor of the electricity grid they are connected to. Nevertheless, they can reduce their Scope 2 emissions by installing on-site renewable energy or buying off-site green power via Power Purchase Agreements (PPAs) or Renewable Energy Credits (RECs) (Building Innovation Hub, 2022). However, with payback periods of around 20 years, there is a high opportunity cost to on-site renewable investments in the absence of feed-in-tariffs and other government incentives (Clark, 2013). Meanwhile, PPA contracts last a long time and involve large sums of money, posing significant risks to power producers and energy customers, especially considering the inherent variability of renewable energy sources (Casey, 2020). Meanwhile, corporate purchases of unbundled RECs are criticised for creating little to no additionality for renewable energy sources (Naik, 2022). Finally, it is argued to be significantly more cost-effective for buildings to decrease their energy usage instead of continuously adding new generating capacity to an overstretched power network (Botten, 2016). The following section outlines how to achieve this objective.

Energy Efficiency and Performance Gaps

Although many academic papers and policy documents use the concepts "energy demand" and "energy efficiency" interchangeably (Bergman, 2019), their linkages to final energy consumption are not equivalent. "Energy efficiency" influences the rate at which energy is lost through a building's physical structure or consumed by its equipment. Meanwhile, "energy demand" determines the rate at which energy is consumed to meet occupants' comfort and productivity needs (UNEP, 2009). Assuming that the number of occupants stays unchanged, increasing energy efficiency and/or decreasing energy demand can achieve a decrease in final energy consumption.

In the past, researchers and policymakers have largely focused on addressing the societal under-adoption of energy efficient goods with a positive net present value, known as the energy efficiency gap (Coyne & Denny, 2021; Jaffe & Stavins, 1994). Specifically, an extensive body of literature suggests that consumers tend to a significantly undervalue future energy savings when purchasing energy-consuming goods (Gillingham and Palmer, 2013).

Yet there are numerous factors that bring the magnitude of the energy efficiency gap into question. Inaccurate modelling, technology failure, inadequate commissioning and improper use of efficiency technology are some of the most widely cited factors that account for buildings' energy consumption surpassing the expected value. Designers of highly energy efficient commercial properties often make unrealistic assumptions about how users will behave in practice (Lenoir et al., 2011). Modelling shortcomings are also attributable to the pre-bound phenomenon, which occurs when a building's energy consumption is lower pre-retrofit than predicted. Sunikka-Blank and Galvin (2012), for instance, discover that actual energy consumption is 30% lower than forecast for a sample of properties with low energy efficiency design.

In addition, emerging studies demonstrate a significant discrepancy between the predicted and actual energy consumption levels delivered by energy efficiency solutions. The over-consumption of energy as a proportion of the design energy rating is known as the energy performance gap (Burman et al., 2014; Carbon Trust, 2012; Cohen & Bordass, 2015; de Wilde, 2014; Menezes et al., 2012; van Dronkelaar et al., 2016). Carbon Trust's (2012) research shows that actual energy usage of commercial buildings can be five times higher than estimated during the design stage. Similarly, a wide discrepancy is shown between predicted and measured electricity consumption in the range of 60–70% for offices and schools participating in the CarbonBuzz initiative (UCL Energy Institute, 2013)..

The Role of Information

The effective development of public policies and voluntary measures requires a deep understanding of the root causes of energy performance and efficiency gaps. The reasons behind these gaps typically align with one of the following categories: market failures, behavioural factors, and hidden costs (Palmer and Walls, 2017). Notably, issues related to information, such as incomplete or imperfect information, split incentives, and lack of attention, play a significant role in these categories (Gillingham and Palmer, 2013). Each of these problems is, in some manner, connected to the availability or perception of information (Palmer and Walls, 2017).

The influence of information provision on consumer choices is well-documented. For example, a controlled field experiment conducted by Allcott and Taubinsky (2015) illustrates that when consumers are informed about the energy consumption of various light bulb options, their willingness to invest in efficient bulbs increases. Some studies have successfully unearthed the impact of imperfect information while controlling for other factors affecting consumer behaviour, such as inattention. One example is a study by Newell and Siikamäki (2014) who find that the lack of relevant information can result in a substantial undervaluation of energy efficiency. In the commercial context, Anderson and Newell (2004) find that although plants implement about 50% of recommended projects, they largely respond to the cost-benefit evaluations from the audits.

Theoretical Foundations

Standard economic theory's assumptions place significant emphasis on the function of information in shaping models of economic behaviours (Darnton, 2008). Expected Value Theory, as the first model designed to comprehend human behaviour, acts as the primary reference point in the realm of cognitive decision-making (ibid). According to this model, economic actors make rational choices based on calculations and information available to them. According to Adam Smith's invisible hand mechanism, the unobservable market force that helps the demand and supply of goods in a free market attain equilibrium, economic actors are driven by self-interest thus leading to optimal outcomes in a free market economy.

Market failure due to incomplete information is one example where government intervention, also known as the "visible hand", may be necessary as it can lead to suboptimal decision-making and market inefficiencies. Incomplete information is one of the most commonly cited barriers to explain why cost-effective energy efficiency opportunities are not adopted in a free market (Vaidyanathan et al., 2013). This market failure occurs when buyers and/or sellers lack the information necessary to make an informed decision (Brown et al., 2019). Energy efficiency characteristics, such as insulation, efficiency of boilers and air handling units, are largely invisible to prospective tenants. Meanwhile, owners of real estate are reluctant to invest in energy efficiency improvements that are invisible to tenants (Farmer et al., 2014). Aligned with the Expected Value theory, the information deficit model proposes that if the public had all the necessary information, they would make economically rational decisions.

Asymmetric information and split incentives are regarded as major barriers to harnessing energy efficiency upgrades in rented commercial buildings (Castellazzi et al., 2017). Efficiency split incentives occur when the financial gains of an energy efficiency investment are attributed to the tenant (who covers utilities payments) rather than the landlord (who pays for the investment) (ibid). Meanwhile, usage split incentives arise under a contractual arrangement where the landlord has an incentive to invest in energy efficiency by virtue of being accountable for energy bills. In contrast, faced with zero marginal cost of consuming a unit of energy, the tenant has no incentive to exert energy-saving effort (Jessoe et al., 2020). The premise of information deficit models can also be applied here: upon provision of information on energy consumption attributed to the landlord (base building) and the tenant, and the implementation of appropriate contractual terms, the problem of split incentives would be overcome.

While information is prerequisite for behaviour, it is commonly acknowledged that information by itself is insufficient to prompt action (e.g. Kolmuss and Agyeman 2002). As such, the information deficit model has been critiqued as overly simplistic and not always effective, as it does not account for factors such as personal beliefs, values, culture, social norms, and emotions, which can greatly influence how information is received and processed. As there are limits to human cognitive capacity to process and evaluate information (Boogen et al., 2021), the theory of bounded rationality suggests rational individuals will opt in for a satisfactory decision rather than an optimal one (Simon, 1990). The theory of rational inattention, an extension of bounded rationality, predicts that when cognitive costs outweigh the expected utility gain of a decision to engage in a certain activity (Liang et al., 2019), it would be rational for a consumer to ignore it (Palmer & Walls, 2017). In the context of energy efficiency investment, decision-makers could suffer from information overload and be required to expend effort to figure out the costs and benefits associated with an energy efficient product or action. Compounding the problem is the fact that real estate transactions present prospective tenants/buyers with a large set of variables when assessing a property, which is a bundled good of many attributes (ibid).

Existing Solutions

Theoretically and practically, the information gap can be addressed by an informed third party, a role many government and private labelling initiatives aim to fulfil (Gerarden et al., 2017). As such, both the "visible hand" and the "invisible hand" of market forces have spurred a variety of schemes, each proposing unique methodologies to tackle informational barriers.

This research, viewed through the lens of both voluntary and regulatory labelling schemes, distinguishes three categories of energy consumption reduction measures: "hard", "soft", and "hybrid". "Hard" interventions aim to bridge the energy efficiency gap, primarily through high-capital expenditure investments such as technology and building retrofits. These interventions focus on the attainment of energy savings via the technical and engineering improvements of a building (Clayton et al., 2021). In contrast, "soft" interventions encompass programmes designed to modify tenant behaviours, thereby influencing energy usage in occupation (ibid.). "Hybrid" solutions, on the other hand, necessitate low-capital expenditure investments coupled with continuous monitoring and measurement of energy consumption. Both soft and hybrid interventions play integral roles in narrowing the energy performance gap.

The ensuing sections offer an in-depth examination of the schemes that mandate or promote each of these intervention types, providing an evaluation of their effectiveness up until now.

Hard Interventions

Premised on the theory that information deficit and information overload result in a sub-optimal allocation of resources in energy efficiency investments, informational energy regulations around energy efficiency standards have gained popularity in recent years (Kontokosta et al., 2020). Energy efficiency labelling has become the holy grail of the energy performance mandates of the European Union Member States. The Energy Performance of Buildings Directive (EPBD), introduced in 2002, is the primary policy framework through which this information mechanism was established. The backbone of this Directive is the Energy Performance Certificate (EPC) scheme, which classifies buildings according to their predicted or theoretical energy consumption, and outlines recommended energy efficiency improvement measures (Castellazzi et al., 2017). The primary aim of this disclosure tool is to provide energy efficiency information to prospective tenants in an unbiased, reliable and understandable manner (DECC, 2014). Implementation of this grading system was rooted in the assumption that information would drive the adoption of energy efficiency improvements. In the context of rented space, the EPC scheme was also meant to overcome the problem of information asymmetry with respect to energy efficiency characteristics existing in the landlord-tenant relationship ex-ante lease arrangement (Allen & Lueck, 2018; Godfrey, 2020).

Similarly, a number of voluntary green design certification and grading systems have emerged, aiming to increase the salience of energy efficiency characteristics and reduce the transaction costs incurred by prospective tenants/buyers in obtaining and processing energy-related information. Among voluntary initiatives, the Building Research Establishment's Environmental Assessment Method (BREEAM) was the world's first green building grading system (Reeder, 2010). For many years, BREEAM has been the de facto standard for sustainable real estate in the UK (Fuerst & van de Wetering, 2015). BREEAM's environmental building quality indicator evaluates nine aspects of sustainability. Buildings earn credits based on how well these criteria are represented, and achieve a grade based on the total number of credits obtained, ranging – worst to best – from "Pass" to "Outstanding". In 1998 the United States Green Building Council (USGBC) followed suit by developing and releasing standards targeted at improving building environmental performance through its Leadership in Energy and Environmental Design (LEED) rating system for new construction (Reeder, 2010). LEED, which remains the most widely used green building rating system in the world, acts as a third party that verifies performance of buildings across a range of environmental themes (USGBC, 2022). This rating scheme offers four levels of certification: Certified, Silver, Gold, and Platinum.

The crucial question is the extent to which these labelling schemes stimulate the required shift in the market. Observing the rise in voluntary certifications such as LEED suggests they might. In 2017, the National Green Building Adoption Index indicated that 38% of commercial office spaces across 30 US markets have attained "green" or "efficient" certification through LEED or Energy Star, a significant leap from less than 5% in 2005 (Gunby, 2017). This steady growth implies sustained interest in energy efficiency and sustainability in the built environment. However, despite this encouraging trend, 20% of UK commercial buildings were estimated to have substandard certifications in 2016 (GCB, 2016). This indicates that while voluntary labelling schemes are a step in the right direction, their collective efficacy may be limited. Hence, beyond market-based labelling schemes, there's a pressing need to understand the extent to which stricter regulations mandating energy performance can move the needle for the commercial real estate market as a whole.

Soft Interventions

Soft interventions are implemented to steer change through the application of psychological and social factors, recognising that social norms, values, and individual attitudes can affect energy consumption. Many soft interventions revolve around initiatives to "increase people's knowledge or understanding" (Staddon, 2016). Similarly to energy efficiency labelling, the proposed mechanism is that information on energy consumption makes energy less abstract and intangible to occupiers (e.g. Buchanan et al., 2014). By becoming more aware of their energy usage, occupants are more likely to make decisions aligned with energy-saving.

In a practical setting, various media such as print materials, emails, and verbal communication are used to deliver information about energy-saving measures (Staddon, 2016). Evidence suggests that targeted feedback on plug-load energy use tends to be more impactful than general information on energy conservation (ibid). Empirical studies also show that the way this information is delivered is crucial because the effectiveness of feedback varies based on its type, frequency, and duration (Abrahamse et al., 2005). Energy savings resulting from feedback delivered by smart meters range widely, from negligible to as high as 20% (Fredericks et al., 2020). Rigorous studies that incorporate controls and account for significant external factors often present more modest findings, with average energy savings dropping to around 2% (ibid).

The implications of financial incentives on behaviour are also significant. Past research into dynamic electricity pricing has demonstrated its effectiveness in transitioning consumption away from peak hours to periods of lower demand and, consequently, lower pricing (Alberts et al., 2016; Faruqui and

Sergici, 2014). Certain studies indicate that feedback provided post-consumption proves most beneficial when coupled with monetary incentives (e.g. Abrahamse, 2005). However, at present many multi-tenant buildings depend on a single meter to monitor energy consumption, and as such, bill non-residential tenants a standard rate regardless of their actual usage. Without accurate energy information, inefficiencies from split incentives would occur because financial gains of energy-saving actions cannot be accurately attributed to the party exerting energy-saving effort.

Recognising that accurate information on tenant consumption is key to steer change, New York's LL88 mandates all commercial buildings meeting certain size requirements to install electrical sub-meters for commercial tenant space and provide monthly energy statements by 2025 (NYC, 2009). Although accurate cost allocation is the primary mechanism to explain the theoretical effectiveness of sub-meters, this regulation does not require the landlord to charge the tenant for electricity based on the readings. The value of sub-metering is also acknowledged by voluntary energy efficiency programs such as LEED schemes. As such, sub-metering forms one of the building blocks of the LEED Commercial Interiors certificate aiming to "provide for the ongoing accountability and optimisation of tenant energy and water consumption over time" (USGBC, 2022). Meanwhile, LEED Core and Shell (C+S) certificate differentiates between base building and tenant submetering thus promoting energy consumption accountability for both the tenant and the landlord.

Despite the presence of mechanisms that enable energy consumption accountability through sub-metering, the broad adoption of this integrated approach remains limited. A plausible explanation for the lacklustre adoption could be the paucity of empirical evidence substantiating the effectiveness of feedback mechanisms (such as sub-metering) in conjunction with financial incentives in the commercial real estate sector. Consequently, there is a distinct call for more extensive research on this subject to elucidate the potential of such synergistic approaches in soft interventions. This will contribute significantly to the scholarly discourse and may potentially inform policy measures and implementation strategies in real-world settings.

Hybrid Interventions

Investments in technology and upgrading equipment generate improved efficiencies, but without maintenance and continuous monitoring the total efficiency potential will not be attained. The lack of adequate control strategies, whether controls fail to function as intended or a building is not fine-tuned during the first few years of use, is a significant contributor to the energy performance gap (Demanuele et al., 2010; Norford et al., 1994). In the quest for achieving energy savings, energy management emerges as an integral hybrid strategy that encompasses the elements of both hard and soft interventions. The essence of energy management is to serve as a complementary approach that ensures that energy performance of a building is maintained throughout its operational phase. The primary advantage of energy management practices such as commissioning is the discovery of issues within a building, which, if left unnoticed, would lead to increased operation and maintenance costs for the facility (Mills, 2011).

As an increasing number of building owners show interest in green assets, momentum for energy management practices such as commissioning has surged (Mills, 2011). This has been further propelled by mandatory commissioning requirements being gradually adopted by building code officials (Kunkle, 2005; Gowri, 2009). LEED, traditionally a design certification, has also evolved to incorporate the critical role of energy management and operational controls in optimising the performance of buildings. This evolution has seen the development of the LEED Existing Buildings Operations and Management (EBOM) label, which emphasises the need for good management and control systems for efficient building operation. The core ethos of these methodologies is identifying and understanding energy consumption patterns within a facility, thereby enabling the monitoring, management and reduction of energy usage without compromising occupant comfort (EMA, 2014).

Despite the evolving landscape of energy management, a thorough exploration of energy management practices, especially within the office space context, remains absent in the extant literature. The pressing need for such research is underscored by a plethora of empirical studies conducted within the manufacturing sector (Caffal, 1995; Christofferson, 2006; Thollander and Ottosson, 2010). These investigations highlight that the appointment of dedicated energy managers and the implementation of long-term energy strategies are pivotal in propelling energy efficiency within industrial organisations (Backlund et al., 2012). Such findings point towards the potential benefits that energy management strategies could bring to the office space sector. However, the translation of these practices from the industrial to the office environment requires a nuanced understanding, considering the distinct energy utilisation patterns, infrastructural nuances, and occupational behaviours within office settings. As such, the dearth of research in this realm represents a significant knowledge gap.

Thesis Aims

The main aim of the thesis is to contribute to a better understanding of behavioural, market and policy aspects of energy demand reduction in existing commercial real estate. Despite recognising the adverse financial implications of disregarding energy consumption, investors face challenges in quantifying the financial savings attached to energy efficiency improvements (DECC, 2014). Meanwhile, policymakers are hard-pressed to prioritise policies with the greatest potential to reduce greenhouse gas emissions. Although they lack adequate financial incentives to engage in energy-saving, office occupants may have non-pecuniary motivations such as signalling their commitment to CSR matters. Overall, increased theoretical understanding of and empirical evidence for the opportunities presented by energy-saving is necessary to counter the lacklustre progress made towards energy reduction by these stakeholders. Given that a multitude of factors and actors influence a building's energy consumption, there is no one measure that could alone present a sizeable and long-lasting solution to energy reduction: the combined effect of building design, operating efficiency, equipment maintenance, and effective tenant engagement strategies is necessary (Lucon et al., 2014). Engineering and other forms of "hard" interventions can improve the theoretical energy efficiency of the commercial building stock. Meanwhile, "soft" interventions that address behavioural aspects of energy usage and "hybrid" measures would ensure that the levels of energy consumption envisaged are achieved by the technologies put in place.

Paper 1 focuses on the Minimum Energy Efficiency Standards (MEES) policy, introduced to accelerate market transformation towards energy efficiency by eliminating the most energy inefficient stock from the private rented sector. With the EPC programme at its core, this regulation targets theoretical energy consumption of buildings, and therefore constitutes a "hard" intervention. This paper aims to answer the following research questions:

- What is the effect of a mandatory minimum energy performance standards programme on the price of the substandard building stock, comprised of properties directly affected by the policy?
- What is the impact of a mandatory minimum energy performance standards programme on the price of the new de facto substandard building stock, comprised of compliant properties close to the non-compliance threshold?

Motivated by the existence of the energy performance gap, the remainder of the thesis focuses on energy conservation programmes implemented during a building's operational stage. Paper 2 investigates the impact of energy management and productivity-enhancing operational measures on the energy consumption and rent of commercial buildings. Echoing the outlined means of distinguishing between "hard" and "soft" interventions, operational management can be considered a hybrid solution. On the one hand, effective operational management can only be facilitated by equipping a building with the necessary infrastructure and technologies. On the other, energy reduction could not be achieved without procedures and methods implemented through human input (UNEP, 2008). This research seeks to answer the following questions:

- Which energy management strategies, if any, can effectively reduce energy consumption?
- Which productivity-enhancing measures, if any, adversely impact energy usage?

- What is the value of energy management and productivity-enhancing operational measures in the eyes of a tenant?

Paper 3 investigates whether sub-metering can negate the adverse effect on energy consumption of the split incentive problem in the landlord-tenant relationship. Following the classification of passive awareness and monitoring programmes adopted by Clayton et al. (2021), sub-metering is considered a "soft" intervention. The research questions of this paper are as follows:

- Can sub-metering reduce energy losses due to the split incentive problem?
- Can sub-metering lower the dispersion of energy usage?
- Do these effects vary depending on which party is responsible for energy costs in a lease contract?
- Does sub-metering bring about uncertainty-reduction benefits for either lease participant?

Thesis Scope and Design

The research questions are assessed in the context of commercial rented properties in the UK and US. While Paper 1 focuses on a policy enacted in England and Wales, Paper 2 and Paper 3 review energy conservation and productivity-enhancing features implemented in the US market on a voluntary basis.

The topic of energy conservation has received attention in numerous research areas, such as economics, engineering, psychology and sociology. In the field of economics and real estate finance, a rich body of literature finds that sustainability attributes can have a favourable impact on financial returns (Fuerst & McAllister, 2009; Eichholtz et al., 2013; Pivo & Fisher, 2010; Wiley et al., 2010; Kahn & Kok, 2014; Szumilo & Fuerst, 2017). Similar to these studies, all three papers adopt a revealed preference method of estimating the demand or value of a building's constituent environmental characteristics (Boyle, 2003). Paper 2 is grounded in the economics of energy management practices in terms of their potential to generate financial savings via lower energy consumption and the extent to which non-energy factors, such as improvement in occupant building comfort and air quality, override these savings. Paper 3 applies a rational choice or expected utility theory as the basis for modelling human behaviour with respect to energy consumption. Recognising that this theory's underlying premise of complete information cannot always be satisfied, Paper 3 intertwines the mechanism of a behavioural model featuring a negative feedback loop. In addition, with energy consumption outcomes being inherently uncertain and decision-makers risk averse, this paper posits that lease participants maximise their expected utility with respect to two variables: the expected energy consumption and dispersion.

In parallel to the theory presented above, the relationships of interest are investigated empirically. Empirical research can be roughly divided into two categories of studies: experimental and observational (Kang, 2013). Although the ideal methodology for establishing evidence of causation between variables is a randomised controlled trial (RCT), the significant costs of conducting experiments present a considerable impediment to this type of research in real estate (Allcott & Rogers, 2014; Qiu & Kahn, 2019). Paper 1 adopts a next best alternative approach to experimental research – quasi-experimental design – which allows one to establish a cause-and-effect relationship by applying specific criteria rather than randomisation (Harris et al., 2006). The primary questions of this paper are investigated using Difference-in-Differences and Fixed Effects econometric models that help address the issue of non-random assignment inherent in empirical research that utilises secondary data sources. Although Paper 2 and Paper 3 are classified as observational studies, measures are undertaken to control for non-random assignment. Apart from controlling for a number of variables that may influence the probability of assignment, these studies employ statistical adjustment techniques to control for confounding due to a lack of comparability between groups (Kang, 2013). The research questions of these two papers are answered using a multilevel modelling approach, a statistical model best suited to data with hierarchical/nested structuring.

Thesis Contribution

One important contribution to knowledge made by this research comes from novel datasets, aggregation of multiple data sources and large sample sizes. All three papers use actual rent data of signed leases, obtained from Radius Data Exchange (Paper 1) and CompStak (Paper 2 and Paper 3). The use of these two datasets for rents is contrary to most previous research, which relies on CoStar's asking rent estimates. Since asking rents rarely reflect actual prices agreed in commercial real estate transactions, they may not be the best proxies (Chiang et al., 2019). Due to data constraints, most studies use information on energy performance certificates aggregated at a building level, exposing the results to ecological fallacy. The problem with this approach is that EPCs are, in many cases, issued to a proportion rather than the whole building. Paper 1 is the first study to employ machine learning to match leases to their respective EPCs and facilitate lease-level analysis. Furthermore, previous research extensively relies on eco-labels such as LEED and Energy Star as proxies for energy performance. An emerging body of literature shows that energy consumption of properties with green certification can be higher than that of their non-certified counterparts (Agdas et al., 2015; Kontokosta, 2015; Menassa et al., 2012; Oates & Sullivan, 2012; Scofield, 2009). Paper 2 and Paper 3 employ actual energy consumption data, which only recently became publicly available on a significant cross-sectional and longitudinal scale in the US.

Paper 1 makes an empirical contribution to the literature on the link between energy performance certificates (EPCs) and pricing in the UK's commercial market. In the past, relatively few researchers were able to delve into this subject due to data paucity of commercial market transactions in the UK. One notable exception is a study by Fuerst et al. (2011), who could not uncover a significant link using data that predates the announcement of the Minimum Energy Efficiency Standards regulations. The first official enactment date of this policy has now passed, and there are compelling grounds to resurface the standing of the UK market on energy performance ratings. A recent attempt in this direction is Booker's (2019) study, which employs cross-sectional methods to estimate the value of EPCs aggregated at the building-level following the enactment of MEES. In addition, Paper 1 is the first empirical study that employs quasi-experimental methods to ascertain the impact of EPCs on rental pricing in the UK commercial market.

Together, Paper 2 and Paper 3 make an empirical contribution to the scarce literature on energy conservation measures that could address the energy performance gap. Paper 2 presents the first empirical examination into the implications of energy management (commissioning and measurement) and indoor environment (air quality and comfort) measures embedded in the LEED Existing Buildings Operations and Management scorecard. Previous research on this matter is limited to examining the bundled rental effect of LEED, and so far, only one study has focused on the LEED EBOM label (Kok et al., 2012). Additionally, there is mixed evidence as to whether productivity or energy-related attributes of LEED drive its value, or whether both do (Reichardt, 2014; Szumilo and Fuerst, 2015). Past studies have drawn conclusions by examining rental differentials between gross and net leases alone, so there is significant scope to assess the contribution of LEED's underlying attributes to rent. Finally, by analysing the impact of these variables on energy consumption, this study not only contributes to a better understanding of the environmental potential of LEED but also their wider applications within commercial real estate.

Paper 3 fills a research gap on the subject of the split incentive problem in commercial real estate, and whether it can be reduced by tenant sub-metering. In addition, it proposes a novel theoretical approach by modelling explicitly the impact of sub-metering on the expected energy usage and its variability. As such, it proposes that a risk-averse decision-maker influences these variables simultaneously vis-à-vis a dynamic mean-variance optimisation process, with the final allocation of effort to reduce these variables being dependent on the decision-maker's risk preference. The theoretical predictions and empirical findings of this study have not been presented by previous research.

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1 Pricing Implications of the Minimum Energy Efficiency Standards: Evidence from the London Commercial Market

Abstract: Regulatory intervention to enhance the energy efficiency of buildings is a prominent policy consideration in many countries. Office markets are a suitable subject for studying the effects of such interventions as they are subject to fewer idiosyncrasies and constraints than the residential market and may thus provide a clearer pricing signal of any policy impacts. This paper focusses on the introduction of Minimum Energy Efficiency Standards in England and Wales. Using machine-learning methods, Difference in Differences (DiD) and Fixed Effects (FE) estimation, a comprehensive database of the London office market is assembled and analysed. The results suggest that the MEES policy has had a measurable and significant impact and lowered the rents of the affected group of substandard energy efficiency office units by 6–8% following the announcement of MEES and in the period prior to coming into force. Additionally, a 5.4% rental discount is detected for the hitherto unaffected class of EPC E-rated office buildings, suggesting that the prospect of a further roll-out of minimum energy efficiency standards into the next higher EPC categories is beginning to be priced in the UK office market.

Keywords: Minimum Energy Efficiency Standards (MEES); commercial real estate; policy evaluation; real estate pricing

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1.1. Introduction

The adverse environmental impact of the UK's outdated building stock has been a topic of contested political debate over the last two decades. The EU's 2002 Energy Performance of Buildings Directive (EPBD) put the UK on a trajectory of policies that target carbon emissions in the property sector, currently estimated at 50% of the UK's total (French, 2020). The principal means has been the energy performance certificate (EPC), a system that grades buildings on a scale of A to G, A being the most efficient. From January 2008, it became a legal requirement to have a valid EPC for any building at a point of sale, leasing, and construction. Unlike its counterpart, the Display Energy Certificate (DEC), an EPC estimates how much it would cost to operate a given building by considering physical characteristics such as fabric, heating, lighting and plant and machinery services. At the same time, it provides a list of energy efficiency recommendations, how much it would cost to implement them, and the potential savings achieved as a result (Behavioural Insights Team et al., 2011). By making energy characteristics more transparent to renters, the aim of this ranking mechanism was to shift demand away from inefficient properties towards those that operate more economically.

A series of more stringent policies later followed as governments announced plans to remove the most energy inefficient buildings from the supply stock. More precisely, the European Commission revised the EPBD in 2018, announcing that public and non-residential buildings will have to be upgraded to at least EPC level F by 2027 and level E by 2030 (EC, 2021). By virtue of the Energy Act, published on 18 October 2011, the domestic and commercial private rented sector became the subject of the Minimum Energy Efficiency Standards (MEES) in England and Wales. This change of tune, in favour of a more enforced regulation mechanism for inefficient properties, was likely prompted by the continuing poor energy performance ratings of a large proportion of buildings in the UK (MHCLG, 2019). The onset of the MEES on 1 April 2018 marked the beginning of a new era for the rented sector in England and Wales, as landlords could no longer offer new leases in properties with EPC ratings of F and G after this date. From 1 April 2023, the minimum EPC requirement of an E band will be extended to all types of lease contracts under these regulations. The repercussions of non-compliance with the non-domestic MEES include a maximum fine of £150,000 if a landlord is found to be in violation for three months or longer (Curnow, 2017). Furthermore, enforcement agencies will be allowed to publish information of the breach on the PRS Exemptions Register, which will be available for at least 12 months and can be viewed by the public (Heathcote, 2020).

The intention behind this austere measure is to reduce the energy efficiency gap, or the difference between the optimal and current implementation of energy efficiency technologies (Andrei & Thollander, 2019). However, the effectiveness of the policy to date is the subject of considerable debate. In 2016, approximately two years before the policy's implementation date, it was estimated that 23% of the UK's building stock had substandard EPC ratings (French, 2020; GCB, 2016). An empirical study by McAllister and Nase (2019) into the London office market shows that during the period 2011–2017, a maximum of 0.65% of F–G office units undertook the necessary upgrades to reach a compliant rating. In addition, some sources suggest that little pricing movement occurred prior to the official introduction of MEES in April 2018, as the market paid little attention to the upcoming legislation (French, 2019). One explanation is that low-grade EPCs are more likely to be owned by smaller landlords, who tend to wait until the last minute to act upon new legislation (BEIS, 2021a). In contrast, the institutional investor group would likely attempt to future-proof their portfolios in response to MEES by retaining properties with higher-than-average EPCs and disposing of low-quality stock (Montlake & Gelb, 2018; Sayce & Hossain, 2020a). Some concerns posit the soft-start nature of MEES, which, as some argue, limits the effectiveness of this legislation until after April 2023 (Sayce & Hossain, 2020a). Yet many industry professionals remain sceptical of whether MEES would move the needle even after it officially comes into force. The degree of flexibility offered by MEES is one of the main causes (McAllister & Nase, 2019). Specifically, owners of substandard properties can file for an exemption if: 1) the investment payback period is greater than seven years; 2) the prevailing lettings have short lease structures of fewer than six months; or 3) tenants refuse to let the landlord undertake the necessary renovation works (BEIS, 2019). The disparity between energy consumption predicted by EPC ratings and energy use in operation also incites concerns among many real estate industry players regarding the suitability of EPCs to deliver emissions reductions (Sayce & Hossain, 2020a). Better Buildings Partnership (2018), for example, has long advocated performance, rather than design measures, after discovering little correlation between the proven energy efficiency and EPC ratings using energy consumption data of its members' buildings in operation.

Research on price effects is essential for testing the effectiveness of environmental interventions, such as the compulsory EPC (Fuerst & McAllister, 2011a). Theoretically, a mandatory green building programme has the potential to drastically alter market norms and increase demand for more efficient properties (Aroul & Hansz, 2012). Insufficient short-run supply would induce a higher premium in compliant (A–E) properties until the supply matches the increased demand (Aroul & Hansz, 2012; Fuerst & McAllister, 2009). Having now passed the first official deadline of MEES in April 2018, the primary aim of this study is to investigate whether this policy has had a significant impact on rents in substandard properties with F–G ratings in the period following the announcement and the first deadline of MEES. Additionally, with the intensified risk of obsolescence and depreciation for the buildings that are next in line to come under the scope of this legislation, this paper examines the impact of the first MEES deadline on rents of units with D and E ratings. The results of this research intend to guide landlords and developers who would be better able to understand the risks posed by properties with low-grade EPC ratings.

1.2. Relevant Literature

To date, the commercial real estate sector research has largely focused on the pricing impact of voluntary third-party green rating systems such as the Leadership in Energy and Environmental Design (LEED), Energy Star and Building Research Establishment Environmental Assessment Method (BREEAM). In the US, the Energy Star programme is the most closely comparable energy assessment tool to the UK's EPC and has received significant research attention in the past. However, there are notable differences between these two assessment tools. While physical characteristics establish a building's final EPC score, actual energy consumption is the primary metric used during an Energy Star assessment. Research mostly demonstrates that Energy Star certificates are associated with significant rental premiums. One such example is a study by Eichholtz, Kok, and Quigley (2010) who find that Energy Star commands 3.3% higher rents. Similarly, Fuerst and McAllister (2011b) uncover a rental premium of 3–4% for this type of certification. BREEAM, the most popular voluntary label in the UK (Fuerst & van de Wetering, 2015), may serve as another valuable point of reference. Using data gathered from EGi, CoStar and Emporis, Chegut, Eichholtz, and Kok (2014) report a 14.7% premium for BREEAM-certified properties. Meanwhile, Fuerst and van de Wetering (2015) uncover a sizeably higher rental premium in the range of 23–26% for the BREEAM-rated group of buildings.

The vast majority of papers that unpack the influence of EPC certification are conducted in the residential sector. One notable example, undertaken by Brounen & Kok (2011), reports that A–C labels transact at a 3.7% price premium within a sample of certified residential houses in the Netherlands. Insight into the Dutch commercial real estate sector is the subject of Kok & Jennen's (2012) paper. These authors report that EPC labels of D or lower suffer a 6.5% discount compared with A–C ratings. By using an instrumental variable approach, Aydin et al. (2020) find that a ten percent improvement in energy efficiency corresponds to a precise 2.2 percent increase in the market value of the dwelling. In the UK, however, data paucity has long stalled empirical research into the pricing effect of commercial EPCs. Fuerst and McAllister's (2011a) is one of few empirical studies on the topic. The authors report that EPC ratings have no significant impact on rental and sales outcomes, but a significant effect on equivalent yields. Yet due to utilising a relatively small dataset (708 properties) consisting of three different commercial property sectors, the authors note that a weak relationship could have been "missed" by this study. Later work by Fuerst et al. (2013) reports a significant rental premium for energy efficient EPCs in state-of-the-art buildings only. Almost a decade later, Booker (2019) explores whether the insignificant finding of Fuerst and McAllister (2011a) could be attributed to the timing of their study, which approximately coincides with the announcement of MEES. By employing a dataset of 5,444 office assets on lease transactions signed after April 2018, this study certainly overcomes the data deficiency concerns encountered by earlier research. The revival of the subject by the author seemingly yields a novel set of findings: a statistically significant discount in F- and G-rated properties of 11.4% and 14.9%, respectively.

Aside from utilising small datasets, omitted variables are a potential issue in previous studies, as many rely on a hedonic econometric approach applied on a cross-sectional basis (Zhu et al., 2022). Failing to control for building characteristics that are systematically associated with substandard properties would negatively bias the coefficients of low-grade EPC bands. Meanwhile, buildings with better energy performance may be associated with higher construction and fitting-out specifications, and may also non-randomly cluster in certain locations (Fuerst & McAllister, 2009). As most studies use data aggregated at a building level, ecological fallacy may pose challenges to making inferences about unit-level EPCs. Finally, many studies utilise appraisal-based or asking rents instead of achieved rents. The following sections detail the ways in which this study addresses these shortcomings.

1.3. Hypotheses

The main aim of this study is to empirically identify the causal impact of MEES policy on rental prices of office units in various EPC categories during the period from 01 January 2008–31 December 2020. Since this period is associated with two MEES trigger points, this study distinguishes between the pre-announcement (1 January 2008–17 October 2011) and post-announcement (18 October 2011–31 December 2020) phases. The latter phase is further sub-divided into the "transitional" window (18 October 2011–31 March 2018), which is followed by the "enactment" period (1 April 2018–31 December 2020). These periods and their respective trigger events are illustrated in Figure 1.1.

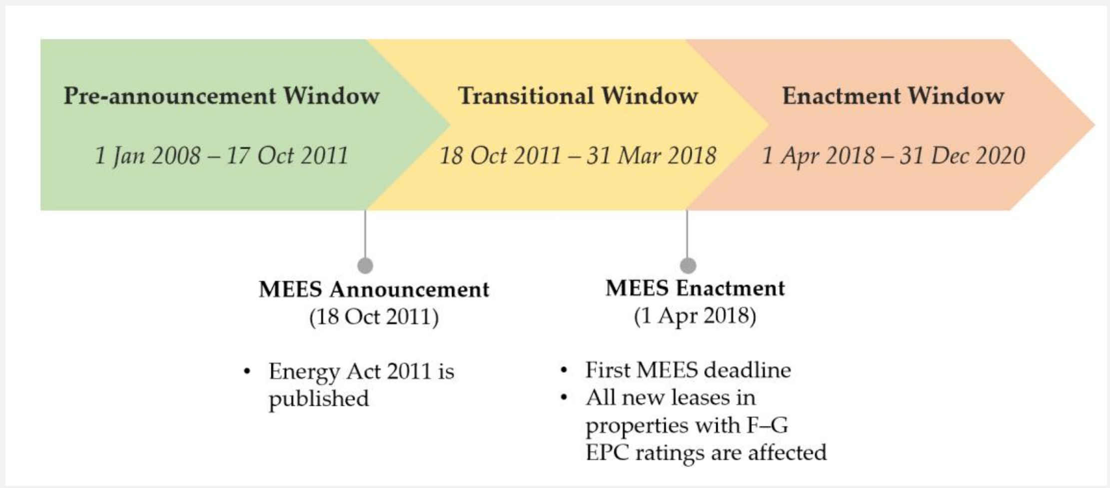

Figure 1.1: The MEES Timeline.

This paper's analysis begins by comparing the rental performance of substandard (F–G rated) properties relative to the compliant (A–E) stock. Should MEES have prompted tenants to engage in "price chipping" of substandard EPCs during rental negotiations (Investment Property Forum, 2007), a "brown" discount in these properties would emerge following the MEES Announcement and MEES Enactment. A significant discount in the substandard EPCs relative to the A–E group during the transitional and enactment periods, respectively, would require acceptance of the following hypotheses:

Hypothesis 1a: The MEES Announcement triggers a rental discount in F–G units.

Hypothesis 1b: The MEES Enactment triggers a rental discount in F–G units.

The following investigation concerns the heterogeneous effect of MEES on F and G ratings. Although this policy equally targets these two substandard EPC bands, G-rated units would exhibit relatively higher refurbishment costs and longer voidance periods to achieve a compliant rating. Additionally, the most substandard EPC (G rating) would arguably be subject to a greater degree of price chipping by tenants. On the other hand, given that the most inefficient buildings are the best MEES exemption candidates for failing to meet the seven-year payback rule, the less inefficient EPC group (F rating) may undergo a greater rental decrease. Since the take-up of exemptions has reportedly been low (BEIS, 2021a), MEES is hypothesised to incur a more adverse rental effect for G-rated buildings. Should the rental discount of G-rated units be significantly higher than their F-rated counterparts relative to the A–E group during a) the transitional window and b) the enactment phase of MEES, the following two hypotheses would be accepted:

Hypothesis 2a: The MEES Announcement triggers a greater discount in G-rated units compared to F-rated ones.

Hypothesis 2b: The MEES Enactment triggers a greater discount in G-rated units compared to F-rated ones.

When a policy includes a time gap between announcement and effective date, time-varying effects may be observed (Wing et al., 2018). This paper therefore investigates the incidence of phase-in effects of the MEES announcement. Specifically, relative to the pre-announcement period (1 January 2011–17 October 2011), the adverse effect of MEES on rents of properties with substandard EPC ratings is expected to increase over time as the first deadline of MEES approaches. This supposition is at least partially attributed to the fact that detailed guidance of MEES had not been issued to landlords until 2017 (Sayce & Hossain, 2020b). As a result, some expected investors would "rush to the top" approximately one year before the deadline (Montlake & Gelb, 2018). The following hypothesis would be accepted if the rental difference between F–G and A–E rated units is the greatest in the period prior to the enactment of MEES compared to the period following the announcement:

Hypothesis 3: During the transitional period of MEES, the greatest decline in the rental value of F–G units occurs prior to the enactment of MEES.

An anticipated widening scope of the policy in the near future may lead to adverse rental effects on the EPC bands closest to the current MEES threshold. According to Fuerst and McAllister (2011a), a group of buildings commanding price premiums will always exist in markets with dynamic energy efficiency standards, putting the rest at a higher risk of obsolescence and value depreciation (Booker, 2019). With only a handful of buildings rated F–G remaining after April 2018, a corollary to this is that units with D and E ratings will form the new de facto substandard group. The next set of hypotheses would be accepted if, relative to the A–C group, during the enactment window of MEES, a) a significant rental discount for E units is uncovered; b) a significant rental discount for D units is uncovered, respectively:

Hypothesis 4a: The MEES Enactment triggers a rental discount in E units.

Hypothesis 4b: The MEES Enactment triggers a rental discount in D units.

1.4. Data

The data gathering was executed using a random sampling methodology. More specifically, all transactional data was downloaded from Radius Data Exchange for the central London market, which was then matched with the EPC database. Compared to the overall number of transactions (by square footage) reported by DeVono (2023) for the central London during the period from 2008–2020, Radius Data Exchange captures around 15% of all transactions within the London office market in any given year.

Datasets

Previously known as Estates Gazette Interactive (EGi), Radius Data Exchange is the primary source of rental data on leases signed during the period from 1 January 2008–31 December 2020. Radius crowdsources data from the UK's main commercial property agents and has information on over 100,000 lease comparables (EGi, 2021). From this source, information on the following variables is obtained: achieved and asking rents, lease execution date, lease term, lease type (lease, sub-letting, assignment), transaction size, grade of leased space (new, second hand – grade A, second hand – grade B), whether the unit is pre-let, and its market location (City Core, City Fringe, Inner London, Mid-town, Outer London, the West End, Docklands, and Southern Fringe). Scarcely available data on rent review, lease break dates, number of rent-free months, business rates and service charges motivate the exclusion of these variables from the final dataset. For ~30% of leases where information on achieved rents is absent, asking rents are used and controlled for.

The second data source is the UK's non-domestic EPC register provided by the Ministry of Housing, Communities and Local Government (MHCLG, 2021). This dataset provides information on EPC rating bands (A–G), asset rating scores, floor area, building environment (air conditioning, mechanical ventilation, etc.), main fuel type (grid-supplied electricity, natural gas, etc.), building complexity level, and the presence of air conditioning. The filtering process for EPC lodgements corresponding to London office space occurs in multiple stages. After downloading a file consisting of all commercial EPC lodgements in England and Wales issued from 2008–2020 in 33 London local authorities, the following property types are filtered for: 1) offices, 2) B1 offices and workshop businesses, and 3) A1/A2 retail and financial/professional services. Following the same approach as McAllister and Nase (2019), any repeat lodgements filed fewer than three months apart, which correspond to the same building reference number, are counted as duplicates. In such instances, the latest entry overrides any earlier ones issued within this period.

Lastly, CoStar (2021) data is employed to complete the dataset. This source provides information on the following variables: construction/renovation year, class, size, number of floors, the presence of a BREEAM rating, and amenities.

1.5. Methods

A hedonic conceptual framework pioneered by Rosen (1974) is traditionally used in real estate research to analyse the effect of energy performance ratings on rental premia alongside other building-level characteristics. However, a simple one-period regression of unit rental prices on a substandard EPC dummy variable would yield an inconsistent estimator where there is covariance between group affiliation and the error term (Wilhelmsson, 2019). For example, Brounen and Kok (2011) show that the quality and characteristics of dwellings influence their certification choices. To yield consistent and unbiased estimators requires an econometric approach that addresses the issue of non-random assignment. A Difference-in-Differences (DiD) design is one of the leading methods for evaluating the causal impacts of policy interventions (Callaway & Sant'Anna, 2021). By assuming that differences between the control and treatment groups are fixed over time, a DiD specification removes any bias from unmeasured group-level characteristics. Using the available data on lease transactions observed for the control and treatment groups before and after the event of interest, one can compute the rental price differential arising from the MEES policy. The generalised DiD set-up employed by this study is represented by the following regression equation:

$$\log\ Rent_{igt} = \gamma_g + \lambda_t + \delta D_{gt} + \beta X_{ig} + cL_{igt} + \varepsilon_{igt} \tag{1}$$

where the dependent variable $Rent_{igt}$ is the rent associated with building i in group g for a lease signed at time t. Since rent distribution has a long right tail, the natural log in the dependent variable is applied (Fuerst et al., 2013; Gabe et al., 2019; Gabe and Rehm, 2014). In this equation, γ_g represents the combined effects of the time-invariant characteristics of the treatment and control groups. Throughout this paper's analysis, the composition of the treatment and control groups changes depending on the question explored. The inclusion of time fixed effects, λ_t, absorbs all changes in the macroeconomic environment that could influence rental prices (Wing et al., 2018). While $D_{gt} = 0$ for both groups in the pre-treatment period, $D_{gt} = 1$ for the treatment group in the treated period. The coefficient δ captures the shifted difference between these two outcomes. X_{ig} encompasses a range of time-invariant hedonic characteristics, such as building class, BREEAM certification status, building size, market location, etc. A vector of time-variant lease characteristics, L_{igt}, encompasses lease term, transaction size, whether asking rent is used and type of contract signed (lease, sub-letting and assignment).

A DiD design requires the differences between groups to be stable over time. It also relies on changes in treatment exposure not being associated with changes in the distribution of covariates. Changes in group composition could occur when data come from repeated cross-sections rather than longitudinal data on individual units (Stuart et al., 2014). The group of substandard units could have theoretically deteriorated in quality after the announcement of MEES, since the worst performers are more likely to receive exemptions, while higher quality buildings switch into the control category. If such compositional changes are significant and sizeable, the DiD estimate would be negatively biased. As a robustness check, a longitudinal DiD estimation is applied, where lease information for the same EPC certificates is available before and after the MEES Announcement. In this estimation, only units with repeat data are included. The average treatment effect on the treated (ATET) of the MEES Announcement is estimated by fitting the following model:

$$\log Rent_{igt} = \alpha_i + \lambda_t + \delta D_{gt} + cL_{igt} + \varepsilon_{igt} \tag{2}$$

where α_i is a fixed component associated with an EPC lodgement i that cancels out in the regression. As such, this regression involves unit-level fixed effects and time fixed effects. The direct implication of this specification is that building-level controls specified in Equation (1) drop out. Other parameters of the above specification are analogous to those described in Equation (1).

The effect of policy intervention may depend on the length of exposure to it. In such cases, exploration of dynamic effects may be of interest (Callaway & Sant'Anna, 2021). One way to investigate time variation in policy effect is through an event study framework that explicitly models anticipation and phase-in effects (Wing et al., 2018). This specification can also be used to explore whether there is evidence of pre-existing trends. As such, equation (1) is modified to resemble a specification of Angrist and Pischke (2009):

$$\log Rent_{igt} = \gamma_g + \lambda_t + \sum_{j=-m}^{q} \beta_j D_{gt}(t = k + j) + \beta X_{ig} + cL_{igt} + \varepsilon_{igt} \tag{3}$$

where k is the time at which the treatment, the announcement of MEES, first switches on. Meanwhile, β_j is the coefficient on the j^{th} lead or lag. Lags and leads capture the difference in rents between treated and control units, compared to the difference in the omitted reference period. Instead of one treatment effect, this equation incorporates m "leads" and q "lags" of the MEES announcement effect.

1.6. Results and Discussion

This section empirically investigates the relationship between various MEES trigger points and rents in the London office market between January 2008 and December 2020. In the final sub-sections, the implications of this study's results are discussed in the context of the outlined hypotheses, and guidance for future research is presented.

Data Summary

Table A.1.1 (Appendix A.1) presents the complete set of variables and their summary statistics. Rental level outliers are eliminated based on the sample distribution with the upper and lower boundaries set at the 99th percentile. As expected, the average rent declines as one moves down the EPC scale, with £68.12 for units rated A and £41.75 for those rated G. The distribution of EPCs in the sample set is broadly in line with the entire population of EPCs issued for office spaces in London from 2008–2020.

Figure 1.2 demonstrates the evolution in the number of lodgements for the primary treatment (F–G ratings) and control (A–E ratings) groups over the years in the sample. As expected, a substantive decline is observed in the number of leases matched to substandard EPC ratings towards the end of the transitional and during the enactment periods of MEES. This observation in line with Table A.1.2 in the Appendix, which shows that the proportion of EPCs with F and G ratings filed in England and Wales decreases significantly (Official Statistics, 2023). Since it would have been illegal to engage in new lease contracts for owners of units with F–G ratings following April 2018, it is useful to gain insight into the possible reasons for encountering these observations in the first place. One explanation is that units where these leases were signed (n=17) had been granted exemptions from MEES. Nearly half of these observations are encountered in buildings constructed during 1500–1900, suggesting that some may be heritage assets and thus potential candidates for exemption. Although exemptions to historical buildings are not granted automatically (Sayce & Hossain, 2020b), an application for EPC exemption can be made if the required energy efficiency modifications "unacceptably alter the character or appearance" of the building (The National Archives, 2012). Additionally, nearly three-quarters of these leases are signed in G-rated units, suggesting many may have received exemptions for failing to meet the 7-year payback rule (the "Golden Rule"). However, upon cross-referencing the list of addresses associated with these leases with the publicly accessible PRS Exemptions Register (BEIS, 2021b), not a single match is found. To ensure these leases have been correctly attributed to the corresponding EPC lodgements during the matching procedure in Python, a series of manual checks are conducted. However, no matching errors are identified. While it is possible that these leases have been signed illegally, one cannot rule out the possibility that their renewed EPC versions have not been entered into the database.

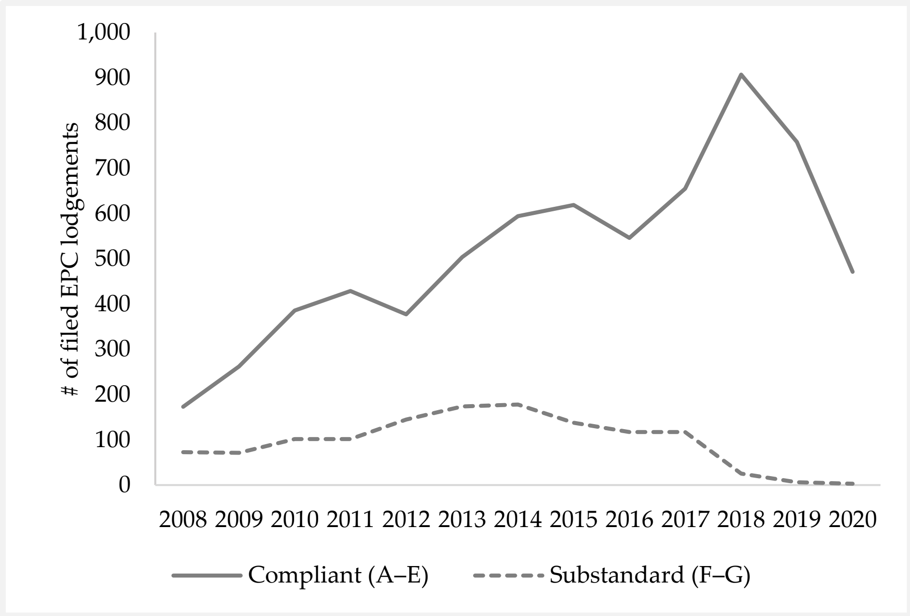

Figure 1.2: Number of EPC lodgements filed for F–G and A–E EPC ratings.

This study also observes the aforementioned downward trend in EPC lodgements with F–G ratings does not correspond to the level of upgrade activity when connecting building reference codes to their respective Energy Performance Certificates (EPCs). Specifically, following the MEES announcement, only 31 units initially graded F–G are found to be attributed to compliant EPC ratings following the announcement of MEES. However, it is crucial to highlight that when a building undergoes resizing or renovation, the building reference code alters, which further complicates the identification of units. As a result, using building reference numbers to gauge the extent of renovation activity might underestimate the true scope.

Figure 1.3 explores the evolution of average rent of substandard F–G vs compliant A–E units. Moderate declines in rents of F–G units are observed during the periods of 2011–2012 and 2015–2016, and much sharper ones in 2017–2018 and 2019–2020. Considering the timing of the MEES Enactment in April 2018, the prima facie evidence presented in Figure 1.3 is in line with expectations. This graph may also serve as an initial test for the presence of parallel trends, which is one of the key identification assumptions in the DiD specification. Figure 1.3 demonstrates that before the announcement of MEES, trends for these two groups exhibit fairly similar patterns. However, trend similarity during the pre-treatment period cannot prove that units in the post-treatment period would have followed similar trends to the control group in the absence of treatment (Clarke & Schythe, 2021). Additionally, this graph merely offers descriptive insights about rental prices without controlling for the key differences across these building groups via a formal regression.

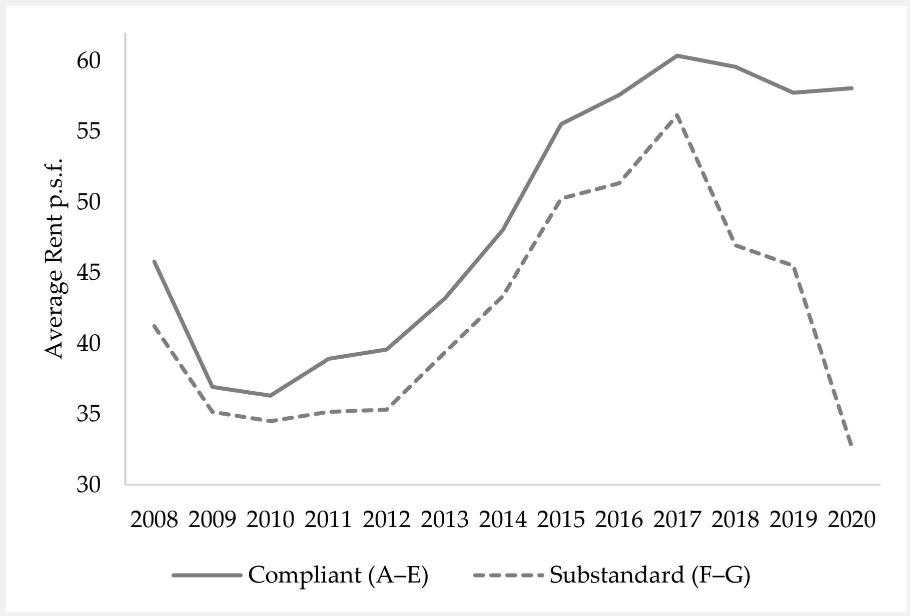

Figure 1.3: Rent trends for F–G and A–E EPC ratings.

Main Results

Following the empirical and methodology strategy described above, the first two models in Table 1.1 investigate the impact of the MEES announcement and enactment on substandard (F & G) properties through a DiD estimation on repeated cross sections. The first model in Table 1.1 captures the combined effect on F–G rated buildings, while the second model shows the rental impact on F and G rated properties separately. The reference group comprises leases signed for buildings rated A to E that are class A, primarily for office-use located in London's City Core. The complete results can be found in A.2.1 (Appendix A.2), which show that many hedonic and lease variables are statistically significant. Rental variations attributed to market heterogeneity align with expectations: buildings in London's West End command the highest premium, while rents in the Docklands market are the cheapest. The first two models in Table 1.1 describe an average rent variance of 42%, with the F-statistic showing that the variables are jointly significant. A graphical diagnostic test reveals that the linear trends model supports the parallel trends assumption in the pre-treatment period. This result is reinforced by the Wald test, which cannot reject the null hypothesis of parallel linear trends in the pre-announcement period. The results of the "DiD Group F–G" model show that the rental value of substandard properties declines by 5.8% during the transitional period of MEES, occurring from 18 October 2011 – 31 March 2018. For a relatively small number of leases signed in non-compliant EPC units after April 2018 (n=17), a significant decrease in rental value of 27.8% is found. The time-invariant coefficient for the F–G group shows a weakly statistically significant difference of 3.5% between substandard and A–E rated units before the announcement of MEES. The results of the "DiD

Separate F&G" model show that during the transitional phase the rental value of F-rated buildings declines significantly by 7.6%. Meanwhile, the DiD coefficient for the most inferior EPC class (G rating) is not statistically significant. However, the interval following the MEES Enactment is associated with a significant and sizeable discount for G-rated EPCs (–33.0%).

Table 1.1: Selected regression results for the logarithm of achieved rent in F–G rated buildings.

Dependent Variable	The Logarithm of Rent per Square Foot			
Econometric Specification	Difference-in-Differences		Fixed Effects	
Data	Repeated Cross Sections		Panel	
Variable / Model Name	DiD Group F–G	DiD Separate F&G	FE Group F–G	FE Separate F&G
Key Independent Variables:				
DiD Announcement (F–G)	–0.058**		–0.076**	
DiD Enactment (F–G)	–0.278***			
DiD Announcement (F)		–0.073***		–0.126***
DiD Announcement (G)		–0.030		0.003
DiD Enactment (F)		–0.121		
DiD Enactment (G)		–0.330**		
EPC Group Controls:				
Substandard (F–G)	–0.035*			
Substandard (F)		–0.025		
Substandard (G)		–0.054		
Other Controls:				
Time Dummies	Included	Included	Included	Included
Lease Controls	Included	Included	Included	Included
Hedonic Controls	Included	Included	Not Included	Not Included
Amenities	Included	Included	Not Included	Not Included
Market Controls	Included	Included	Not Included	Not Included
Observations	7,801	7,801	2,200	2,200
R-squared	0.420	0.420	0.694	0.695

Notes: This table reports the results for the logarithm of rent from January 2008 to December 2020. The reference group comprises units with A–E ratings. Error terms are normally distributed. No autocorrelation in the residuals is identified. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Following the rule of strict exogeneity, future treatment exposure should not be anticipated (Wing et al., 2018). To test the validity of this assumption prior the announcement of MEES, we investigate dynamic effects using a Granger-Type causality test. Time variables are aggregated annually to increase the number of lease observations occurring at specified moments. To align with annual time variables rather than quarterly intervals that precisely match the announcement and enactment of MEES, lease transactions signed between 18 October 2011–31 December 2011 and 1 April 2018–31 December 2018 are excluded. Lag and lead coefficients are computed relative to the passage of time since the MEES Announcement, set at Year 2011 (1 January 2011–17 October 2011). The absence of statistically significant lead coefficients confirms that pre-announcement outcomes are not associated with the forthcoming announcement of MEES. Additionally, a Wald test indicates that the linear trends between the treatment and control groups are parallel before the announcement. This model also explores whether the impact of the MEES Announcement varies since the time of first exposure. The coefficients of Lag0, Lag2, Lag6–Lag8 are significant (Figure 4). The greatest significant adverse rental impact during the MEES transitional interval occurs in the lead-up of the MEES enactment, capturing the first quarter of 2018. Although the coefficients for the years following the MEES Enactment are notable, the observed discounts exhibit weak statistical significance. Event study framework regression results can be found in Table A.2.1, Appendix A.2.

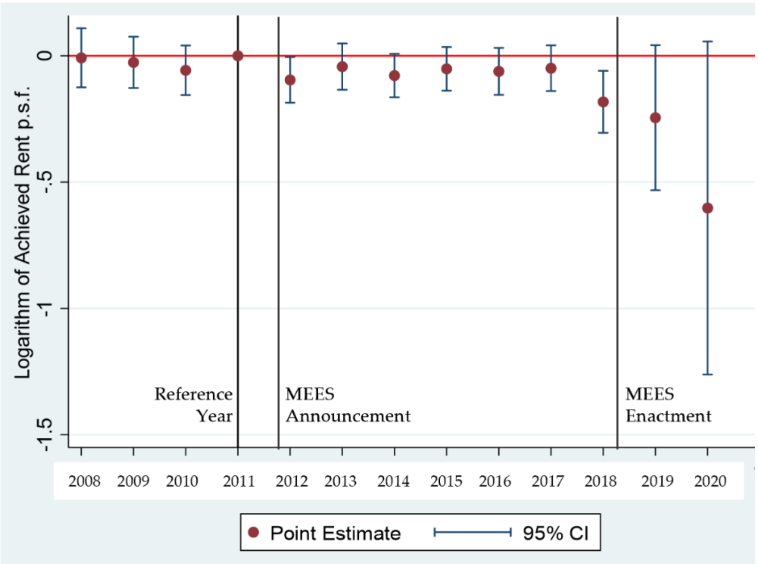

Figure 1.4: Event Study Framework Plot.

If MEES exposure and group affiliation are related, a key identifying assumption of DiD would be violated. To assess whether there is a selection bias in the observed characteristics over time, Table A.1.4 in Appendix A.1 compares time trends in the characteristics of the control and treatment groups. However, drawing conclusive inferences from this table alone is challenging. Therefore, covariate balance regressions are employed to examine this aspect of DiD validity (Wing et al., 2018). Various hedonic characteristics, including building size, building class, grade of space, number of storeys, and age, are regressed on the same variables as in the "DiD Group F–G" model in Table 1.1. In these covariate balance regressions, all DiD coefficients related to the transitional and enactment phases are modest and statistically insignificant. One exception is buildings in the treatment group appear to have a lower number of storeys after the announcement.

However, selection bias may still exist in features not captured by this research. By focusing solely on within-unit variation, the issue of compositional bias in hedonic characteristics can be mitigated. The reduced sample comprises 2,200 leases signed in 503 EPC units. This sample is limited to the transitional period of MEES since there are no repeat unit-level F–G observations after the enactment of MEES. The results of this reduced dataset analysis are presented in the second half of Table 1.1, and the complete findings are available in Table A.2.2 in Appendix A.2. This analysis reveals an average rental discount of 7.6% for substandard units during the transitional period ("FE Group F–G " model). This result is more conservative compared to the reference model, which employs the DiD method on repeat cross sections using the same sample without explicitly accounting for within-unit variation (Table A.2.2; Appendix A.2). Consistent with DiD findings, the adverse impact of the MEES Announcement appears to be entirely absorbed by the F band, while being insignificant for the most substandard EPC rating. As an additional robustness check, observations involving asking rents are excluded, showing no substantial difference from the results reported above.

In Table 1.2, the focus shifts to examining the rents of D and E units compared to those rated A–C. The complete findings are available in Table A.2.3 in Appendix A.2. Using the DiD method on repeat cross sections, a statistically significant discount of 3.8% is observed in D–E rated units post-enactment. Furthermore, D–E ratings transact at a 4.0% rental discount before the enactment. The following model reveals that this effect is primarily driven by E-rated units. The last three models in Table 1.2 show the Fixed Effects results on a sample of repeat unit observations before and after the enactment of MEES. These models confirm that the adverse rental effect of the MEES enactment is solely attributed to E-rated units.

Table 1.2: Selected regression results for the logarithm of achieved rent in D–E rated buildings.

Dependent Variable	The Logarithm of Rent per Square Foot			
Econometric Specification	Difference-in-Differences		Fixed Effects	
Data	Repeat Cross Sections		Panel	
Variable / Model Name	DiD Group D–E	DiD Separate D&E	FE Separate D [a]	FE Separate E [b]
Key Independent Variables:				
DiD Enactment (D–E)	–0.038**			
DiD Enactment (D)		–0.024	–0.024	
DiD Enactment (E)		–0.060***		–0.054*
EPC Group Controls:				
D–E ratings	–0.040***			
D rating		–0.033***		
E rating		–0.050***		
Other Controls:				
Time Dummies	Included	Included	Included	Included
Lease Controls	Included	Included	Included	Included
Hedonic Controls	Included	Included	Not Included	Not Included
Amenities	Included	Included	Not Included	Not Included
Market Controls	Included	Included	Not Included	Not Included

Dependent Variable	The Logarithm of Rent per Square Foot			
Econometric Specification	Difference-in-Differences		Fixed Effects	
Data	Repeat Cross Sections		Panel	
Variable / Model Name	DiD Group D–E	DiD Separate D&E	FE Separate D [a]	FE Separate E [b]
Number of EPC Groups			362	362
Observations	6,558	6,558	1,563	1,404
R-squared	0.416	0.416	0.729	0.753

Notes: This table reports the results for the logarithm of rent from January 2008 to December 2020. The reference group comprises units with A–C EPC ratings. Error terms are normally distributed. No autocorrelation in the residuals is identified. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

[a] E-rated units are excluded from the sample set.

[b] D-rated units are excluded from the sample set.

While this study's sample set comprises leases signed for office spaces only, a small proportion of these units are located in properties primarily used for other commercial purposes, such as retail and manufacturing activities. As a robustness check, the same series of regressions as above is conducted using a sample of office-space units located in buildings used primarily for offices. No substantial deviation in the coefficients of interest is uncovered (Table A.2.4; Appendix A.2).

Discussion

Using a Difference-in-Differences (DiD) approach, this study finds evidence in support of Hypothesis 1a, which asserts that MEES has adversely influenced rents of the EPCs that come under this legislation's immediate scope during the policy's transitional window. The adverse impact of the announcement of MEES on the substandard EPC group is verified using longitudinal repeat lease data signed for the same EPC units before and after the announcement using the Fixed Effects specification – an approach deemed the most robust in evaluating policy instruments (McAllister & Nase, 2019). The uncovered market movement during this period can be explained by demand-side factors and short-run inelasticity of supply (Aroul & Hansz, 2012). With respect to demand elements, Sayce and Hossain (2020b) suggest that "MEES raised awareness among those not previously engaged in corporate social responsibility practices and climate change mitigation" (p. 11). Similarly, by surveying a group of landlords and agents after the announcement of MEES and prior to its first implementation deadline, Mulliner and Kirsten (2017) report that 70% of landlords and 65% of agents experienced "potential increased difficulties in selling or leasing properties with low EPCs" (p. 186). Probing deeper, it is possible that tenants' increased awareness of EPC ratings has improved their understanding of the possible adverse implications of substandard ratings on occupancy costs. Although empirical research in support of this link is relatively scarce, Fuerst et al. (2013), for instance, find that service charges are lower in the most energy-efficient EPC ratings, although the result is limited to modern buildings.

One source of uncertainty in the data is the inexplicable occurrence of leases matched to non-compliant EPCs after April 2018, as none could be attributed to the exemptions database. Nevertheless, an initial attempt to uncover a rental decline in the substandard group of EPCs after the enactment of MEES yields a DiD coefficient that is consistent with this study's a priori expectations, the magnitude of which is notably larger after April 2018 compared to the transitional period. However, it is questionable whether the size of the coefficient is attributed to the enactment of MEES alone or the exodus of high-quality buildings from the treatment group. Although no significant deterioration in the quality of the substandard stock is uncovered in its observable features in a series of covariate balance regressions, an omitted variable bias is a concern. Data insufficiency in repeat lease observations for the same EPC units before and after the enactment prevents this research from checking this result for robustness. Therefore, there is insufficient evidence in support of Hypothesis 1b.

In exploring cross-sectional heterogeneity in the effect of MEES on F and G ratings, some puzzling findings emerge. Hypothesis 2a must be rejected, as the adverse effect of the MEES Announcement on substandard EPCs is entirely driven by F-rated units, rather than those rated G. This finding is also supported by the Fixed Effects specification. One plausible explanation is that a significant proportion of G-rated units in this study's sample systematically possesses some other (unobserved) characteristic, prompting the market to anticipate that this building category would be left intact by the upcoming legislation. It is possible that investors anticipated that G-rated buildings would be left intact by the upcoming legislation for failing to meet the 7-year payback period. Since elimination of the most inefficient building stock is the primary motivation behind MEES, were this assertion true, the success of the MEES initiative would be undermined. Notwithstanding the market response during the transitional period into MEES, events following its official enactment would technically bear more weight in considering this policy's efficacy. In this regard, the significant and sizeable negative coefficient associated with the G-rated group after April 2018 indicates that the MEES Enactment has drastically under-priced the most inefficient stock. Negative stigma associated with having the worst EPC rating (BEIS, 2021a) may explain the magnitude of this coefficient. In contrast, units with F ratings are not found to decrease significantly in rental value during this crucial policy period. However, the lack of significance could be due to the low number of lease observations adhering to this EPC rating during the enactment period. As a result, the findings pertaining to the MEES enactment window cannot be verified using the Fixed Effects specification due to data insufficiency. Therefore, this study cannot find enough evidence to accept Hypothesis 2b either.

By investigating the temporal dimension of rental prices following the announcement of MEES, the uncovered results corroborate Hypothesis 3. Precisely, the most substantial decrease in rents of F–G units occurs in the final period (Q'1 2018) prior to the MEES Enactment (1 April 2018). This finding could explain the lack of visibility of the MEES impact on rents before this policy officially came into force (French, 2020). As the author of this paper notes, the UK market seems to have adopted an "ostrich approach by burying their heads in the sand" (French, 2020, p. 4), as before April 2018 prices did not reflect energy efficiency attributes of buildings, and those players affected by the policy seemed to have ignored it.

It is well-known that the government plans to increase the stringency of MEES regulations in the foreseeable future to encompass further low-grade EPC bands. While E-rated properties are set to be affected by 2025, those rated D will come under the MEES scope by 2030 (French, 2019). Some note that investors already recognise that E rating is next to become MEES non-compliant, and that a decline in value of this rating is already visible (ibid). Support for these claims is also found in qualitative research by Mulliner and Kirsten (2017), whose survey shows that 72% of landlords and 48% of agents consider assessing risk exposure of E-rated spaces in anticipation of future policy to be "important" and "very important". At first, using the DiD approach, an adverse effect of D–E ratings on rents following the MEES Enactment emerges. However, upon investigating the impact of D and E ratings separately using repeat EPC data, this finding seems entirely driven by E-rated premises, while the rental effect of MEES Enactment is insignificant for those rated D. These results therefore lead to accepting Hypothesis 4a and rejecting Hypothesis 4b.

Limitations and Future Research Guidance

Despite addressing some methodological and data gaps encountered by previous research, this study is not without drawbacks. The granularity of address information provided by EPC assessors is one area of concern. To be precise, in the process of matching, it was discovered that some EPC lodgements had insufficient unit-level data, introducing uncertainty in allocating EPC lodgements to leases in buildings with multiple EPCs. Since landlords can request removal of their EPCs from the public database, it is possible that some leases in the dataset that (should) adhere to the missing EPCs have been incorrectly matched to the non-missing records. It would be empirically problematic if, for instance, EPC renewals had been systematically withdrawn from the database, resulting in more recent lease observations being erroneously matched to their older EPC versions. However, since MEES should have given rise to EPC renewals with more efficient ratings relative to their antecedent versions, there would be no incentive for landlords to request the removal of more efficient EPCs from the register. Given that there is no reason to believe that withdrawal of EPCs from the register occurred non-randomly, this shortcoming should not present significant identification problems to this paper's empirical strategy.

It must be noted that, having solely focused on the London market, the results of this paper cannot be generalised to other regions of England and Wales. London's market response to MEES is likely to have been more pronounced compared to other regions, since due to its relatively high transactional activity, London is subject to greater regulatory scrutiny. Booker (2019) confirms this supposition by finding that certain northern regions exhibit the lowest uptake of this policy among the 12 NUTS regions in the UK. London's enhanced regulatory and investor scrutiny may also explain the low number of lease observations signed in F–G units after the enactment of MEES, limiting the conclusions drawn from this study to the transitional period of MEES. Therefore, future research may look into the behaviour of rental prices of the substandard building stock during this crucial policy period in other regions, especially after April 2023, when continuing leases in F–G units are set to be affected.

While this study provides valuable insights into the impact of the MEES, it is important to note its limitations in methodological approach. One such limitation pertains to the likely varying rent growth patterns across different submarkets. However, due to data insufficiency an implementation of an interaction between time and submarkets is not possible, as it would lead to a considerable loss of degrees of freedom. For instance, in specific submarkets such as the Southern fringe, data availability for certain years is scarce. This limitation underscores the necessity for more comprehensive datasets that can accurately capture the variations in how different submarkets respond to MEES.

1.7. Conclusions

In economics, prices provide key information to market participants and incentivise the purchase and sale of goods and services, including those concerned with energy conservation. When prices do not accurately reflect the societal costs of energy inefficiency, government intervention becomes necessary. This paper focuses on the introduction of MEES in England and Wales in the context of the London office market between January 2012 and December 2020. With MEES officially coming into force on 1 April 2018, directly to affect all new leases in properties with F–G EPC ratings, the primary aim of this study is to examine whether this policy has yielded a notable rental movement during the periods following the announcement and the official implementation of MEES. This study's design seeks to address some shortcomings of previous empirical work. The key differentiating features of this paper stem from the use of a) an econometric approach that accounts for systematic group-level differences between substandard and compliant building groups, and one that controls for within-EPC variation, thus reducing the likelihood of an omitted variable bias; b) a significant proportion of achieved as opposed to asking rent, thus yielding more representative estimates; c) a dataset that facilitates unit- rather than building-level analysis, which addresses ecological fallacy.

The results of this research suggest that the MEES policy has shaken the status quo of the office market in London. Specifically, they show that MEES significantly under-priced the targeted EPC stock during the transitional phase of MEES, defined as the period between this policy's first announcement and the first official deadline. However, a significant decline in rental value during this period is only uncovered in F-rated units, rather than those rated G. Additionally, since this regulation has also triggered a mass withdrawal of F–G rated properties from the market, there is a shortage of repeat lease observations adhering to the enactment period of MEES, thus preventing this study from finding conclusive evidence into the rental impact of the enactment period of MEES on the F–G group of EPCs. Nevertheless, insufficient observations pertaining to this period may be viewed as an indication that the primary aim of MEES policy to eliminate some of the most inefficient buildings from the market has been fulfilled. Another favourable finding is that MEES has taken a toll on the EPC rating closest to the current compliance threshold following the first official MEES deadline. Therefore, this regulation may have propelled the commercial market participants to take notice of energy performance ratings and the risk presented by the intensifying standards.

Appendix A.1

Matching Procedure

Without unique building identifiers across these datasets and with considerable building address variation, the matching of leases to their corresponding building addresses and unit-level EPCs is primarily conducted using a fuzzy comparison of address text strings in Python (van Rossum, 2020). Firstly, data is pre-processed/cleaned in Excel by removing punctuation, double spaces and stop words, as well as converting words to lower case and conducting spell-checks. Next, Python's Google Maps geocoder library (2021) is used to convert building addresses to latitude and longitude. An added advantage of using this library is the standardisation of addresses, or the removal of unnecessary address variation. Next, address strings are divided into the following set of standardised variables: first line (suite/unit/floor), building name/number, street name and postcode. All variables except for the first line of address and the coordinates are treated as string variables, whose similarity is calculated using affine gap string distance. A cosine similarity metric is applied to the first line of address, which measures the number of words the strings have in common. Coordinate variables (latitude and longitude) are compared using the Haversine formula.

Python's record linkage methods are often criticised for producing many false positives (incorrect matches) and negatives (missed matches) in instances where incorrect blocking rules are applied (Juvenal, 2018). Blocking is a procedure that involves indexing records by a common aggregate characteristic (street, postcode, borough, etc.), which is employed to minimise processing time by restricting the number of possible record pairs. Another criticism of record linkage stems from an arbitrary assignment of weights to indicate the relevance of each field (ibid). These weights, together with the specified similarity functions, establish the overall matching score for each indexed pair. A machine learning library, Dedupe (2021), largely addresses these drawbacks by automatically calculating blocking and weighting rules. These rules are computed during Dedupe's training stage, when the user is prompted to provide feedback on a series of potential matches by marking them as "Yes", "No", or "Maybe". The only arbitrary input required by Dedupe is the acceptable matching threshold, or a confidence statistic above which any identified match is deemed correct. This research applies the standard threshold of 90%.

In addition to accounting for the similarity of address text strings, several temporal restrictions are imposed during the process of matching. Firstly, the lodgement date of an EPC must precede the date of lease execution. Since EPC certificates are only valid for ten years, the maximum difference between the date of an EPC lodgement date and lease execution must also be ten years.

Table A.1.1: Variables and their summary statistics.

Variable Name	Variable Description	N	μ	σ^2	Min	Max
Dependent Variable:						
Rent	The logarithm of (achieved) rent per square foot	7,801	3.83	0.41	2.45	5.14
Key Independent Variables:						
Substandard (F)	Dummy variable is 1 for F-rated units	7,801	0.09	0.29	0.00	1.00
Substandard (G)	Dummy variable is 1 for G-rated units	7,801	0.07	0.25	0.00	1.00
MEES Announcement (F)	Dummy variable is 1 for leases signed in F-rated units after 18 October 2011 and before 1 April 2018	7,801	0.07	0.25	0.00	1.00
MEES Announcement (G)	Dummy variable is 1 for leases signed in G-rated units after 18 October 2011 and before 1 April 2018	7,801	0.05	0.22	0.00	1.00
MEES Enactment (F)	Dummy variable is 1 for leases signed in F-rated units after 1 April 2018	7,801	0.00	0.04	0.00	1.00
MEES Enactment (G)	Dummy variable is 1 for leases signed in G-rated units after 1 April 2018	7,801	0.00	0.05	0.00	1.00
D	Dummy variable is 1 for D-rated units. F–G ratings are excluded.	6,558	0.34	0.47	0.00	1.00
E	Dummy variable is 1 for E-rated units. F–G ratings are excluded.	6,558	0.22	0.42	0.00	1.00
MEES Enactment (D)	Dummy variable is 1 for leases signed in D-rated units after 1 April 2018. F–G ratings are excluded.	6,558	0.09	0.29	0.00	1.00
MEES Enactment (E)	Dummy variable is 1 for leases signed in E-rated units after 1 April 2018. F–G ratings are excluded.	6,558	0.06	0.23	0.00	1.00
Lease Controls:						
Lease Term	Length of the lease in years	7,801	6.74	3.48	0.00	50.00
Transaction size	The logarithm of the total amount of space (in square feet) leased by the tenant	7,801	8.01	1.03	4.45	12.51
Sub-letting	Dummy variable is 1 for sub-lettings	7,801	0.07	0.26	0.00	1.00
Assignment	Dummy variable is 1 for assignments	7,801	0.04	0.20	0.00	1.00
Asking	Dummy variable is 1 if asking rent is used instead of achieved rent	7,801	0.30	0.46	0.00	1.00
Pre-let	Dummy variable is 1 for pre-let spaces	7,801	0.00	0.07	0.00	1.00

(continued on the next page)

Table A.1.1 *(continued)*

Variable Name	Variable Description	N	μ	σ^2	Min	Max
Second-Hand Grade A	Dummy variable is 1 for second-hand grade A space	7,801	0.33	0.47	0.00	1.00
Second Hand Grade B	Dummy variable is 1 for second-hand grade B space	7,801	0.52	0.50	0.00	1.00
Hedonic Controls:						
Building size	The logarithm of building size in square feet	7,801	10.29	1.26	6.35	14.07
Storeys	Number of storeys	7,801	8.01	5.74	1.00	87.00
Age	Number of years since the building was built/last renovated	7,801	52.33	65.25	0.00	343.00
Class B	Dummy variable is 1 for Class B properties	7,801	0.91	0.28	0.00	1.00
Class C	Dummy variable is 1 for Class C properties	7,801	0.01	0.09	0.00	1.00
BREEAM	Dummy variable is 1 for BREEAM certified properties	7,801	0.15	0.36	0.00	1.00
Retail	Dummy variable is 1 for primarily retail buildings	7,801	0.04	0.19	0.00	1.00
Industrial	Dummy variable is 1 for primarily industrial buildings	7,801	0.00	0.04	0.00	1.00
City Fringe	Dummy variable is 1 for properties in London's City Fringe	7,801	0.18	0.39	0.00	1.00
Docklands	Dummy variable is 1 for properties in London's Docklands	7,801	0.02	0.12	0.00	1.00
Inner London	Dummy variable is 1 for properties in inner London	7,801	0.02	0.16	0.00	1.00
Mid-town	Dummy variable is 1 for properties in the mid-town of London	7,801	0.14	0.35	0.00	1.00
Southern Fringe	Dummy variable is 1 for properties in London's Southern Fringe	7,801	0.05	0.22	0.00	1.00
West End	Dummy variable is 1 for properties in London's West End	7,801	0.42	0.49	0.00	1.00

Notes: Amenities are excluded from this table. The reference group comprises leases with achieved rents signed in newly renovated spaces located in primarily office Class A buildings of London's City Core market.

Table A.1.2: The proportion of EPCs filed over time in England and Wales:

Year	A/A+	B	C	D	E	F	G
2008	0.2%	6%	31%	31%	18%	7%	7%
2009	0.2%	5%	27%	29%	18%	8%	12%
2010	0.4%	5%	27%	29%	17%	9%	12%
2011	0.4%	7%	28%	28%	17%	9%	11%
2012	0.5%	6%	24%	29%	17%	10%	13%
2013	1.5%	8%	27%	28%	16%	8%	11%
2014	2.0%	9%	25%	30%	17%	8%	10%
2015	2.3%	8%	23%	33%	18%	7%	10%
2016	4.3%	8%	24%	34%	17%	5%	7%
2017	2.5%	8%	27%	35%	18%	4%	5%
2018	2.4%	11%	31%	33%	19%	2%	3%
2019	3.4%	12%	36%	31%	15%	1%	1%
2020	3.2%	14%	37%	32%	13%	1%	1%

Source: Official Statistics (2023)

Table A.1.3: The evolution of building characteristics for the substandard (F–G) and compliant (A–E) EPCs.

	Class		**NIA**		**Storeys**		**Age**		**BREEAM**		**Grade of Space**	
Year	*F–G*	*A–E*	*F–G*	*A–E*	*F–G*	*A–E*	*F–G*	*A–E*	*F–G*	*A–E*	*F–G*	*A–E*
2008	1.97	1.93	48,242	76,507	7.51	8.13	107.15	46.58	0.08	0.14	2.66	2.28
2009	1.96	1.93	58,824	84,064	7.73	8.52	90.9	52.24	0.01	0.12	2.7	2.37
2010	1.94	1.9	66,887	84,282	8.38	8.08	73.53	42.3	0.03	0.22	2.58	2.3
2011	1.94	1.91	41,192	74,065	9.38	8.25	71.23	51.46	0.05	0.14	2.64	2.34
2012	1.97	1.95	43,070	62,843	6.95	7.57	74.25	51.99	0.03	0.13	2.47	2.37
2013	1.96	1.89	42,781	69,809	7.36	8.04	82.22	46.73	0.07	0.19	2.43	2.42
2014	1.96	1.88	51,674	77,437	7.44	8.77	63.03	46.24	0.10	0.22	2.62	2.36
2015	1.99	1.89	43,624	95,845	6.32	9.39	77.79	43.35	0.06	0.25	2.67	2.3
2016	1.98	1.93	43,591	64,922	7.32	7.93	71.24	43.5	0.09	0.17	2.65	2.31
2017	1.97	1.93	56,599	67,637	7.92	8.07	75.64	48.12	0.13	0.14	2.47	2.32
2018	1.96	1.93	45,357	64,080	7.64	8.04	68.36	49.43	0.04	0.17	2.64	2.38
2019	2.00	1.96	21,971	60,352	6.25	7.55	83.67	50.67	0.13	0.11	2.50	2.40
2020	2.00	1.91	18,709	70,938	7.00	8.20	61.33	48.7	0.00	0.13	2.33	2.15

Notes: Averages are computed using a scale of 1–3 for Building Class (A–C) and Grade of Space (New – Second Hand B).

Appendix A.2

Table A.2.1: Complete DiD regression results for the logarithm of rent in F–G rated units.

Dependent Variable	The Logarithm of Rent per Square Foot		
Econometric Specification	Difference-in-Differences		
Data	Repeat Cross Sections		
Variable / Model Name	DiD Group F–G [a]	DiD Separate F&G [a]	Event Study [b]
Key Independent Variables:			
DiD Announcement (F–G)	–0.058**		
DiD Enactment (F–G)	–0.278***		
DiD Announcement (F)		–0.076***	
DiD Announcement (G)		–0.029	
DiD Enactment (F)		–0.121	
DiD Enactment (G)		–0.329**	
EPC Group Controls:			
F–G ratings	–0.035*		–0.014
F rating		–0.025	
G rating		–0.054	
Event Study Controls:			
Lead4 (2008)			–0.033
Lead3 (2009)			0.005
Lead2 (2010)			–0.038
Lag0 (2012)			–0.104**
Lag1 (2013)			–0.081
Lag2 (2014)			–0.084*
Lag3 (2015)			–0.059
Lag4 (2016)			–0.080
Lag5 (2017)			–0.059
Lag 6 (2018)			–0.184**
Lag7 (2019)			–0.273*
Lag8 (2020)			–0.656*
Lease Controls:			
Lease term	0.016***	0.016***	0.016***
Transaction size	–0.000	–0.000	0.001
Sub-letting	–0.009	–0.009	–0.004
Assignment	0.026	0.026	0.035*
Other Lease Types	–0.113*	–0.111*	–0.089
Asking	0.021**	0.021**	0.022***
Pre-let	0.055*	0.072**	0.072**
Second Hand – Grade B	–0.092***	–0.092***	–0.093***
Second Hand – Grade C	–0.160***	–0.160***	–0.165***
Hedonic Controls:			
Building size	–0.023***	–0.023***	–0.023***
Storeys	0.004***	0.004***	0.004***
Built/ren	0.000	0.000	0.000
Retail	0.021	0.021	0.017
Industrial	–0.206*	–0.209*	–0.184
Other	0.031	0.030	0.035
Class B	–0.096***	–0.096***	–0.100***
Class C	–0.094**	–0.093**	–0.098*
BREEAM	0.063***	0.063***	0.062***

(continued on the next page)

Table A.2.1 *(continued)*

Dependent Variable	The Logarithm of Rent per Square Foot		
Econometric Specification	Difference-in-Differences		
Data	Repeat Cross Sections		
Variable / Model Name	DiD Group F–G [a]	DiD Separate F&G [a]	Event DiD F–G [b]
Amenities:			
Air conditioning	0.057***	0.057***	0.060***
All-day access	0.010	0.010	0.006
Food/restaurant on site	–0.034***	–0.035***	–0.042***
Conference facilities	0.015	0.016	0.018
Manager on site	–0.016	–0.016	–0.008
Fitness centre	0.027	0.026	0.026
Roof terrace	0.061***	0.061***	0.065***
Atrium	–0.033**	–0.033**	–0.039***
Reception	0.038***	0.039***	0.040***
Lift access	–0.012	–0.012	–0.012
Market Controls:			
City Fringe	–0.088***	–0.089***	–0.095***
Docklands	–0.400***	–0.400***	–0.405***
Inner London	–0.206***	–0.206***	–0.205***
Mid-town	0.019	0.018	0.021
Southern Fringe	–0.093***	–0.093***	–0.096***
West End	0.170***	0.170***	0.170***
Time Dummies:			
2009	–0.189***	–0.189***	–0.198***
2010	–0.201***	–0.200***	–0.202***
2011	–0.148***	–0.147***	–0.165***
2012	–0.088***	–0.087***	–0.086***
2013	–0.019	–0.018	–0.023
2014	0.097***	0.098***	0.094***
2015	0.263***	0.264***	0.255***
2016	0.314***	0.315***	0.310***
2017	0.359***	0.359***	0.350***
2018	0.339***	0.340***	0.334***
2019	0.350***	0.351***	0.346***
2020	0.309***	0.310***	0.307***
Constant	3.880***	3.875***	3.887***
Observations	7,801	7,801	7,001
R-squared	0.419	0.419	0.415

Notes: This table reports the results for the logarithm of rent from January 2008 to December 2020. The reference group consists of properties with A–E ratings. Error terms are normally distributed. No autocorrelation in the residuals is identified. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

[a] The first treatment effect, MEES Announcement, commences on 18 October 2011, followed by the second treatment window, MEES Enactment, on 1 April 2018.

[b] Leases signed from 18 October 2011–31 December 2011 and 1 April 2018–31 December 2018 are excluded from the sample set to avoid ambiguity in the MEES announcement/enactment phases.

Table A.2.2: Complete regression results using repeat EPC data for the logarithm of rent in F–G rated units.

Dependent Variable	The Logarithm of Rent per Square Foot		
Econometric Specification	Difference-in-Differences	Fixed Effects	
Data	Repeat Cross Sections	Panel	
Variable / Model Name	DiD Group F–G Restricted	FE Group F–G	FE Separate F–G
Key Independent Variables:			
DiD Announcement (F–G)	–0.091***	–0.073**	
DiD Announcement (F)			–0.127***
DiD Announcement (G)			0.008
EPC Group Controls:			
F–G ratings	–0.018		
F rating			
G rating			
Lease Controls:			
Lease term	0.020***	0.018***	0.017***
Transaction size	–0.004	0.004	0.004
Sub-letting	0.014	–0.038	–0.038
Assignment	0.079**	–0.001	–0.004
Other Lease Types	–0.099	–0.189	–0.201
Asking	0.026*	0.011	0.010
Pre-let	0.072**	0.072**	0.169**
Second Hand – Grade B	–0.141***	–0.132***	–0.136***
Second Hand – Grade C	–0.195***	–0.176***	–0.181***
Hedonic Controls:			
Building size	–0.012		
Storeys	0.002		
Built/ren	0.000	0.000	0.000
Retail	–0.008		
Industrial			
Other			
Class B	–0.158***		
Class C	–0.104		
BREEAM	0.012		
Amenities:			
Air conditioning	–0.000		
All-day access	0.034**		
Food/restaurant on site	–0.042***		
Conference facilities	0.053**		
Manager on site	–0.031		
Fitness centre	–0.034		
Roof terrace	0.082***		
Atrium	–0.036		
Reception	0.048**		
Lift access	–0.025		
Market Controls:			
City Fringe	–0.251***		
Docklands	–0.396***		
Inner London	–0.151***		
Mid-town	0.005		
Southern Fringe	–0.101***		
West End	0.145***		

(*continued on the next page)*

Table A.2.2 *(continued)*

Dependent Variable	The Logarithm of Rent per Square Foot		
Econometric Specification	Difference-in-Differences	Fixed Effects	
Data	Repeat Cross Sections	Panel	
Variable / Model Name	DiD Group F–G Restricted	FE Group F–G	FE Separate F–G
Time Dummies:			
2009	–0.204***	–0.209***	–0.204***
2010	–0.216***	–0.235***	–0.229***
2011	–0.142***	–0.175***	–0.167***
2012	–0.115***	–0.133***	–0.124***
2013	–0.061	–0.073*	–0.065
2014	0.068*	0.061*	0.071**
2015	0.191***	0.175***	0.183***
2016	0.257***	0.266***	0.279***
2017	0.262***	0.274***	0.286***
2018	0.218***	0.216***	0.227***
Constant	3.832***	3.639***	3.640***
Observations	2,200	2,200	2,200
R-squared	0.383	0.691	0.692

Notes: This table reports the results for the logarithm of rent from 1 January 2008 to 31 March 2018, using a reduced dataset of leases signed for repeat EPC units. The reference group consists of units with A–E ratings. The treatment period, MEES Announcement, commences on 18 October 2011. Error terms are normally distributed. No autocorrelation in the residuals is identified. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

Table A.2.3: Complete regression results for the logarithm of rent in D–E rated units.

Dependent Variable	The Logarithm of Rent per Square Foot			
Econometric Specification	Difference-in-Differences		Fixed Effects	
Data	Repeat Cross Sections		Panel	
Variable / Model Name	DiD Group D–E	DiD Separate D&E	FE Separate D [a]	FE Separate E [b]
Key Independent Variables:				
DiD Enactment (D–E)	–0.038**			
DiD Enactment (D)		–0.024		–0.030
DiD Enactment (E)		–0.060***	–0.050*	
EPC Group Controls:				
D–E ratings	–0.040***			
D rating		–0.033***		
E rating		–0.050***		
Lease Controls:				
Lease term	0.017***	0.016***	0.016***	0.013***
Transaction size	–0.001	–0.001	0.010	0.008
Sub-letting	–0.008	–0.008	–0.044	–0.031
Assignment	0.013	0.012	–0.047	–0.048
Other Lease Types	–0.094	–0.092	–0.047	–0.113
Asking	0.014	0.014	0.020	0.015
Pre-let	0.041	0.072**	0.072**	0.072**
Second Hand – Grade B	–0.079***	–0.080***	–0.102***	–0.120***
Second Hand – Grade C	–0.150***	–0.151***	–0.129***	–0.129***
Hedonic Controls:				
Building size	–0.023***	–0.022***		
Storeys	0.005***	0.005***		
Built/ren	0.000	0.000	0.000	0.000
Retail	0.025	0.025		
Industrial	–0.225**	–0.226**		
Other	0.013	0.014		
Class B	–0.088***	–0.086***		
Class C	–0.090**	–0.088**		
BREEAM	0.042***	0.041***		
Amenities:				
Air conditioning	0.057***	0.057***		
All-day access	0.006	0.006		
Food/restaurant on site	–0.029**	–0.029**		
Conference facilities	0.006	0.005		
Manager on site	–0.008	–0.008		
Fitness centre	0.029	0.025		
Roof terrace	0.052***	0.052***		
Atrium	–0.027**	–0.028**		
Reception	0.031***	0.032***		
Lift access	–0.014	–0.014		
Market Controls:				
City Fringe	–0.095***	–0.095***		
Docklands	–0.417***	–0.418***		
Inner London	–0.200***	–0.202***		
Mid-town	0.007	0.006		
Southern Fringe	–0.100***	–0.101***		
West End	0.156***	0.155***		

(Continued on the next page)

Table A.2.3 *(continued)*

Dependent Variable	The Logarithm of Rent per Square Foot			
Econometric Specification	Difference-in-Differences		Fixed Effects	
Data	Repeat Cross Sections		Panel	
Variable / Model Name	DiD Group D–E	DiD Separate D&E	FE Separate D [a]	FE Separate E [b]
Time Dummies:				
2009	–0.198***	–0.198***	–0.219***	–0.221**
2010	–0.198***	–0.198***	–0.224***	–0.213**
2011	–0.156***	–0.155***	–0.147**	–0.182**
2012	–0.083***	–0.083***	0.009	–0.050
2013	–0.021	–0.021	–0.073	–0.105
2014	0.096***	0.096***	0.082	0.094
2015	0.257***	0.257***	0.202***	0.173**
2016	0.314***	0.314***	0.342***	0.318***
2017	0.354***	0.353***	0.318***	0.295***
2018	0.351***	0.352***	0.323***	0.307***
2019	0.358***	0.359***	0.350***	0.338***
2020	0.325***	0.323***	0.353***	0.332***
Constant	3.905***	3.902***	3.933***	3.748***
Observations	6,558	6,558	1,563	1,404
R-squared	0.416	0.416	0.729	0.753

Notes: This table reports the results for the logarithm of rent for the period from January 2008 to December 2020. The reference group is comprised of A–C ratings. The treatment effect, MEES Enactment, commences on 1 April 2018. Error terms are normally distributed. Units with F–G ratings are excluded from the sample set. No autocorrelation in the residuals is identified. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

[a] D-rated units are excluded from the sample set.

[b] E-rated units are excluded from the sample set.

Table A.2.4: Complete Fixed Effects regression results for the logarithm of rent in office buildings only.

Dependent Variable	The Logarithm of Rent per Square Foot	
Econometric Specification	Fixed Effects	
Data	Panel	
Variable / Model Name	FE Group F–G Office [a]	FE Separate E [b]
Key Independent Variables:		
DiD Enactment (F–G)	–0.071**	
DiD Enactment (E)		–0.057*
Lease Controls:		
Lease term	0.018***	0.013***
Transaction size	0.004	0.009
Sub-letting	–0.040	–0.032
Assignment	0.000	–0.046
Other Lease Types	–0.190	–0.112
Asking	0.006	0.012
Pre-let	0.168**	0.072**
Second Hand – Grade B	–0.134***	–0.123***
Second Hand – Grade C	–0.176***	–0.124***
Time Dummies:		
2009	–0.205***	–0.206**
2010	–0.238***	–0.211**
2011	–0.171***	–0.179**
2012	–0.131***	–0.051
2013	–0.070*	–0.113
2014	0.065**	0.089
2015	0.174***	0.173**
2016	0.269***	0.319***
2017	0.277***	0.293***
2018	0.219***	0.306***
2019		0.340***
2020		0.332***
Constant	3.641***	3.745***
Observations	2,149	1,354
R-squared	0.685	0.738

Notes: Error terms are normally distributed. No autocorrelation in the residuals is identified. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

[a] The results for the logarithm of rent for the period from 1 January 2008 to 31 March 2008. The reference group is comprised of A–E ratings. The treatment effect, MEES Announcement, commences on 18 October 2011.

[b] The results for the logarithm of rent for the period from 1 January 2008 to 31 December 2020. The reference group is comprised of A–C ratings. Units with F–G ratings are excluded from the sample set. The treatment effect, MEES Enactment, commences on 1 April 2018. E-rated units are excluded from the sample set.

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Article

2 People or Systems: Does Productivity Matter More than Energy Management in LEED Certified Buildings?

Abstract: This study examines the impact of energy management and indoor environment measures, implemented as part of LEED Existing Buildings Operations and Management certification, on site energy use intensity and rental premiums of office spaces using data on four major US markets. Energy management practices, comprised of commissioning and performance measurement, are hypothesised to reduce energy usage. Conversely, improving air quality and occupant comfort in an effort to increase worker productivity may, in turn, lead to higher overall energy consumption. The willingness to pay for these features in rental office buildings is hypothesised to depend not only on the extent to which productivity gains enhance the profits of a commercial tenant but also on the lease arrangements for passing any energy savings to the tenant. This paper applies a multilevel modelling approach with a panel data structure. The results indicate that energy management and indoor environment practices have the expected effect on energy consumption, as described above. However, the magnitude of the achieved rental premiums appears to be independent of the lease type.

Keywords: green certification; commercial real estate; energy performance gap; facilities management

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2.1. Introduction

The commercial real estate sector contributes significantly to climate change as it is responsible for approximately 18% of greenhouse gas emissions in the UK and 29% in the US (Carbon Trust, 2009; Leung, 2018). Despite extensive government-led efforts to decarbonise the industry by providing financial support for retrofitting the existing building stock, numerous studies conclude that these one-off structural solutions will not deliver energy savings to their fullest potential. According to OECD (2013), many buildings have been designed and built using highly efficient technologies and systems, recognised with awards such as LEED Platinum (Min et al., 2016). However, some often fail to meet their intended energy-saving objectives and use up to three times their projected energy usage levels (Zou & Alam, 2020). Bridging the energy performance gap between projected and measured performance is critical to ensuring the building sector delivers on its greenhouse gas emissions reduction targets (de Wilde, 2014). Many researchers and industry players emphasise the need to start looking beyond “hard” building interventions towards “soft” measures that target facilities management and building occupants (Clayton et al., 2021).

The primary reasons for the existence of the energy performance gap are (1) occupants using more energy than implied by the design features, (2) more occupants than originally foreseen, and (3) energy efficient technologies failing or degrading (Liang et al., 2019). This paper focuses on measures that address the third factor, which is more likely to occur in properties that are operated in a "fix and forget" manner. Mechanically ventilated buildings, which have become the new norm in response to meeting tenants' demand for optimum comfort conditions, possess a range of features that require routine adjustment and fine-tuning, such as temperature set points and control schedules. Many systems installed in high-performance buildings are becoming increasingly reliant on software, which requires regular upgrades in order to keep up with changes in the internal environment (America et al., 2012). Without maintenance and monitoring of these complex systems, excessive energy losses can arise and unnecessarily drain cash flows. It has been reported that while poor operational practices can increase energy consumption in the range of 49–79%, good practices can reduce it by 15–29% (van Dronkelaar et al., 2016; Wang et al., 2012).

A proactive approach to building facilities management can minimise the adverse effects of technological failures. Additionally, it can help to address some of the unpredictable aspects of human behaviour in buildings where occupants have greater control over operating systems such as temperature, ventilation, lighting, and hot water (Dobiáš & Macek, 2014). Effectively, facilities management can act as a bridge between occupiers' need for optimum comfort conditions and landlords' energy consumption objectives (Axon et al., 2012). Operational flaws may not only result in higher than necessary energy levels but also create an environment of an "unhealthy" building, issues which a proactive facilities management would address simultaneously. In certain situations, there may be a conflict between these areas, such as when a building has an insufficient external air supply; fixing this problem would enhance interior environmental quality but may raise energy usage. With workforce being the most substantial expense for commercial occupants, prioritisation of these measures in an effort to boost employee productivity may therefore compromise energy reduction efforts.

This paper explores in tandem the impact of energy management and indoor environment measures embedded in the LEED EBOM scorecard on both energy conservation and rent. This approach reflects the complexity of decision-making processes in real estate, where cost-saving measures like energy efficiency and financial variables such as rent are intertwined. The nexus between energy usage and rent is critical as energy-saving and indoor management strategies are often influenced by their potential implications on rental returns. Specifically, this paper evaluates whether the emphasis on the indoor environment (air quality and comfort) influences energy consumption adversely, while energy management processes (commissioning and performance measurement) result in energy savings. Whether a rental premium in a LEED EBOM building is the product of the achieved energy savings (if any), productivity-enhancing features, or both, is then analysed. The following paragraphs introduce the LEED EBOM programme and its underlying scorecard features that are of interest to this study; consequently, previous studies related to this field are analysed, and this paper's hypotheses are presented.

LEED Existing Buildings Operations and Management

There are many green classification systems adopted by owners to signal buildings' environmentally friendly design, construction, and operation processes that result in enhanced indoor environmental conditions for their occupants and a reduction in the utilisation of natural resources (Gui & Gou, 2021; Wang et al., 2012). While most assessment schemes relate to energy consumption levels predicted during the design stage, as a response to failing to address in-use building operations, LEED Existing Building Operations and Management (LEED EBOM) system was officially launched by USGBC in 2004 (Saunders, 2008). This rating system puts great emphasis on activities under the control of facilities management and presents an opportunity for earning credits in water efficiency, energy performance, commissioning, and green cleaning (Jones et al., 2009). Tracking of environmental performance is at the core of this system since a building will lose its certification after five years should it fail to demonstrate empirically that its key performance indicators are congruent with LEED EBOM certification.

This study undertakes a quantitative analysis of building inventory credits to assess the impact of energy and atmosphere (EA) and indoor environmental quality (IEQ) practices. Among measures deemed to reduce energy losses associated with operating heating, ventilation and air conditioning (HVAC) and automation applications are commissioning and performance measurement. Improved commissioning is known for delivering operational savings, identifying installation flaws, addressing occupant discomfort, enhancing indoor air quality and thermal comfort, prolonging equipment lifespan, and many other benefits (Elzarka, 2009). In order to gain points in this category, engagement with a professional consultancy is required to verify if there are discrepancies between the design intents and owners' needs (Kuo & Low, 2016). The LEED EBOM scorecard encompasses various commissioning stages, including investigation and analysis, implementation, and ongoing commissioning. Meanwhile, installing metering equipment can enable accurate quantification of energy use. Such equipment provides ongoing accountability for building energy use over time and facilitates verification of energy savings (Gurgun & Arditi, 2018).

Improved indoor environmental quality (IEQ) is another critical component of green building design since it has been positively associated with self-assessed employee productivity (Altomonte & Schiavon, 2013). A summary of 15 case studies related to this theme reports that, on average, higher indoor air quality is associated with a 0.5–11% increase in employee productivity (Loftness et al., 2006). Air quality problems, such as inadequate ventilation and chemical pollutants from indoor and outdoor sources, are seen as major contributors to what has been identified as Sick Building Syndrome (SBS). Palacios et al. (2020) carried out a longitudinal analysis involving a group of people who shifted from a regular building to a sustainable one. The evidence gathered suggests that the improved working conditions (for example, better air quality) resulting from this change significantly boosted the health of the participants, as well as diminished the symptoms related to SBS.

LEED EBOM certification allows earning credits for improved comfort conditions, such as providing occupants with control of indoor temperature settings. Thermal comfort is often considered the most critical indoor air quality component (Frontczak & Wargocki, 2011). Complaints about being excessively hot or cold are frequently accompanied by headaches, tiredness, and mucosal irritation — all of which can adversely impact productivity (Hodgson, 2002). To prevent occupants from experiencing these conditions, LEED EBOM mandates continuous monitoring of air temperature and humidity along with frequent assessments of air speed and radiant temperature.

Energy Consumption of Green Buildings

The nimbus of green buildings regarding their energy-saving credentials is not unequivocally supported by empirical evidence. Early work, such as a study by Turner and Frankel (2008), shows some promising energy use findings. By examining a sample of 552 properties (of which 121 are LEED certified), it finds that the median energy use intensity of LEED buildings is 32% lower than the mean energy use intensity in the Commercial Buildings Energy Consumption Survey (CBECS). Despite being one of the most comprehensive studies in this field, the lack of rigorous statistical analysis casts doubt on the validity of the findings (Al-Zubaidy, 2015). Using the same dataset, Newsham, Mancini, and Birt (2009) provide a supplemental statistical analysis to this study, showing that LEED buildings deliver an 18–39% reduction in energy use. Similarly, Baylon and Storm (2008) find that the average energy used per square foot in 12 LEED buildings is 10% lower than in 39 non-certified buildings. Using a difference-in-differences approach, Eichholtz et al. (2019) find that the roll-out of LEED certification is associated with a significantly lower energy usage. The authors note, however, that the uncovered decrease varies significantly depending on the level of certification and the LEED programme, as well as the duration of the label. Specifically, LEED for Building Design and Construction (BD+C) is associated with the lowest decrease in energy consumption (–13.3%), followed by LEED EBOM (–9.7%), while the energy consumption of LEED Core and Shell (CS) buildings is significantly higher (11.1%).

However, some empirical work shows that LEED buildings do not necessarily consume less energy than their non-certified counterparts (Kontokosta, 2015). At least eight peer-reviewed studies published since 2009 examine the energy use of LEED buildings, none of which support the conclusion that they use less energy than non-certified buildings. This conclusion applies to studies focusing on source and site energy use intensity (Agdas et al., 2015; Menassa et al., 2012; Oates & Sullivan, 2012). It is possible that the finding is attributed to the fact that LEED-certified buildings tend to be newer and of higher quality, and researchers find an inverse relationship between the age and quality of buildings and their electricity consumption (e.g. Kahn et al., 2014). For instance, Scofield (2009) revisits the earlier studies by Turner and Frankel (2008) and Newsham et al. (2009), and after performing further statistical analysis on the same dataset, finds no energy savings in LEED buildings. A source of disagreement is the comparison of median and mean values, which allowed LEED buildings to appear more efficient compared to CBECS-rated structures. These disparities in the results can be attributed to a variety of factors, including the research design used to determine energy efficiency, the design orientation of the LEED criteria, the LEED certification design, differences in the time of construction of the buildings, and unexpected occupancy numbers (Al-Zubaidy, 2015). Overall, the existing literature does not provide conclusive evidence that green-certified buildings have smaller carbon footprints in operation than similar non-certified buildings.

Rent Premium in LEED Buildings

Green office buildings are known to provide financial and non-financial advantages to owners through several channels, resulting in property and rental premiums, higher occupancy rates, and a favourable corporate social responsibility image (Robinson et al., 2017). A tenant's willingness to pay higher rents in certified buildings may be due to perceived improvement in productivity since employee costs represent about 90% of the total business costs for a typical office tenant (Clark, 2013). Out of the 39 peer-reviewed and published papers in this field commissioned by the Department of Energy, 27 papers consistently report a positive association between green building certifications and rents: rental premiums for LEED and Energy Star are estimated to be about 5% and in some cases fluctuate up to 20% (Eichholtz et al., 2010; Fuerst & McAllister, 2009; Kahn and Kok, 2014; McEwen et al., 2013; Wiley et al., 2010; Wu et al., 2013; Zhu et al., 2022). These premiums are dynamic over time, space, and market segment (Das & Wiley, 2014; Robinson & McAllister, 2015). Among the few studies specifically looking into the effect of LEED EBOM, a 7.1% rental premium is uncovered (Kok et al., 2012). A distinction in rents between different LEED certification schemes is captured by Holtermans and Kok (2017) who find a significant rent increase for buildings falling under the New Construction programme only as opposed to those with the LEED EBOM certification.

There is still a lack of consensus relating to the impact of sustainability certification on operating expenses (Leskinen et al., 2020). Additionally, less apparent is whether the reported premiums are the result of some underlying building characteristics leading to such certifications (i.e., green attributes such as energy and water efficiency) or the designations and labels themselves (Zhu et al., 2022). Robinson, Simons, and Lee (2017) use a revealed preferences approach to assess the impact of factors such as air quality, efficient systems, and recycling alongside LEED certification. The labelling effect itself is found to be the most valued characteristic, followed by water conservation, access to natural light, and efficient heating, ventilation, and air conditioning (HVAC). These findings largely support these authors' earlier work that employs a stated preferences method: the highest-ranking green features are all oriented towards space users, such as natural light, proximate public transportation, indoor air quality, and localised temperature controls (ibid).

The majority of previous studies estimate the effect of certification using a hedonic pricing model laid out by Rosen (1974). Such studies tend to be cross-sectional, with only a few employing a pooling approach using longitudinal data (Eichholtz et al., 2010; Szumilo & Fuerst, 2012). Cross-sectional methods are not able to address omitted variable bias: since the measured certification effect is likely to be correlated with other premium features of a building, it is vital to use methods that isolate the effect of certification from other confounding variables (Zhu et al., 2022). Similarly, failure to account for energy-expending features bundled with LEED EBOM certification, such as higher quality finishes and amenities, would result in the estimated effect suffering from a positive bias in energy regressions. Therefore, there is still substantial scope for studies that utilise panel and quasi-experimental methods to verify the existence of a green premium.

Mechanisms and Hypotheses

Before examining the effect of energy management and indoor environment operating features, the impact of the LEED EBOM certificate is analysed both in terms of energy consumption and rent. As a baseline case, this paper compares the average energy performance of LEED EBOM buildings to a period before these buildings gain certification. A LEED EBOM certification premium is anticipated to echo the findings of previous studies reporting that green certificates correlate with increased economic value. Additionally, the premium is expected to depend at least partially on the lease provisions for utility payments. If tenants pay directly for their energy, they will also benefit directly from any savings, whereas benefits tend to accrue to landlords when a bulk rate is charged, or utility costs are not separated from the overall payable rent.

This study then proceeds with analysing the impact of energy management and indoor environmental quality features on energy consumption. It is hypothesised that these two categories have an opposing effect on energy consumption in an office building:

Hypothesis 1: Energy management features reduce energy consumption.

Hypothesis 2: Indoor environment quality features increase energy consumption.

The second part of this paper's empirical analysis focuses on investigating the impact of the same scorecard components on the rental premium of office buildings. Should empirical support for Hypothesis 1 be uncovered, a rental premium is expected in the presence of active energy management practices in net leases since the tenant is the primary beneficiary of increased operating efficiency:

Hypothesis 3: Energy management features incur a rental premium in leases where tenants pay for utilities.

Since the tenant would benefit from productivity-enhancing features in all lease types, the rental premium is expected to vary positively with the indoor environment quality score in both gross and net leases:

Hypothesis 4: Indoor environment features incur a rental premium in all lease types.

2.2. Data

The empirical analysis draws on an integrated database that combines LEED scorecard information obtained from the US Green Building Council (USGBC, 2021a) with municipal benchmarking reports from various cities and the Green Building Information Gateway (GBIG, 2021). Lease and building characteristics are obtained from CompStak (2021) and CoStar (2021). Table 2.1 provides a list of all datasets and the main variables used for the analysis. Further insight into the variables and their descriptive statistics can be found in Table B.1.1 (Appendix B.1).

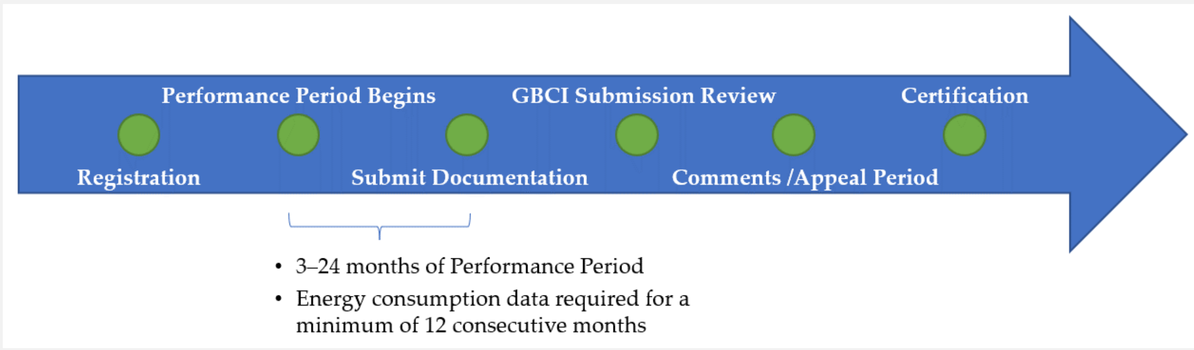
Table 2.1: Summary of data sources.

Data	Measures	Sources
Energy Consumption	Weather normalised site energy use intensity (kBtu per square foot)	Municipal benchmarking reports during 2011–2019
LEED	Energy management and indoor environment scores LEED certification status	USGBC LEED EBOM Project Data (2011–2019), downloaded separately for each project

Data	Measures	Sources
		High-level data on the certification status for all project types are downloaded from the USGBC website
Lease Data	Achieved starting rent per square foot Lease terms and concessions	CompStak (2011–2019)
Building Characteristics	Vacancy rates Building size, number of storeys, construction material, etc.	CoStar (2011–2019) CompStak (2011–2019)
Other Environmental Data Sources	Environmental data checks	The Green Building Information Gateway (GBIG)

Address data such as building name, street name, and zip code are used to identify matching building pairs between these datasets. String comparison of addresses is undertaken in Excel using fuzzy matching, which generates a matching score specifying the closeness of the identified match. Matches below the 90% threshold are discarded. The time dimension is incorporated using lease execution and certification dates, which help to establish whether a given lease applies to a building with LEED EBOM certification. This paper assumes the lease execution date must either coincide with or occur in a period later than the date of certification for a given building. Unlike other types of LEED certificates, LEED EBOM is only valid for five consecutive years, while LEED's design-stage labels do not expire. In the absence of any reported information on building recertification within five years, LEED EBOM certification is assumed to revert to non-certified status.

The LEED EBOM programme is based on the concept of a "performance period", a time interval during which internal project teams collect performance data for Green Business Certification evaluation. Following the completion of a performance period, the USGBC decides at what level to certify the building based on the information gathered by the project team (FacilitiesNet, 2013). LEED EBOM certification timeline is presented in Figure 2.1. The performance period must be at least three months long but cannot exceed 24 months. The duration of the performance period for each building in the sample is not disclosed, meaning the exact implementation date of the measures prescribed in the scorecard is unknown to this study. However, it is possible to approximate the duration of the performance period by computing the difference between a project's registration and certification dates. Approximately 70% of projects certify within a year of first registering for LEED EBOM. For these projects, it is assumed that the LEED EBOM performance period starts in the year of registration. For the remaining set of projects, the LEED EBOM performance phase is assumed to begin one year prior to the date of certification.



Source: USGBC (2021b); BuildingGreen (2017).

Figure 2.1: LEED EBOM certification timeline.

Municipal Benchmarking Reports

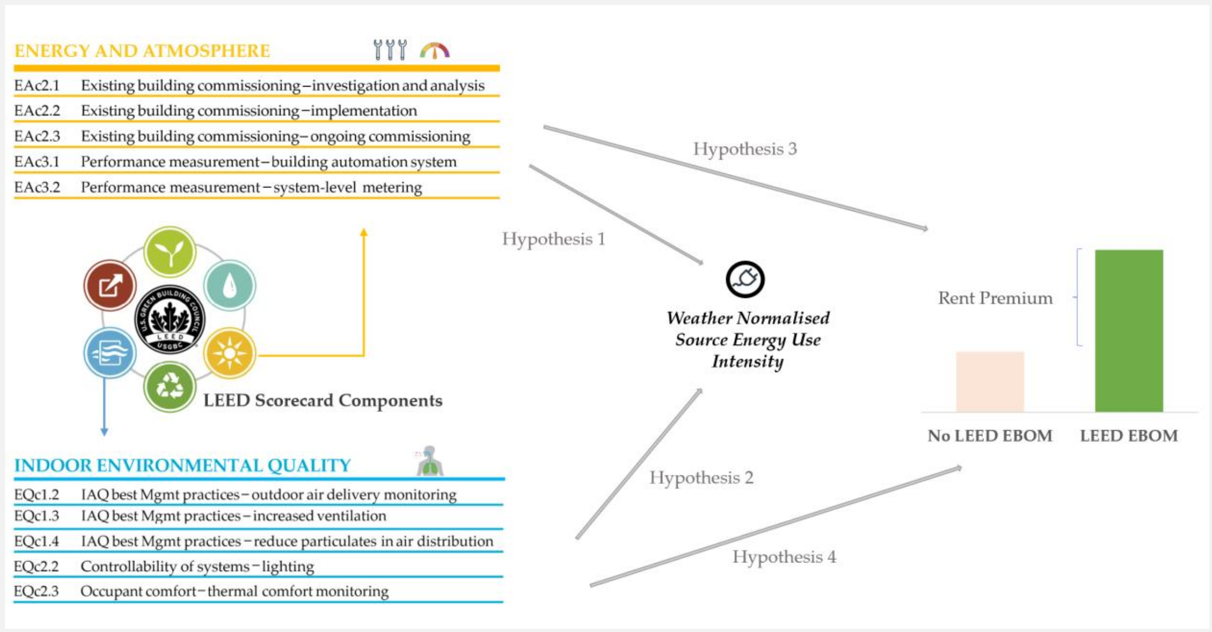
Energy performance data from municipal disclosure databases are obtained for a period of 2011–2019 for the following cities: New York, San Francisco, Washington DC, and Chicago (City and County of San Francisco, 2021; DC Department of Energy & Environment, 2021; NYC Mayor's Office of Sustainability, 2021; The City of Chicago, 2021). These cities document annual energy and water use and the carbon emissions data of large commercial buildings. The decision to use these cities is driven by the fact that they were the first to mandate energy consumption disclosure of commercial buildings in the US, obliging building owners to enter their building energy data into Energy Star's Portfolio Manager (Scofield, 2013). Additionally, these markets have the largest number of LEED EBOM certified office buildings. Building size determines whether a building is required to disclose its energy data. However, the requirements mandating disclosure vary between these cities, which are continuously updated to capture an ever-increasing number of buildings. Due to the different timings of these cities' legislative mandates, data availability throughout 2011–2019 is not uniform, resulting in an unbalanced panel dataset.

The key dependent variable is site energy use intensity (EUI), expressed in thousands of British thermal units (kBtu) per square foot per year. This variable is weather normalised, accounting for different weather patterns (cooling and heating degree days), thus correcting for year-to-year and state-to-state weather differences. The rationale for using site rather than source EUI is that source EUI incorporates efficiency factors of the whole fuel mix required during building operations (including off-site energy losses associated with the production and delivery of energy to a building). In contrast, site EUI only considers heat and electricity consumed on the premises (EPA, 2022). Since this research aims to understand the impact of operational management on individual buildings, site EUI is more compatible with the objectives of this study.

Finally, information from the Building Performance Database (BPD) (DOE, 2021) is used to cross-reference the sample of observations and identify outliers. BPD has the most extensive collection of data in the United States on the energy-related features of commercial and residential buildings. Data collected by federal, state, and municipal governments, utilities, energy efficiency initiatives, building owners, and commercial organisations are aggregated, cleaned, and anonymised (ibid). According to BPD, the average consumption and standard deviation of an office building in the US are 198 kBtu/sf and 160 kBtu/sf, respectively. Based on these figures, observations above 700 kBtu/sf (99.9th percentile) are excluded from this study's sample.

LEED Certification and Scorecards

From the USGBC (2021a) website, scorecards for all the projects listed in California, Illinois, New York, and the District of Columbia are first obtained. The LEED scorecard is a one-page document that provides a detailed breakdown of the credits, where points can be earned across seven sections: sustainable sites, water efficiency, energy and atmosphere, materials and resources, indoor environmental quality, innovation, and regional priority. The sum of the points earned determines which certification level is achieved (Certified, Silver, Gold, and Platinum). For the purposes of this research, credits are extracted from two sections in the scorecard: energy and atmosphere (EA) and indoor environmental quality (IEQ). Since the LEED EBOM certificate has undergone a number of updates, to ensure a like-for-like comparison, this study solely focuses on LEED EBOM v2009, as this version is most abundant in observations. The specific credits and their relationship to the main hypotheses are demonstrated in Figure 2.2. Further details of the specific criteria that must be fulfilled to earn points for each of these credits are documented in Table B.1.2 (Appendix B.1).



Source: USGBC (2021a).

Figure 2.2: Credits, variables, and hypotheses.

As shown in Figure 2.2, the Energy and Atmosphere section has two distinct components, commissioning and performance measurement. The first commissioning credit, Investigation & Analysis, involves identifying possible conservation measures. During the second commissioning stage, Implementation, low-cost and no-cost energy efficiency measures identified during the Investigation & Analysis stage are implemented. Meanwhile, the third commissioning credit, Ongoing Commissioning, mandates repeating these two commissioning activities over a two-year cycle. Meanwhile, the performance measurement category is captured by the "Building Automation System" and "System-level Metering" credits. Building Automation System ("BAS") monitors and regulates lighting and HVAC systems, while system-level metering allows operators to detect under-performance issues associated with individual system components.

Indoor environment quality credits are divided into the following categories: air quality and comfort. Among air quality credits investigated in this study are Outdoor Air Delivery Monitoring, Increased Ventilation, and Particulates Reduction. The first credit concerns alarming building operators if the minimum outdoor airflow rate falls more than 15% below the minimum rate. The second air quality credit, Increased Ventilation, is earned in buildings with ventilation rates at least 30% higher than the industry standard (ASHRAE). The final credit in the air quality category is earned for the presence of high-quality air filters at outside air intakes. Controllability of Lighting Systems and Thermal Comfort Monitoring constitute the comfort category of indoor air quality features. While the former credit is earned for spaces with lighting controls for more than 50% of occupants, the latter is awarded for continuous monitoring of air temperature and humidity and periodic measurement of air speed and radiant temperature.

In addition to the scorecard data available for LEED EBOM projects, high-level information for all certification types and versions is separately obtained from the USGBC website. Among the variables of interest are LEED certification type (LEED EBOM, LEED NC, LEED BD+C, etc.), certification version (v2.0, v2008, v2009, and v4), project size, and certification and registration dates. Any project that has not been certified after registering is omitted. Projects that apply to a proportion of a building (such as LEED Commercial Interiors) are excluded since energy in the municipal reports is measured at the whole-building level.

Leases and Building Characteristics

Having collected energy and LEED scorecard data, rental information for the matched property sample is obtained from CompStak (2021), a crowd-sourced real estate data platform which provides detailed insight into lease-level transactions. The variables obtained from CompStak are starting rent, lease term, lease execution date, lease commencement date, lease expiry date, lease type (gross, net, double net, triple net, modified gross, industrial gross, etc.), transaction size, and concessions. Although various property types are included in this study's sample, lease observations other than for office space are excluded. Alongside lease information, CompStak reports on some building-level variables such as building size, number of storeys, renovation year, and construction year. Lease types were divided into the following two categories: those that oblige the tenant to pay for their electricity consumption (net leases) and those where energy charge is automatically included in the rent (gross leases). Missing building-level information is supplemented with CoStar, which reports on additional hedonic variables such as building construction material, amenities, and vacancy rates.

Data Representativeness

CBECS data indicates that the United States has approximately 5.9 million commercial buildings, encompassing a total area of 97 billion square feet (EIA, 2018). The analysis was initiated by acquiring data on LEED-EBOM buildings, finding that the coverage of LEED EBOM certified properties amounts to 927,184,053 square feet (using certification data from 2007–2020), representing approximately 0.96% of the total commercial building area. When considering the average minimum size requirement for mandatory disclosure, the coverage decreases to 0.88%. Consequently, questions may arise regarding the representativeness of this study's sample in relation to the broader population of commercial buildings. Specifically, it is worth noting that municipal reporting practices tend to skew the dataset towards larger properties. As there is a correlation between property size and energy consumption, the findings of this study may predominantly apply to larger properties.

Additionally, since this study focuses exclusively on LEED-certified buildings, it is possible that the effects observed in this analysis may differ for buildings without LEED certification.

2.3. Methodology

The following section outlines this study's methodological approach in investigating the impact of the variables of interest on energy consumption and starting rent.

Study Design Considerations

This section investigates whether this study's data is consistent with an independent random draw. It is well-known that the costs and economic benefits of implementing LEED building standards vary depending on the project's location, type, and scale, as well as the intended certification level (Rysman, 2014). Therefore, the aggregation of observations across different geographies must be justified based on the similarity of green building strategies across the cities in the sample. Table B.1.3 (Appendix B.1) shows that the distribution of LEED EBOM certification levels is indeed heterogeneous across the cities in the sample. Previous research suggests energy savings may also vary by the level of certification. For instance, Scofield (2021) finds that the greatest energy savings are achieved by Certified projects (10%), followed by Platinum and Gold (9%), and finally Silver (2%). A 2-sample t-test (Table B.1.4; Appendix B.1) confirms that there is a significant difference in source energy consumption between different certification levels. According to this table, the greatest energy savings emanate from the Platinum level of EBOM. A Generalised Boosted Model (GBM) is employed to eliminate any potential selection bias that could result from pooling buildings with different hedonic and locational characteristics. This model enables the estimation of propensity scores for multinomial treatment (varying certification levels) (McCaffrey et al., 2013; Ridgeway et al., 2013) using the following specification:

$$Pr(EBOM\ Level = 1 \mid X_i) = \phi(X_i'\gamma) \tag{1}$$

where $EBOM\ Level$ represents different certification levels. Due to a relatively scarce number of Certified level observations, Certified and Silver certification levels are combined. The assumption of common support also motivates this study to combine Gold and Platinum projects, as there is a lack of Platinum level observations for the city of New York. Meanwhile, X_i' captures a range of hedonic characteristics, including building size, building class, the number of storeys, and years since the building was built or last renovated. These controls account for a possibility that buildings with higher certification levels are newer, larger, and of better quality. Additionally, X_i' encompasses city-level controls, thus allowing this study to re-weight the sample and correct for the imbalance in the proportion of observations for each certification level in the four cities.

Multilevel Model

The presence of a hierarchical/nested data structure in this study requires an approach where heterogeneity can be incorporated at the building and higher level locational levels (Bell et al., 2019). Figure 2.3 provides a visual snapshot of the lease dataset's structure: lease observations are nested within buildings, while buildings are nested within submarkets and submarkets within cities. Multiple leases can be executed per unit of time (quarter) in any given building. Aggregation of lease variables to higher order ones would result in a diminished within-variation, potentially causing ecological fallacy (Portnov et al., 2007). Similarly, Figure 2.4 shows the data structure for energy observations, which are recorded annually: energy observations (annual occasions) are nested within buildings, which are nested within cities.

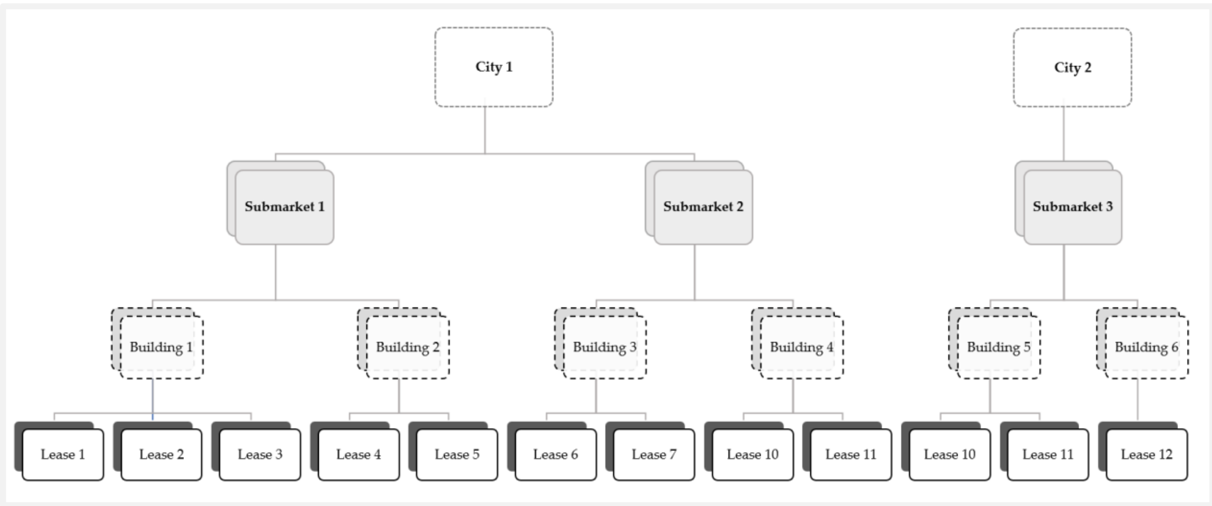


Figure 2.3: Nested data structure snapshot — lease observations.

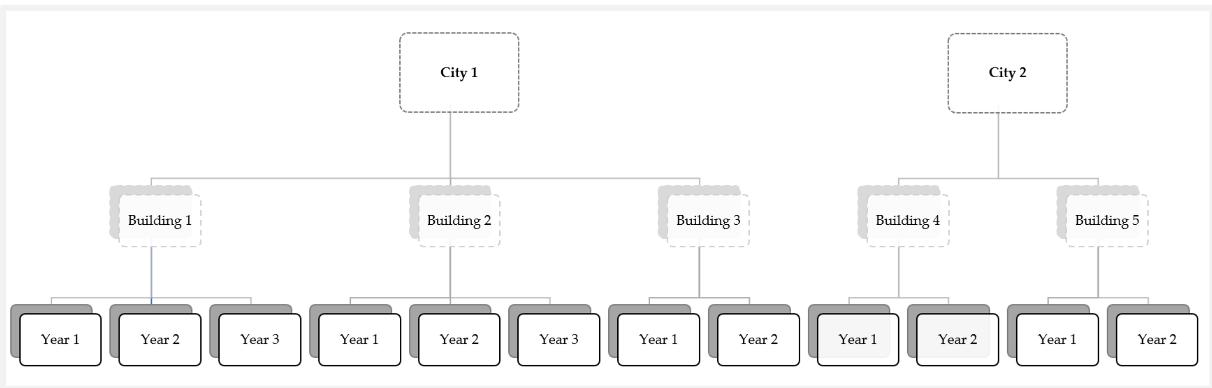


Figure 2.4: Nested data structure snapshot — energy observations.

A multilevel model (MLM) is a widely used approach to deal with nested datasets, where variation across different clusters is assumed to be random and uncorrelated with the independent variables in the model (Greene, 2007). This specification is a modified form of a hedonic pricing model since it has the same overall structure, which consists of fixed and random effects (Keskin et al., 2017). This model allows intercepts and slopes to have their own distributions across clusters, which can be summarised by a set of parameters, such as mean and variance. In addition, this approach accounts for within-variation to control for the time-invariant building characteristics, which influence the probability of obtaining green certification (Qiu & Kahn, 2019).

The multilevel specification is represented by the following model:

$$\log(Y)_{itl} = \alpha + \delta EBOM_{it} + \gamma L_{it} + \omega B_i + \mu T_t + \tau Z_l + \varphi_i + \rho_l + \varepsilon_{itl} \quad (2)$$

where $log\ (Y)_{itl}$ is the logarithm of starting rent (source energy use intensity) for a lease (energy observation) recorded in period t in building i located in l submarket; γ, ω and μ represent the effects of fixed covariates associated with lease, building and time features, respectively. A logarithm transformation of the dependent variable is used to account for the observed positive skewness in the distributions of both source energy and starting rent, capturing the percentage change in these variables. Meanwhile, φ_i and ρ_l represent level 2 (building-level) and level 3 (locational) random intercept controls. In energy regressions, locational random-effects controls are omitted as the number of cities in the sample is less than five, which is considered to be insufficient to estimate group-level variation (Gelman & Hill, 2006). In these instances, city-level fixed effects are employed instead. Vectors of time-invariant hedonic building and time-variant lease features are represented by B_i and L_{it}, respectively. To control for macroeconomic factors such as inflation and interest rates that influence all buildings systematically, T_t is applied on a quarterly (annual) basis for the rental (energy) regressions. Finally, the effects of interest, the aggregate LEED EBOM certificate and its individual scorecard features, are captured by $EBOM_{it}$.

2.4. Results and Discussion

This section begins by presenting the results of regressing the logarithm of weather normalised source energy use intensity on the LEED EBOM certificate and a range of its underlying scorecard characteristics. Next, using lease-level data for the buildings, the outcomes of regressing the logarithm of starting rent on the same set of variables are presented. Finally, the results are discussed, and study limitations are presented.

EBOM Features and Energy Consumption

Table 2.2 presents the selected results for regressions relating LEED EBOM certification to site energy use intensity. The complete set of results can be found in Table B.2.1 (Appendix B.2). Modified Wald test for group-wise heteroskedasticity firmly rejects the null hypothesis of constant variance among panel units. Additionally, Wooldridge (2001) test for serial correlation in panel-data models rejects the null hypothesis of no serial correlation among the residuals. Cluster-robust standard errors are employed to address these issues (Hoechle, 2007). Finally, no substantial deviation from normality is observed in the distribution of the residuals. Hausman (1978) test cannot reject the null hypothesis of the difference between random and fixed effects not being systematic. This outcome justifies the use of a random effects specification, such as mixed effects. Within-building correlation, or intraclass correlation, is also sufficiently high (80%). All regressions presented in this section employ propensity weights of the generalised boosted model to account for the varying distribution of LEED EBOM certification levels of the cities in the sample. The first model in Table 2.2 enables a comparison of the energy performance of LEED EBOM buildings before and after the performance period. As such, the LEED EBOM timeframe encompasses the period when building owners would have begun implementing energy management and productivity measures in order to comply with the standards set by LEED EBOM. The reference category comprises uncertified Class A multi-tenant masonry buildings operating under gross/full-service gross leases in San Francisco. As shown in the "Aggregate EBOM" model in Table 2.2, LEED EBOM certification yields a 4.1% decrease in source energy consumption compared to the pre-performance period. To gain a deeper understanding of the temporal dimension of LEED EBOM certification, the "EBOM Phases" model differentiates between the LEED performance and post-certification periods. The results of this regression demonstrate that during the performance period, the energy consumption of LEED EBOM buildings falls by 2.6%. Meanwhile, energy consumption decreases further during the first year (4.1%) and second year (4.8%). However, the decrease in the third year (3.8%) is less substantial in magnitude. Among other variables, the most sizeable impact on energy usage occurs due to an increase in vacancy rates. Another interesting finding is that the energy consumption of buildings in the sample noticeably decreases over time, which is likely attributed to the intensifying stringency of energy regulations in the studied cities.

Table 2.2: Energy regressions — Part 1. Selected results.

Dependent Variable	The Logarithm of Energy Use Intensity	
Econometric Specification	Multilevel Model	
Variable / Model	Aggregate EBOM	EBOM Phases
Fixed Effects:		
EBOM Certification	–0.041**	
EBOM Performance Period		–0.026*
EBOM Certification Period (Year 1)		–0.041**
EBOM Certification Period (Year 2)		–0.048**
EBOM Certification Period (Year 3)		–0.038**
EBOM Certification Period (Years 4-5)		–0.024
Hedonic and Lease Controls	Included	Included
City Controls	Included	Included
Year Controls	Included	Included
Random Effects:		
Building	Included	Included
Number of Buildings	303	303
AIC	–19,883	–20,081
BIC	–19,690	–19,883
Observations	1,570	1,570

Notes: In the above models, GBM-generated sampling weights are employed. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

Next, the impact of energy management features, such as commissioning and performance measurement, on energy use intensity is investigated in Table 2.3. Although the roll-out of these energy management credits is expected to have begun during the performance period, their effect on energy consumption is likely to lag. As a result, this paper assumes that these credits come into fruition one year after their expected implementation during the performance period. Additionally, since the roll-out of an effective commissioning programme likely hinges upon the presence of measurement systems, the measurement and commissioning credits may be correlated. To account for this, these two groups of variables are first investigated in two separate semi-univariate regressions. According to the "Commissioning" model, the Ongoing Commissioning reduces energy consumption by 4.0%. Meanwhile, the "Measurement" model shows that the presence of building automation systems (BAS) reduces energy usage by 2.8%.

Table 2.3: Energy regressions — Part 2. Selected results.

Dependent Variable	The Logarithm of Energy Use Intensity				
Econometric Specification	Multilevel Model				
Variable / Model	Commissioning	Measurement	Air Quality	Comfort	Multivariate
Commissioning Credits:					
Investigation & Analysis	–0.024				–0.026
Implementation	–0.011				–0.006
Ongoing Commissioning	–0.040**				–0.043**
Measurement Credits:					
BAS		–0.028*			–0.029**
Systems		0.022			0.026
Air Quality Credits:					
Outdoor Air Delivery Monitoring			0.086*		0.110**
Increased Ventilation			0.011		0.014
Particulates Reduction			–0.005		0.002
Comfort Credits:					
Thermal Comfort				0.026	0.028
Lighting Controls				–0.008	–0.007
Other Controls:					
Hedonic and Lease controls	Included	Included	Included	Included	Included
City Controls	Included	Included	Included	Included	Included
Year Controls	Included	Included	Included	Included	Included
Random Effects:					
Building	Included	Included	Included	Included	Included
Number of buildings	303	303	303	303	303
AIC	–4,790	–4,781	–4,783	–4,778	–4,793
BIC	–4,581	–4,578	–4,574	–4,574	–4,547
Observations	1,570	1,570	1,570	1,570	1,570

Notes: In the above models, GBM-generated sampling weights are employed. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

The energy impact of the indoor environmental quality (IEQ) category is investigated in the remaining two models in Table 2.3. Unlike energy management credits, IEQ measures are expected to have an immediate effect on energy consumption upon their introduction during the performance period. Therefore, air quality and comfort features, the two primary components of IEQ in this study, are assumed to come into effect at the outset of the performance period. As shown in the "Air Quality" regression, the incidence of Outdoor Air Delivery Monitoring is associated with an 8.6% increase in energy use. Meanwhile, the credits concerned with a reduction of particulates in air distribution and improved ventilation are not statistically significant in this model. As shown in the "Comfort" regression, none of the investigated comfort features has a statistically significant effect on energy consumption either. The final regression presented in Table 2.3 investigates the effect of all these features via a standard multivariate model. This specification can be used to check whether the omission of other credits from the regression biases the coefficients of interest. The findings of this model show that among energy management credits, Ongoing Commissioning is associated with a statistically significant reduction in energy usage of 4.3%. Meanwhile, Outdoor Air Delivery Monitoring is associated with an increase in energy consumption of 11.0%.

EBOM Features and Rental Premium

Table 2.4 presents the second set of regression results where the logarithm of starting rent is regressed on the LEED EBOM status followed by this certificate's scorecard features. As before, parametric tests are first conducted to verify the validity of the proposed econometric approach. No autocorrelation and heteroscedasticity issues in the residuals are detected. Hausman test cannot reject the null hypothesis of no systematic difference between the fixed effects and random effects specifications. Intraclass correlation coefficients are sufficiently high: 86% and 77% for building and submarket random effects, respectively, reinforcing the inclusion of these variables as random controls. The first model in Table 2.4 investigates the aggregate effect of the LEED EBOM label on rents, followed by one that considers the varying effect of LEED EBOM for gross and net lease types. In the rental setting, the onset of the LEED EBOM label is expected to take place after a building's official certification date, as opposed to the beginning of the performance period. As such, the "Aggregate EBOM" model shows that LEED certification is associated with a rental premium of 2.8%. As per the second model in this table ("EBOM Interaction"), in addition to a premium of 2.1% paid for all lease types, tenants that sign net lease contracts pay an additional premium of 6.6% for spaces with LEED EBOM certification.

Table 2.4: Rent regressions — Part 1. Selected results.

Dependent Variable	The Logarithm of Starting Rent per Square Foot	
Econometric Specification	Multilevel Model	
Variable / Model	Aggregate EBOM	EBOM Interaction
Fixed Effects:		
EBOM Certification	0.028***	0.021**
EBOM Certification * Net Lease		0.066***
Net Lease	–0.077***	–0.108***
Other Controls:		
Hedonic and Lease Controls	Included	Included
Quarterly Dummies	Included	Included
Random-Effects Parameters:		
Submarket	Included	Included
Building	Included	Included
Number of Submarkets	35	35
Number of Buildings	303	303
Observations	4,020	4,020
AIC	−18,096	−18,127
BIC	−17,609	−17,634

Notes: In the above models, GBM-generated sampling weights are employed. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

The rental impact of energy management features, such as commissioning and performance measurement, is documented in Table 2.5. The complete results can be found in Table B.2.5 (Appendix B.2). As before, collinearity concerns motivate this study to initially explore the impact of these categories vis-à-vis two separate semi-univariate regressions. The results of the "Commissioning" model in Table 2.5 show that none of the commissioning credits has a significant effect on rent. These credits remain statistically insignificant when they are interacted with the net lease dummy, as per the "Commissioning Interaction" model. However, BAS is associated with a 4.4% increase in the rental premium. However, the following interaction model shows that this premium does not significantly vary between different lease types.

Table 2.5: Rent results — Part 2. Selected results.

Dependent Variable	The Logarithm of Starting Rent per Square Foot			
Econometric Specification	Multilevel Model			
Variable / Model Name	Commissioning	Commissioning Interaction	Measurement	Measurement Interaction
Commissioning Credits:				
Investigation & Analysis	–0.005	–0.002		
Implementation	0.026	0.027		
Ongoing Commissioning	0.031	0.027		
Investigation & Analysis * Net Lease		–0.051		
Implementation * Net Lease		–0.007		
Ongoing Commissioning * Net Lease		0.026		
Measurement Credits:				
BAS			0.044**	0.045**
Systems			–0.026	–0.029
BAS * Net Lease				–0.007
Systems * Net Lease				0.027
Net	–0.077***	–0.076***	–0.077***	–0.076***
Other Controls:				
Hedonic and Lease Controls	Included	Included	Included	Included
Quarterly Dummies	Included	Included	Included	Included
Random-Effects Parameters:				Included
Submarket	Included	Included	Included	Included
Building	Included	Included	Included	Included
Number of Submarkets	35	35	35	35
Number of Buildings	303	303	303	303
Observations	4,020	4,020	4,020	4,020
AIC	–4,109	–4,107	–4,112	–4,108
BIC	–3,725	–3,704	–3,734	–3,717

Notes: All models employ GBM-generated sampling weights. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

The rental impact of indoor environmental quality (IEQ) components, followed by a multivariate regression involving all investigated scorecard features, is presented in Table 2.6. The first model in this table, "Air Quality", shows that Increased Ventilation raises the rental premium by 4.6%. As per the "Comfort" model, Lighting Controls result in a 2.1% increase in rents, while Thermal Comfort has no significant effect. However, the results of a multivariate regression show that only Increased Ventilation credits are associated with a statistically significant premium of 4.1%. In addition, the interaction between Increased Ventilation and lease type shows no significance (Table B.2.7 in Appendix B).

Table 2.6: Rent results — Part 3. Selected results.

Dependent Variable	The Logarithm of Starting Rent per Square Foot		
Econometric Specification	Multilevel Model		
Variable / Model Name	Air Quality	Comfort	Multivariate
Commissioning Credits:			
Investigation & Analysis			–0.004
Implementation			0.014
Ongoing Commissioning			0.020
Measurement Credits:			
BAS			0.030
Systems			–0.047
Air Quality Credits:			
Outdoor Air Delivery Monitoring	0.019		–0.008
Increased Ventilation	0.046*		0.041*
Particulates Reduction	0.013		–0.002
Comfort Credits:			
Thermal Comfort		0.039	0.038
Lighting Controls		0.021*	0.003
Other Controls:			
Hedonic and Lease Controls	Included	Included	Included
Quarterly Dummies	Included	Included	Included
Random-Effects Parameters:			
Submarket	Included	Included	Included
Building	Included	Included	Included
Number of Submarkets	35	35	35
Number of Buildings	303	303	303
AIC	–4,114	–4,107	–4,113
BIC	–3,730	–3,729	–3,685
Observations	4,020	4,020	4,020

Notes: All presented models employ GBM-generated sampling weights. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

Robustness Checks

In this study, a series of comprehensive robustness checks are conducted. As such, the energy analysis is expanded to include all scorecard characteristics beyond the primary ones under consideration (see Appendix B.2, Table B.2.3). This exercise is undertaken to ensure that energy savings observed are not erroneously associated with the categories of this study's main interest, thereby addressing the possibility of neglecting potential contributions from other factors. The results of this inclusive analysis indicates minimal shifts in the observed impacts. For instance, when considering the outdoor air monitoring feature, a corresponding increase in energy consumption by 11.2% is observed. Furthermore, the energy-saving influence of the third commissioning stage sees only a slight decrease from 4.3% to 3.8%.

An evaluation is merited to ascertain whether the increased rent associated with the Increased Ventilation credit can be attributed solely to this feature, or if its correlation with other premium-boosting attributes plays a contributory role. The Increased Ventilation credit's distribution is analysed across various certification levels, uncovering a higher prevalence in Platinum buildings. Nevertheless, controlling for the total number of LEED EBOM points scored, the impact of Increased Ventilation on rent remained unchanged, as demonstrated in Appendix B, Table B.2.7 (within the "Robustness (1) – Total Points" Model). Moreover, to examine the possible association of Increased Ventilation with higher-quality buildings, a logistic estimation is used to regress Increased Ventilation on a broad set of hedonic and location characteristics. The analysis indicates no significant evidence that this credit is associated with higher quality buildings.

Finally, to account for potential temporal variations across different submarkets, a further robustness check was incorporated into the analysis where the rental transaction quarter is treated as a random effect within each submarket. This adjustment allows the analysis to capture the nuances in the relationship between time and the dependent variable across the diversity of submarkets. This method does not reveal a substantial deviation from the primary findings of this study. For instance, the impact of LEED EBOM certification on rent increased slightly from 2.8% to 3.1%, while the influence of LEED EBOM certification in net leases is associated with a minor reduction from 6.6% to 6.3%. Meanwhile, the rental impact of Enhanced Ventilation increases from 4.1% to 5.5%. However, all other scorecard features of interest remain consistent, reinforcing the robustness of the analytical approach and the reliability of the results obtained.

Discussion

The findings of this paper are important for policymakers seeking ways to lower greenhouse gas emissions, as well as commercial real estate investors looking to improve their bottom line via lower operating expenses. Prior to the analysis of individual LEED EBOM features, this paper first investigates the impact of the LEED EBOM label on energy use intensity and rental premium. As such, energy savings in the range from 2.6%–4.8% are discovered, for buildings receiving this label. The uncovered reduction in energy consumption upon certification is expected to be priced into lease contracts where tenants are liable for energy expenses. The results of the rental regression confirm this supposition, as tenants pay a LEED EBOM premium of 6.6% for net leases, in addition to a 2.1% premium for all lease types. Since the increased rental premium in both contract types suggests that LEED EBOM certification carries both energy-saving and productivity benefits in the eyes of the tenants, the primary aim of this study is to uncover whether these premia can be attributed to energy management and indoor environment features that form the basis of this certification. In parallel, it aims to disentangle the impact of these credits on energy use intensity.

The energy-reduction effect of energy management features is confirmed in the semi-univariate regression featuring the variable that represents different commissioning stages. Specifically, the third (Ongoing Commissioning) stage significantly lowers energy use intensity by 4.0%, respectively. The significance of the Ongoing Commissioning is in line with expectations, as this credit mandates repeating activities of the first and second commissioning stages over ongoing two-year cycles (BuildingGreen, 2020a). The insignificant result of the first commissioning stage, Investigation & Analysis, could be attributed to the fact that auditing activities cannot by themselves guarantee energy savings. Without the first stage of commissioning, however, building operators would not be able to identify any system problems necessary for the following two commissioning stages (ibid). A separate semi-univariate regression of measurement features also shows that BAS reduces energy use intensity by 2.8%. The multivariate regression confirms the significance of the Ongoing Commissioning and Measurement credits, which reduce energy consumption by 4.3% and 2.9%, respectively. The significance of Ongoing Commissioning and BAS in the multivariate regression corroborates Hypothesis 1, confirming that energy management practices have a favourable effect on the energy efficiency of buildings in operation.

With respect to productivity-enhancing practices, Outdoor Air Delivery Monitoring is associated with a significant increase in energy use intensity of 8.6% in the semi-univariate regression involving air quality features. Although conceptually, this credit does not trigger an increase in the ventilation rate, by alarming building operators if the minimum outdoor airflow rate falls more than 15% below the minimum rate, building operators can promptly address inadequate outdoor air delivery and avoid complaints of stale air and odours (BuildingGreen, 2020b). The continuous nature of this credit is likely attributable to its large magnitude. However, Increased Ventilation is not found to significantly increases energy consumption. However, a robustness check using the logarithm of source energy use intensity as a dependent variable shows that Increased Ventilation raises energy use by 2.5%. Despite generating greater resistance to airflow in the air distribution system, Particulates Reduction does not statistically significantly affect energy use. Yet, the significant positive impact of Outdoor Air Delivery Monitoring on energy use intensity in the multivariate regression leads this research to accept Hypothesis 2.

In spite of the uncovered energy-reduction effect of Ongoing Commissioning, this paper does not find a significant positive link between commissioning activities and net lease rent, leading to the rejection of Hypothesis 3. One possible reason for this outcome is that tenants may be insufficiently informed about the energy-saving potential of commissioning practices. Alternatively, the delayed effect of commissioning on energy consumption could lead tenants under this type of contract to heavily discount these credits' future energy-reduction benefits. Another interesting observation relates to the significant and sizeable BAS premium of 4.4% in all lease types (rather than exclusively in net lease contracts) in a semi-univariate rental regression of measurement features. It is possible that the uncovered BAS premium captures some omitted features: landlords who choose to enhance their building operations with indoor environment quality measures may systematically choose to adopt BAS to ensure their seamless operation. Further attestation to this supposition is achieved in the multivariate rental regression, as the significance of this variable does not extend to this setting. Finally, the significant and sizeable rental premium associated with Increased Ventilation attests to tenants' willingness to pay for spaces with high indoor environment quality, a finding in support of Hypothesis 4. The significance of this particular feature is unsurprising, as increased ventilation rates can bring about a range of health and productivity benefits to building occupants (BuildingGreen, 2020c).

The key finding of this study relates to the trade-off between premium-enhancing air quality measures and the energy efficiency of buildings in operation. With higher energy consumption and associated costs implied by higher indoor environment quality adversely impacting the bottom line, commercial real estate landlords would unequivocally benefit from implementing measures that do not carry a high energy price tag. The Controllability of Lighting Systems credit is one such candidate, as, according to this study's findings, it does not statistically significantly increase energy usage. Additionally, there is some evidence of the premium-boosting advantages offered by this credit, as in a semi-univariate regression encompassing comfort credits, Controllability of Lighting Systems delivers a significant rental premium of 2.1%. In contrast to the findings of this research, there is literature documenting that a task-based lighting approach supposed by this credit could theoretically lead to energy usage savings (Clark, 2013). However, the effectiveness of this strategy depends not only on the flexibility to adjust lighting settings to specific visual tasks but also on how smoothly the lights are integrated with available daylight (BuildingGreen, 2020d). In addition, providing occupants with increased controllability may prove counterproductive from a behavioural standpoint for reasons such as the rebound effect. Considering the energy-saving potential of this credit, future research is necessary to understand under what circumstances it could deliver energy savings.

Limitations and Future Research Guidance

There are several limitations of this study that must be noted. With energy disclosure policies implemented at the state rather than federal level, there is variability in the disclosure requirements among jurisdictions in the sample. As indicated, requirements vary based on minimum building size and types of real estate, and many jurisdictions regularly introduce energy disclosure updates to gradually expand the scope of building sizes falling under their mandates. The sheer size of the New York City market and its earliest enactment date (relative to other cities in the sample set) to mandate disclosure of non-residential buildings at least 50,000 square feet in size means it dwarfs other cities in terms of the number of buildings and total floor area in the sample during 2011–2020. The lack of energy data verification is another concern, which is only required by Chicago (IMT, 2021) out of the four cities constituting the sample set. Assuming that data entry errors in other cities are randomly distributed, the internal validity of the findings would not be compromised.

This research employs an econometric approach to capture the energy and rental performance of LEED EBOM buildings before and after certification with the intent of controlling for within-building heterogeneity and thus accounting for possible selection bias. Since scorecard data provides a snapshot of the operating features of interest at the time of certification, the lack of pre-certification data on these variables has led this paper to assume that none of these characteristics had been present prior to obtaining the LEED EBOM label. Yet, it cannot be ruled out that some scorecard features, particularly those that may be pre-determined by design characteristics, could have been introduced in the pre-certification period of LEED EBOM. In such a case, the magnitude of the uncovered energy management and indoor environmental quality measures would be underestimated.

The omission of some variables may bias the results; in any case, their inclusion would increase the overall predictive power of the regression models. More precisely, key occupational factors, such as worker density, number of computers per person, and building operating hours, which are known to influence energy consumption considerably (Kontokosta, 2013), are absent from this study. However, a separate regression for the city of New York, which allows to control for some of these operational variables, does not reveal a bias in the key coefficients. Information on building energy efficiency characteristics, such as the type of ventilation (mechanical, natural, or hybrid), is also missing. However, by employing a panel method on a longitudinal panel of observations of LEED EBOM buildings before and after certification, the impact of these time-invariant features should be removed. Omitted tenant characteristics (tenant firm type, credit rating, size, and behaviour) may pose additional internal validity concerns. For instance, if environmentally conscious tenants systematically choose to locate in buildings with commissioning practices, any observed reduction in energy consumption could be subject to a negative bias. However, it is unlikely for energy management practices to be at the forefront of the decision-making of office tenants when choosing a lease.

2.5. Conclusions

Environmental certification has become the primary signalling channel for superior green credentials in the commercial real estate market. In recent years, attention has shifted from energy efficient design features to in-use energy performance. With a focus on operational energy consumption, LEED EBOM may address the dilemma of the energy performance gap arising due to the discrepancy between these two measures. This research examines the impact of this label and its underlying scorecard features on both energy consumption and rents. Features can be grouped into improving operational energy performance, such as commissioning and measurement, or enhancing productivity, such as occupant comfort and air quality. The dataset comprises LEED EBOM certified properties located in San Francisco, New York, Washington DC, and Chicago. The analysis conducted in this study (a) combines novel datasets that report on buildings' actual, rather than estimated, energy consumption and rental figures; (b) applies panel data methods, thereby controlling for unobservable building-level characteristics; (c) differentiates between operating and design types of LEED certification; and (d) analyses the effect of individual LEED components on the aforementioned outcomes.

The results of this research show that LEED EBOM certification results in lower energy consumption. This effect is positively priced into leases that oblige the tenant to cover energy expenses. In addition, the fact that a rental premium is associated with all lease types (irrespective of who bears responsibility for the utilities) is indicative of this certification's productivity-related benefits. Although a significant energy-reduction effect of the last commissioning stage is uncovered, it is not reflected in a net lease premium. Meanwhile, increased air quality commands a rental premium for all lease types but leads to adverse energy consumption outcomes. While there may be measures that can simultaneously enhance user productivity and energy conservation from a theoretical perspective, empirically there appears to be a trade-off between these two objectives. Since this intersection may jeopardise climate change mitigation efforts, it must be considered by policymakers and green certification bodies.

Appendix B.1

Table B.1.1: Description of variables and summary statistics.

Variable Name	Variable Description	N	μ	σ^2	Min	Max
Dependent Variables:						
Starting Rent	The logarithm of starting rent per square foot	4,020	3.85	0.45	2.06	5.37
Site EUI	The logarithm of weather normalised site energy use intensity (kBtu per square foot)	1,570	5.16	0.25	4.50	5.98
Certification:						
EBOM Certification	Dummy variable is 1 for buildings that achieve LEED EBOM certification (v2009)	4,020	0.44	0.50	0	1
Commissioning:						
Investigation & Analysis	Dummy variable is 1 for projects with an "Existing building commissioning – investigation and analysis" credit	4,020	0.07	0.26	0	1
Implementation	Dummy variable is 1 for projects with an "Existing building commissioning – implementation" credit	4,020	0.28	0.45	0	1
Ongoing Commissioning	Dummy variable is 1 for projects with an "Existing building commissioning – ongoing commissioning" credit	4,020	0.16	0.37	0	1
Measurement:						
BAS	Dummy variable is 1 for the presence of a "Building Automation Systems" credit	4,020	0.16	0.37	0	1
Systems	Dummy variable is 1 for the presence of "System-level metering" credits	4,020	0.03	0.16	0	1
Air Quality:						
Outdoor Air Delivery Monitoring	Dummy variable is 1 for projects with an "IAQ best management practices – outdoor air delivery monitoring" credit	4,020	0.04	0.18	0	1
Increased Ventilation	Dummy variable is 1 for projects with an "IAQ best management practices – increased ventilation" credit	4,020	0.10	0.30	0	1
Particulates Reduction	Dummy variable is 1 for projects with an "IAQ best management practices – reduce particulates in air distribution" credit	4,020	0.51	0.50	0	1
Comfort:						
Lighting Controls	Dummy variable is 1 for projects with a "Controllability of systems – lighting" credit	4,020	0.39	0.49	0	1
Thermal Monitoring	Dummy variable is 1 for projects with an "Occupant comfort – thermal comfort monitoring" credit	4,020	0.01	0.11	0	1
Other Control Variables:						
Net Lease	Dummy variable is 1 for lease structures where the tenant pays for utilities	4,020	0.09	0.29	0	1

(continued on the next page)

Table B.1.1 *(continued)*

Variable Name	Variable Description	N	μ	σ^2	Min	Max
LEED Design	Dummy variable is 1 for design-stage LEED certifications such as LEED Core + Shell (LEED-CS) and LEED for Building Design and Construction (LEED BD+C)	4,020	0.07	0.26	0	1
Class B	Dummy variable is 1 for Class B properties	4,020	0.12	0.33	0	1
Building size	The logarithm of building size in square feet	4,020	13.22	0.77	11.34	15.10
Age	Number of years since the building was built or last renovated	4,020	20.16	15.81	0	109
Vacancy	Percentage of vacant space in a building at the time of the transaction (quarterly)	4,020	0.12	0.12	0	1
Single Tenant	Dummy variable is 1 for single-tenant buildings	4,020	0.01	0.09	0	1
Renewal	Dummy variable is 1 for renewal leases	4,020	0.28	0.45	0	1
Expansion/Extension	Dummy variable is 1 for expansion/extension leases	4,020	0.11	0.32	0	1
Other Transaction	Dummy variable is 1 for all other transaction types (excluding new transactions)	4,020	0.03	0.17	0	1
Lease Term	Lease length in years	4,020	6.76	3.67	0.08	26.92
Transaction Size	The logarithm of the total amount of space leased by the tenant in the transaction (in square feet)	4,020	9.15	1.17	4.66	14.29
Metal	Dummy variable is 1 for metal buildings	4,020	0.01	0.08	0	1
Concrete	Dummy variable is 1 for concrete buildings	4,020	0.14	0.34	0	1
Steel	Dummy variable is 1 for steel buildings	4,020	0.67	0.47	0	1
Location Controls:						
Washington DC	Dummy variable is 1 for buildings located in Washington DC	4,020	0.22	0.42	0	1
Chicago	Dummy variable is 1 for buildings located in Chicago	4,020	0.22	0.42	0	1
New York	Dummy variable is 1 for buildings located in New York	4,020	0.20	0.40	0	1

Notes: Amenities, submarket, and time control variables are excluded from this table. The reference category comprises new lease transactions obliging the landlord to cover utilities (gross leases) signed in Class A masonry buildings in San Francisco in (Q'1) 2011.

Table B.1.2: Independent variables. Scorecard components.

	Category	Credits	Main Requirements	Included
Energy Management	Commissioning	Investigation & Analysis	• Determine possible conservation measures. • Develop a report, compile a systems manual, and develop an ongoing commissioning plan.	✓
		Implementation	• Implement all no-/low-cost measures and provide training to building staff.	✓
		Ongoing Commissioning	• Repeat system testing and evaluation every two years.	✓
	Performance measurement	Building Automation System (BAS)	• The building must have a Building Automation System (BAS) that monitors and controls HVAC and lighting systems.	✓
		System-level metering	• Submetering of end-uses such as space heating and cooling, area lighting, and ventilation fans.	✓
Indoor Environmental Quality	Air	IAQ management program	• Develop and implement an ongoing indoor air quality (IAQ) management program with the intent of maintaining good IAQ and preventing problems.	×
		Outdoor air delivery monitoring	• Install permanent monitoring systems that alert operators when the rate of air outflow drops more than 15% below the minimum set point.	✓
		Increased ventilation	• Increase ventilation rates throughout the building to achieve at least 30% higher than the industry standard (ASHRAE 62.1–2007).	✓
		Reduction of particulates in air distribution	• Use high-quality air filters at outside air intakes (MERV 13 filters must be used at all outside air intakes; no spaces may be omitted).	✓
	Comfort	Comfort Survey	• Implement an indoor environment survey and take steps to remedy problems identified through survey responses.	×
		Lighting Controls	• Provide lighting controls for at least 50% of occupants.	✓
		Thermal Monitoring	• Implement continuous monitoring of air temperature and humidity and periodic measures of air speed and radiant temperature.	✓
		Daylight and Views	• Achieve daylighting in at least 50% of all regularly occupied spaces.	×

Source: BuildingGreen, USGBC.

Table B.1.3: Distribution of LEED EBOM projects by certification level and city.

Certification Level	San Francisco	Washington DC	Chicago	New York
Certified	4.00%	1.19%	1.39%	10.34%
Silver	5.33%	19.05%	25.00%	27.59%
Gold	62.67%	63.10%	55.56%	62.07%
Platinum	28.00%	16.67%	18.06%	0.00%

Table B.1.4: Two-sample t-test of energy consumption means by certification level and city.

City	Certified	Silver	Gold	Platinum
San Francisco	0.17 (0.02)	0.07 (0.18)	−0.03 (0.33)	−0.09 (0.02)
Washington DC	−0.25 (0.05)	0.02 (0.55)	0.03 (0.45)	−0.08 (0.03)
Chicago	0.13 (0.25)	−0.06 (0.13)	−0.11 (0.00)	−0.02 (0.60)
New York	−0.10 (0.01)	0.01 (0.80)	−0.06 (0.05)	n/a
Aggregate	**0.10 (0.02)**	**0.08 (0.00)**	**−0.04 (0.04)**	**−0.14 (0.00)**

Notes: Energy savings have a negative coefficient sign. *p*–values are shown in brackets. The results are computed relative to the LEED EBOM pre-registration period.

Appendix B.2

Table B.2.1: Energy regressions — Part 1. Complete results.

Dependent Variable	The Logarithm of Energy Use Intensity	
Econometric Specification	Multilevel Model	
Variable / Model Name	Aggregate EBOM	EBOM Phases
Main Effects:		
EBOM Certification	–0.041**	
EBOM Performance Period		–0.026*
EBOM Certification Period (Year 1)		–0.041**
EBOM Certification Period (Year 2)		–0.048**
EBOM Certification Period (Year 3)		–0.038**
EBOM Certification Period (Years 4-5)		–0.024
Other Controls:		
Net Lease	–0.142	–0.049*
LEED Other	0.022	0.024
Vacancy	–0.629***	–0.596***
Age	–0.000	–0.000
Class B	0.072**	0.069**
Size	0.062**	0.055**
Single	0.055	0.069
Metal	–0.074	–0.096
Reinforced Concrete	–0.019	–0.035
Steel	–0.009	–0.012
Washington DC	0.157***	0.145***
Chicago	0.339***	0.309***
New York	0.458***	0.432***
Amenities:	0.004	0.014
Food Facilities	0.019	0.018
Fitness Centre	0.007	–0.008
Air Conditioning	0.018	0.006
Manager	–0.076*	–0.072*
Dry Cleaner	–0.010	–0.012
Atrium	–0.062**	–0.059**
All-day Access	–0.030	–0.028
Conference	0.081	0.067
Concierge	0.007	0.028
Roof Terrace	0.015	0.011
Balcony	–0.142	
Time Controls:		–0.044**
2012	–0.022	–0.070***
2013	–0.023	–0.092***
2014	–0.059***	–0.111***
2015	–0.093***	–0.122***
2016	–0.079***	–0.153***
2017	–0.146***	–0.165***
2018	–0.067*	–0.164***
2019	–0.079*	0.014

(continued on the next page)

Table B.2.1 *(continued)*

Dependent Variable	The Logarithm of Energy Use Intensity	
Econometric Specification	Multilevel Model	
Variable / Model Name	Aggregate EBOM	Aggregate EBOM
Constant	3.343***	3.472***
Random-Effects Parameters:		
Building Intercept	0.025	0.025
Residual	0.006	0.006
Number of buildings	303	303
AIC	–19,883	–20,081
BIC	–19,690	–19,883
Observations	1,570	1,570

Notes: All presented models employ GBM-generated sampling weights. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

Table B.2.2: Energy regression — Part 2. Complete results.

Dependent Variable	The Logarithm of Energy Use Intensity				
Econometric Specification	Multilevel Model				
Variable / Model	Commissioning	Measurement	Air Quality	Comfort	Multivariate
Commissioning Credits:					
Investigation & Analysis	–0.024				–0.026
Implementation	–0.011				–0.006
Ongoing Commissioning	–0.040**				–0.043**
Measurement Credits:					
BAS		–0.028*			–0.029**
Systems		0.022			0.026
Air Quality Credits:					
Outdoor Air Delivery Monitor.			0.086*		0.110**
Increased Ventilation			0.011		0.014
Particulates Reduction			–0.005		0.002
Comfort Credits:					
Thermal Comfort				0.026	0.028
Lighting Controls				–0.008	–0.007
Other Controls:					
EBOM Certification	–0.027*	–0.030*	–0.031***	–0.030***	–0.027*
Net Lease	–0.034**	–0.033**	–0.035**	–0.035**	–0.035**
LEED Other	0.027	0.021	0.027	0.023	0.030
Vacancy	–0.527***	–0.529***	–0.518***	–0.525***	–0.521***
Age	–0.000	–0.000	–0.000	–0.000	–0.000
Class B	0.066**	0.066**	0.065**	0.067**	0.062**
Size	0.057**	0.054**	0.053**	0.053**	0.055**
Single	0.062	0.067	0.062	0.064	0.067
Metal	–0.095	–0.089	–0.099	–0.104	–0.084
Reinforced Concrete	–0.033	–0.033	–0.036	–0.034	–0.032
Steel	–0.007	–0.009	–0.012	–0.009	–0.005
Washington DC	0.150***	0.146***	0.149***	0.147***	0.153***
Chicago	0.312***	0.302***	0.299***	0.304***	0.303***
New York	0.436***	0.429***	0.438***	0.433***	0.436***

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Table B.2.2 *(continued)*

Dependent Variable	The Logarithm of Energy Use Intensity				
Econometric Specification	Multilevel Model				
Variable / Model	Commissioning	Measurement	Air Quality	Comfort	Multivariate
Amenities:					
Food Facilities	0.014	0.015	0.017	0.014	0.017
Fitness Centre	0.018	0.018	0.020	0.019	0.019
Air Conditioning	–0.003	–0.002	–0.007	–0.005	–0.002
Manager	0.007	0.007	0.011	0.009	0.010
Dry Cleaner	–0.069*	–0.068	–0.074	–0.071	–0.070*
Atrium	–0.011	–0.009	–0.016	–0.013	–0.013
All-day Access	–0.056**	–0.059**	–0.060**	–0.058**	–0.058**
Conference	–0.029	–0.030	–0.026	–0.028	–0.030
Concierge	0.068	0.071	0.058	0.068	0.060
Roof Terrace	0.028	0.029	0.028	0.028	0.026
Balcony	0.008	0.008	0.005	0.008	0.005
Time Controls:					
2012	–0.040*	–0.042*	–0.043***	–0.042***	–0.041*
2013	–0.056**	–0.060**	–0.061***	–0.060***	–0.057**
2014	–0.081***	–0.083***	–0.085***	–0.084***	–0.081***
2015	–0.097***	–0.100***	–0.101***	–0.100***	–0.096***
2016	–0.107***	–0.110***	–0.112***	–0.111***	–0.106***
2017	–0.137***	–0.143***	–0.145***	–0.143***	–0.136***
2018	–0.163***	–0.168***	–0.170***	–0.168***	–0.161***
2019	–0.162***	–0.170***	–0.169***	–0.168***	–0.160***
Constant	3.434***	3.479***	3.485***	3.483***	3.456***
Random-Effects Parameters:					
Building Intercept	0.024	0.024	0.024	0.024	0.023
Residual	0.007	0.007	0.007	0.007	0.007
Number of buildings	303	303	303	303	303
AIC	–4,790	–4,781	–4,783	–4,778	–4,793
BIC	–4,581	–4,578	–4,574	–4,574	–4,547
Observations	1,570	1,570	1,570	1,570	1,570

Notes: All presented models employ GBM-generated sampling weights. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

Table B.2.3: Energy regression — Part 3. Robustness Checks.

Dependent Variable	The Logarithm of Energy Use Intensity
Econometric Specification	Multilevel Model
Variable / Model	All Scorecard Features
Commissioning Credits:	
Investigation & Analysis	–0.027
Implementation	–0.009
Ongoing Commissioning	–0.038**
Measurement Credits:	
BAS	–0.027**
Systems	0.014
Air Quality Credits:	
Outdoor Air Delivery Monitor.	0.112**
Increased Ventilation	0.021
Particulates Reduction	–0.006
Comfort Credits:	
Thermal Comfort	0.007
Lighting Controls	–0.013
Other Controls:	
Additional Scorecard Features:	
Sustainable Sites	–0.001
Solid Waste Management	–0.009
Sustainable Purchasing	0.005
Green Cleaning	–0.010
Water	0.008**
Onsite and Offsite Renewable Energy	–0.003
Refrigerant Management	–0.019
Emissions reductions reporting	0.019
Occupant survey	–0.012
IAQ management program	0.009
Management for facility Alterations	0.015
Daylight and Views	0.034
Other Controls:	
Net Lease	–0.044*
LEED Other	0.029
Vacancy	–0.596***
Age	–0.000
Class B	0.070**
Size	0.057**
Single	0.088
Metal	–0.076
Reinforced Concrete	–0.031
Steel	–0.010
Washington DC	0.147***
Chicago	0.309***
New York	0.436***

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Table B.2.3 *(continued)*

Dependent Variable	The Logarithm of Energy Use Intensity
Econometric Specification	Multilevel Model
Variable / Model	All Scorecard Features
Amenities:	
Food Facilities	0.022
Fitness Centre	0.022
Air Conditioning	–0.008
Manager	0.008
Dry Cleaner	–0.072
Atrium	–0.019
All-day Access	–0.058**
Conference	–0.029
Concierge	0.066
Roof Terrace	0.022
Balcony	0.005
Time Controls:	
2012	–0.048***
2013	–0.074***
2014	–0.097***
2015	–0.117***
2016	–0.128***
2017	–0.160***
2018	–0.169***
2019	–0.169***
Constant	3.428***
Random-Effects Parameters:	
Building Intercept	0.035
Residual	0.008
Number of buildings	303
AIC	–4,289.08
BIC	–3,952
Observations	1,570

Notes: All presented models employ GBM-generated sampling weights. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

Table B.2.4: Rent regression — Part 1. Complete results.

Dependent Variable	The Logarithm of Starting Rent per Square Foot	
Econometric Specification	Multilevel Model	
Variable / Model	Aggregate EBOM	EBOM Phases
Fixed Effects:		
EBOM Certification	0.028***	0.021**
EBOM Certification * Net Lease		0.066***
Net Lease	–0.077***	–0.108***
Other Controls:	0.031	0.033
Renewal	0.043***	0.043***
Expansion/Extension	0.028*	0.028**
Other Lease Types	0.021	0.024
Class B	–0.084***	–0.084***
Vacancy	–0.004	–0.004
Lease term	0.006***	0.006***
Transaction Size	0.002	0.002
Age	0.000	0.000
Amenities:		
Air Conditioning	–0.027	–0.028
All-day Access	0.001	0.000
Atrium	–0.013	–0.014
Balcony	–0.015	–0.014
Conference	–0.007	–0.007
Dry Cleaner	–0.034	–0.034
Food Facilities	0.023	0.024
Manager	0.007	0.008
Roof Terrace	0.051**	0.052**
Time Controls:		
2011 – Q2	–0.035	–0.039
2011 – Q3	–0.007	–0.014
2011 – Q4	–0.010	–0.015
2012 – Q1	–0.118**	–0.123**
2012 – Q2	–0.092*	–0.096*
2012 – Q3	–0.140**	–0.142**
2012 – Q4	–0.063	–0.065
2013 – Q1	–0.068	–0.070
2013 – Q2	–0.045	–0.048
2013 – Q3	–0.004	–0.006
2013 – Q4	–0.065	–0.068
2014 – Q1	–0.023	–0.025
2014 – Q2	–0.001	–0.003
2014 – Q3	0.042	0.040
2014 – Q4	0.070	0.067
2015 – Q1	0.093	0.092
2015 – Q2	0.122**	0.122**
2015 – Q3	0.113*	0.112*
2015 – Q4	0.129**	0.126*
2016 – Q1	0.159**	0.157**
2016 – Q2	0.161**	0.158**
2016 – Q3	0.190***	0.187***
2016 – Q4	0.116	0.116*

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Table B.2.4 *(continued)*

Dependent Variable	The Logarithm of Energy Use Intensity	
Econometric Specification	Multilevel Model	
Variable / Model	Aggregate EBOM	EBOM Phases
2017 – Q1	0.193***	0.191***
2017 – Q2	0.174***	0.173***
2017 – Q3	0.163**	0.162**
2017 – Q4	0.187**	0.185**
2018 – Q1	0.204***	0.203***
2018 – Q2	0.202**	0.200**
2018 – Q3	0.234***	0.231***
2018 – Q4	0.252***	0.251***
2019 – Q1	0.224**	0.224**
2019 – Q2	0.219**	0.215**
2019 – Q3	0.265***	0.264***
2019 – Q4	0.253***	0.249***
Constant	3.682***	3.688***
Random-Effects Parameters:		
Submarket Intercept	0.136	0.136
Building Intercept	0.019	0.019
Residual	0.027	0.027
Number of submarkets	35	35
Number of buildings	303	303
AIC	−18,096	−18,127
BIC	−17,609	−17,634
Observations	4,020	4,020

Notes: All presented models employ GBM-generated sampling weights. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

Table B.2.5: Rent regression — Part 2. Complete results.

Dependent Variable	The Logarithm of Starting Rent per Square Foot			
Econometric Specification	Multilevel Model			
Variable / Model Name	Commissioning	Commissioning Interaction	Measurement	Measurement Interaction
Commissioning Credits:				
Investigation & Analysis	–0.005	–0.002		
Implementation	0.026	0.027		
Ongoing Commissioning	0.031	0.027		
Investigation & Analysis * Net Lease		–0.051		
Implementation * Net Lease		–0.007		
Ongoing Commissioning * Net Lease		0.026		
Measurement Credits:				
BAS			0.044**	0.045**
Systems			–0.026	–0.029
BAS * Net Lease				–0.007
Systems * Net Lease				0.027
Other Controls:	0.027	0.027	0.024	0.024
Net Lease	–0.077***	–0.076***	–0.077***	–0.076***
Renewal	0.043***	0.043***	0.043***	0.043***
Expansion/Extension	0.028*	0.027*	0.028*	0.028*
Other	0.021	0.021	0.021	0.021
Class B	–0.081***	–0.082***	–0.081***	–0.081***
Vacancy	0.000	0.000	–0.002	–0.002
Lease term	0.006***	0.006***	0.006***	0.006***
Transaction Size	0.001	0.001	0.002	0.002
Age	0.000	0.000	0.000	0.000
Amenities:				
Air Conditioning	–0.030	–0.030	–0.034	–0.034
All-day Access	0.001	–0.000	0.003	0.002
Atrium	–0.010	–0.009	–0.016	–0.016
Balcony	–0.018	–0.016	–0.015	–0.015
Conference	–0.006	–0.006	–0.005	–0.006
Dry Cleaner	–0.034	–0.035	–0.039	–0.039
Food Facilities	0.024	0.024	0.025	0.025
Manager	0.006	0.007	0.006	0.006
Roof Terrace	0.050**	0.052**	0.048*	0.048*
Time Controls:				
2011 – Q2	–0.036	–0.036	–0.037	–0.037
2011 – Q3	–0.006	–0.006	–0.006	–0.006
2011 – Q4	–0.008	–0.012	–0.005	–0.005
2012 – Q1	–0.119**	–0.119**	–0.116**	–0.116**
2012 – Q2	–0.093*	–0.093*	–0.088*	–0.088*
2012 – Q3	–0.138**	–0.139**	–0.134**	–0.134**
2012 – Q4	–0.058	–0.058	–0.053	–0.053
2013 – Q1	–0.072	–0.071	–0.065	–0.065
2013 – Q2	–0.046	–0.045	–0.038	–0.038
2013 – Q3	–0.002	–0.002	0.004	0.004
2013 – Q4	–0.061	–0.060	–0.054	–0.055
2014 – Q1	–0.028	–0.028	–0.022	–0.022
2014 – Q2	–0.002	–0.002	0.004	0.004
2014 – Q3	0.045	0.045	0.052	0.052

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Table B.2.5 *(continued)*

Dependent Variable	The Logarithm of Starting Rent per Square Foot			
Econometric Specification	Multilevel Model			
Variable / Model Name	Commissioning	Commissioning Interaction	Measurement	Measurement Interaction
2014 – Q4	0.075	0.074	0.082	0.082
2015 – Q1	0.087	0.088	0.095	0.095
2015 – Q2	0.122**	0.123**	0.130***	0.130***
2015 – Q3	0.118**	0.118*	0.127**	0.127**
2015 – Q4	0.135**	0.135**	0.144**	0.144**
2016 – Q1	0.153**	0.153**	0.163***	0.162***
2016 – Q2	0.158**	0.158**	0.169**	0.168**
2016 – Q3	0.195***	0.195***	0.206***	0.206***
2016 – Q4	0.124*	0.124*	0.134**	0.134**
2017 – Q1	0.185***	0.185***	0.198***	0.198***
2017 – Q2	0.171***	0.171**	0.183***	0.183***
2017 – Q3	0.162***	0.163***	0.175***	0.174***
2017 – Q4	0.195***	0.195***	0.206***	0.206***
2018 – Q1	0.194***	0.195***	0.204***	0.204***
2018 – Q2	0.197**	0.197**	0.209**	0.209**
2018 – Q3	0.232***	0.231***	0.244***	0.244***
2018 – Q4	0.257***	0.258***	0.270***	0.270***
2019 – Q1	0.215**	0.214**	0.229**	0.229**
2019 – Q2	0.213*	0.212*	0.226**	0.225**
2019 – Q3	0.259***	0.258***	0.270***	0.270***
2019 – Q4	0.259***	0.259***	0.273***	0.273***
Constant	3.682***	3.680***	3.678***	3.678***
Random-Effects Parameters:				
Submarket Intercept	0.138	0.139	0.134	0.134
Building Intercept	0.019	0.019	0.020	0.020
Residual	0.027	0.027	0.027	0.027
Number of submarkets	35	35	35	35
Number of buildings	303	303	303	303
Observations	4,020	4,020	4,020	4,020
AIC	–4,109	–4,107	–4,112	–4,108
BIC	–3,725	–3,704	–3,734	–3,717

Notes: All presented models employ GBM-generated sampling weights. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

Table B.2.6: Rent regression — Part 3. Complete results.

Dependent Variable	The Logarithm of Starting Rent per Square Foot		
Econometric Specification	Multilevel Model		
Variable / Model	Air Quality	Comfort	Multivariate
Commissioning Credits:			
Investigation & Analysis			–0.004
Implementation			0.014
Ongoing Commissioning			0.020
Measurement Credits:			
BAS			0.030
Systems			–0.047
Air Quality Credits:			
Outdoor Air Delivery Monitoring	0.019		–0.008
Increased Ventilation	0.046*		0.041*
Particulates Reduction	0.013		–0.002
Comfort Credits:			
Thermal Comfort		0.039	0.038
Lighting Controls		0.021*	0.003
Net Lease	–0.077***	–0.078***	–0.077***
Other Controls:	0.033	0.030	0.028
Renewal	0.043***	0.044***	0.043***
Expansion/Extension	0.028*	0.028*	0.028*
Other	0.021	0.021	0.021
Class B	–0.084***	–0.084***	–0.080***
Vacancy	–0.007	–0.005	–0.003
Lease term	0.006***	0.006***	0.006***
Transaction Size	0.002	0.002	0.002
Age	0.000	0.000	0.000
Amenities:			
Air Conditioning	–0.032	–0.029	–0.035
All-day Access	0.001	–0.001	0.002
Atrium	–0.013	–0.010	–0.016
Balcony	–0.020	–0.018	–0.021
Conference	–0.007	–0.008	–0.007
Dry Cleaner	–0.037	–0.033	–0.039
Food Facilities	0.023	0.024	0.024
Manager	0.008	0.005	0.008
Roof Terrace	0.054**	0.053**	0.055**
Time Controls:			
2011 – Q2	–0.036	–0.037	–0.038
2011 – Q3	–0.002	–0.004	–0.004
2011 – Q4	–0.008	–0.007	–0.010
2012 – Q1	–0.122**	–0.122**	–0.122**
2012 – Q2	–0.095*	–0.095*	–0.094*
2012 – Q3	–0.140**	–0.139**	–0.140**
2012 – Q4	–0.060	–0.060	–0.059
2013 – Q1	–0.071	–0.072	–0.072
2013 – Q2	–0.044	–0.044	–0.045
2013 – Q3	–0.001	–0.002	–0.002
2013 – Q4	–0.060	–0.060	–0.062
2014 – Q1	–0.028	–0.030	–0.030
2014 – Q2	–0.004	–0.003	–0.005

(continued on the next page)

Table B.2.5 *(continued)*

Dependent Variable	The Logarithm of Starting Rent per Square Foot		
Econometric Specification	Multilevel Model		
Variable / Model	Air Quality	Comfort	Multivariate
2014 – Q3	0.045	0.044	0.043
2014 – Q4	0.075	0.074	0.072
2015 – Q1	0.089	0.088	0.086
2015 – Q2	0.121**	0.121**	0.119**
2015 – Q3	0.119**	0.118**	0.116*
2015 – Q4	0.137**	0.134**	0.134**
2016 – Q1	0.154**	0.153**	0.151**
2016 – Q2	0.161**	0.159**	0.157**
2016 – Q3	0.198***	0.197***	0.195***
2016 – Q4	0.127*	0.125*	0.124*
2017 – Q1	0.188***	0.186***	0.186***
2017 – Q2	0.174***	0.172***	0.171***
2017 – Q3	0.167***	0.165***	0.163***
2017 – Q4	0.198***	0.197***	0.195***
2018 – Q1	0.197***	0.195***	0.193***
2018 – Q2	0.199**	0.198**	0.196**
2018 – Q3	0.236***	0.234***	0.232***
2018 – Q4	0.260***	0.259***	0.258***
2019 – Q1	0.219**	0.217**	0.215**
2019 – Q2	0.221**	0.216**	0.214**
2019 – Q3	0.263***	0.261***	0.258***
2019 – Q4	0.267***	0.258***	0.264***
Constant	3.681***	3.687***	3.681***
Random-Effects Parameters:			
Submarket Intercept	0.137	0.135	0.136
Building Intercept	0.020	0.019	0.019
Residual	0.027	0.027	0.027
Number of submarkets	35	35	35
Number of buildings	303	303	303
AIC	–4,114	–4,107	–4,113
BIC	–3,730	–3,729	–3,685
Observations	4,020	4,020	4,020

Notes: All presented models employ GBM-generated sampling weights. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

Table B.2.7: Rent regression — Part 4. Robustness checks.

Dependent Variable	The Logarithm of Starting Rent per Square Foot		
Econometric Specification	Multilevel Model		
Variable / Model	Robustness (1) – Total Points	Robustness (2) – Interaction	Robustness (3) – All Credits
Commissioning Credits:			
Investigation & Analysis	–0.006	–0.006	–0.028
Implementation	0.007	0.007	0.006
Ongoing Commissioning	0.013	0.014	0.009
Measurement Credits:			
BAS	0.029	0.029	0.029
Systems	–0.047	–0.048	–0.038
Air Quality Credits:			
Outdoor Air Delivery Monitor.	–0.015	–0.014	–0.026
Increased Ventilation	0.045*	0.047**	0.054***
Increased Ventilation * Net Lease		–0.024	
Particulates Reduction	–0.015	–0.014	–0.026
Comfort Credits:			
Thermal Comfort	0.041		
Lighting Controls	–0.000		
Additional Credits:			
Green Cleaning			0.003
Sustainable Sites			–0.001
Water			0.002**
Sustainable Purchasing			0.000
Solid Waste Management			0.005
Onsite Renewable Energy			0.002
Emissions Reporting			–0.010
Daylight and Views			–0.015
IAQ Management Program			–0.068*
Management for Facility Alterations			–0.060***
Occupant Survey			–0.016
Other Controls:			
Net	–0.077***	–0.075***	–0.076***
LEED Design	0.030	0.030	0.030
Total Points	0.000**	0.000**	
Renewal	0.028*	0.029*	0.027*
Expansion/Extension	0.022	0.022	0.023
Other	–0.081***	–0.081***	–0.100***
Class B	–0.004	–0.004	–0.002
Vacancy	0.006***	0.006***	0.006***
Lease term	0.002	0.002	–0.000
Transaction Size	0.000	0.000	0.001
Age	0.028*	0.029*	0.027*
Amenities:			
Air Conditioning	–0.034	–0.034	–0.035
All day Access	0.003	0.003	0.015
Atrium	–0.018	–0.018	–0.015
Balcony	–0.020	–0.020	–0.008
Conference	–0.007	–0.007	–0.008
Dry Cleaner	–0.038	–0.037	–0.056*

(continued on the next page)

Table B.2.7 *(continued)*

Dependent Variable	The Logarithm of Starting Rent per Square Foot		
Econometric Specification	Multilevel Model		
Variable / Model	Robustness (1) – Total Points	Robustness (2) – Interaction	Robustness (3) – All Credits
Food Facilities	0.023	0.023	0.018
Manager	0.009	0.010	0.010
Roof Terrace	0.056**	0.056**	0.043*
Time Controls:			
2011 - Q2	–0.036	–0.036	–0.036
2011 - Q3	–0.006	–0.006	–0.008
2011 - Q4	–0.013	–0.013	–0.018
2012 - Q1	–0.120**	–0.120**	–0.126**
2012 - Q2	–0.093*	–0.093*	–0.097*
2012 - Q3	–0.142**	–0.142**	–0.149**
2012 - Q4	–0.062	–0.063	–0.070*
2013 - Q1	–0.069	–0.069	–0.077
2013 - Q2	–0.045	–0.046	–0.055
2013 - Q3	–0.004	–0.004	–0.013
2013 - Q4	–0.066	–0.066	–0.075
2014 - Q1	–0.025	–0.025	–0.034
2014 - Q2	–0.004	–0.004	–0.016
2014 - Q3	0.041	0.041	0.033
2014 - Q4	0.068	0.068	0.056
2015 - Q1	0.091	0.091	0.080
2015 - Q2	0.119**	0.119**	0.111**
2015 - Q3	0.112*	0.112*	0.097
2015 - Q4	0.127**	0.127**	0.117*
2016 - Q1	0.156**	0.156**	0.145**
2016 - Q2	0.159**	0.158**	0.148**
2016 - Q3	0.190***	0.190***	0.183***
2016 - Q4	0.116	0.116	0.112
2017 - Q1	0.192***	0.192***	0.179***
2017 - Q2	0.173***	0.173***	0.161**
2017 - Q3	0.162**	0.161**	0.148**
2017 - Q4	0.186***	0.186***	0.176**
2018 - Q1	0.201***	0.201***	0.189***
2018 - Q2	0.200**	0.200**	0.186**
2018 - Q3	0.232***	0.232***	0.219***
2018 - Q4	0.251***	0.251***	0.243***
2019 - Q1	0.221**	0.221**	0.219**
2019 - Q2	0.217**	0.217**	0.209**
2019 - Q3	0.266***	0.266***	0.252***
2019 - Q4	0.258***	0.258***	0.251***
Constant	3.680***	3.680***	3.763***
Observations	4,019	4,019	4,019

Notes: All presented models employ GBM-generated sampling weights. Heteroscedasticity in the error terms is addressed using the Huber-White error estimation. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

Appendix B.3

The GBM is implemented using twang Stata package, which is executed in R. The selected option involves running 10,000 iterations with a maximum of three interactions between covariates and shrinkage of 0.01 to increase the smoothness of the resulting model. As a stopping rule, the weights generated from GBM iterations are employed to minimise mean standardized bias (effect size). Estimation of the weights is followed by a range of diagnostic checks to ensure that the specified number of iterations is sufficient. Among those are an investigation of the convergence and optimisation plots as well as propensity score box plots to check that there is sufficient overlap between the explored certification levels. Finally, the balance between the covariate distributions is assessed for the treatment and control groups prior to the investigation of the causal effects.

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3 Sub-metering – an Antidote to the Split Incentive Conundrum?

Abstract: This study analyses the impact of sub-metering and responsibility over utilities payments using a sample of green certified office buildings in the US on a) energy usage and variability and b) rental premiums. In examining these effects, information on the presence of sub-metering reported in LEED Core and Shell and LEED Commercial Interiors certifications, energy disclosure data, CompStak's lease transactions, and CoStar's hedonic characteristics are combined for seven US cities. A multilevel model with an adjustment for the propensity of a net lease is applied to study these relationships, showing that separate tenant metering has a significant negative impact on average energy consumption levels in gross leases. However, an adverse effect of sub-metering on energy usage is encountered in net leases. Additionally, via a random-effects Tobit model, this study shows that sub-metering reduces volatility in energy use in net lease contracts. Finally, a sizeable increase in the net lease premium in sub-metered properties is uncovered, suggesting that sub-metering may offer significant risk-reduction benefits for tenants.

Keywords: commercial real estate; energy performance gap; green certification; sub-metering; split incentives

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3.1. Introduction

In the United States, the private rented sector represents 52% of the commercial building space, amounting to roughly 35 billion square feet (EIA, 2016; White et al., 2020). One of the main impediments to a reduction in greenhouse gas emissions in this sector is the problem of misaligned incentives. It occurs when either the tenant or the landlord fails to undertake energy efficiency upgrades or behave in an environmentally friendly manner because the benefits do not accrue to the same party bearing the costs (Schleich, 2009). It is estimated that realignment of financial incentives in commercial leases can unleash energy savings of up to 22% (Feierman, 2015; Tweed, 2015). At the root of the split incentive problem is the traditional structure of lease contracts, which, as many argue, is not in a position to accommodate environmental best practices in tenanted spaces. Since these contracts unilaterally assign responsibility over operational expenses over the lease term to only one party, the other has no financial incentive to conserve (Gabe et al., 2019; Kaplow, 2009; Roussac & Bright, 2012).

Many believe that green leases offer a gateway to overcoming, at least to some degree, the split incentive problem (Janda et al., 2016; Yang et al., 2020). Principal-agent literature suggests that the first-best solution to mitigating market failures arising due to information asymmetry between the tenant and the landlord is via ex-post disclosure facilitated by these emerging contractual arrangements (Allcott & Greenstone, 2012). By means of data-sharing, green leases aim to give rise to a landlord-tenant collaboration by encouraging these parties to work together towards meeting pre-set environmental targets (Janda et al., 2016). As there is no universal definition or international standard of what exactly constitutes a green lease (Sayce et al., 2009), green clauses can range from "light green", imposing the minimum amount of responsibility, to "dark green", setting relatively stringent conditions surrounding environmental targets (Janda et al., 2016).

It is clear that without adequate measurement technologies upon which environmental metrics can be assessed, leases can only be classified as light green, thus remaining aspirational and limited in efficacy. Therefore, visibility of energy consumption is at the core of an effective green lease programme, enabled by sub-metering technologies that separate the tenant's load from the rest of the building. Studies have shown that simply metering and sub-metering energy use and providing accountability for the users can produce savings of 5% to 10% annually (Capehart et al., 2011). The reason is that once building users become aware that the owner has the means to verify their energy use, they will change their behaviour to fit the owner's energy-saving aims (ibid). And by tracking their energy consumption in near real-time, these parties can detect any abnormalities in a timely manner and undertake corrective measures before major energy losses occur.

Design classification schemes and policies that target the structural and mechanical characteristics of buildings have recently been subject to criticism due to emerging evidence reporting significant discrepancies between energy consumption predicted by these measures and energy use during operation (van Dronkelaar et al., 2016). Known as the "energy performance gap" (Burman et al., 2014; Carbon Trust, 2012; Cohen & Bordass, 2015; de Wilde, 2014; Menezes et al., 2012; van Dronkelaar et al., 2016), this phenomenon is significantly driven by occupant behaviour, and due to its sheer magnitude can no longer be overlooked (Clayton et al., 2021). Evidence for these claims is available in many previous research papers. For example, one study shows that approximately 40% of energy usage in office buildings is attributed to the plug load (Hafer, 2017), while another demonstrates that 75% of the plug load in private office space is consumed during non-operating hours (Gunay et al., 2016). Yet due to the paucity of energy consumption data in the commercial real estate sector, the environmental potential of various green interventions, particularly concerning in-use energy performance, is considerably under-researched.

The primary aim of this paper is to investigate the impact of the split incentive problem on energy consumption and rental premia and whether tenant sub-metering may reduce its adverse outcomes. Application of the principles of utility maximisation and mean-variance control theory allows this paper to empirically test whether sub-metering practices can effectively reduce the size of the split incentive problem in gross leases and even further in net lease contracts. This paper extends the existing literature by moving beyond mean energy consumption as the primary assessment criteria of the effectiveness of a green intervention. With utility expenses being intrinsically volatile, uncertainty over energy expenses may have a large adverse impact on owners' net operating income (Zhu et al., 2022). Therefore, whether sub-metering may offer an added benefit of less volatile energy use is investigated.

3.2. Background and Theory

This section outlines previous research on the split incentive problem, behavioural models of energy consumption, and lease pricing theory.

The Split Incentive Problem

The allocation of payments for operating expenses (including, but not limited to, energy usage) between the landlord and the tenant is defined in a lease contract. Full-service leases, net leases, and modified gross leases are the three most frequent types of commercial lease contracts (Kahn et al., 2014). In the US, approximately 17% of commercial building occupants rent space with electricity included in their monthly rent (Jessoe et al., 2020). Lease structures where the landlord covers all variable operating expenses in exchange for a flat fee are known as "gross". In gross leases, the tenant has an effective marginal cost of zero for consuming an extra unit of energy, and therefore no incentive to take energy-saving actions (Brewer, 2022), giving rise to usage split incentives (USI). As a result, landlords often overspend on energy efficiency equipment and automation technologies to make up for their lack of control (IEA, 2007). On the other hand, when the tenant pays for utilities under a triple net or net of electric lease, efficiency split incentives (ESI) emerge. Because the tenant will reap the benefits of a retrofit via lower utility bills, it is not in the landlord's immediate financial interest to make structural changes to the property or install energy efficient equipment. These types of split incentives are presented in Table 3.1. Further complications arise in properties where multi-tenant split incentives (MSI) are present, when the landlord prorates energy expenses based on the occupied floor area rather than charges based on individual sub-metered readings (Matschoss et al., 2013). Although tenants' aggregate energy consumption directly influences their bottom line, the marginal productivity of their individual energy-saving action is negligible due to their inability to control other occupants' behaviour.

Table 3.1: Split incentive types in the owner-occupant relationship.

Who pays for utilities?	Occupant owns	Occupant Rents
Occupant	No split incentives	ESI / MSI
Landlord	USI / ESI	USI

Source: Adopted from Gillingham (2012).

The prevalence of usage split incentives (USI) is well-documented in the residential sector. For example, Gillingham et al. (2012) find that occupants who pay for heating are 16% more likely to alter their heating settings at night. Meanwhile, homeowners are 20% more likely to invest in energy efficiency and insulate their ceilings than those tenants whose heat is included in a contract. However, findings from the residential sector must be taken with a grain of salt, as the mechanisms that affect landlord-tenant problems are likely to differ in the commercial sector (Sorrell et al., 2011). One of a few studies examining the split incentive conundrum in the commercial real estate sector shows that energy consumption by tenants paying their own bills is 20% lower than in owner-occupied premises (Kahn et al., 2014). With commercial buildings typically being over-cooled over the summer months, another study investigates firms' sensitivity of electricity consumption to the outside temperature (Jessoe et al., 2020). For the top decile of consumers, tenants who pay for their own electricity consume, on average, 3% less energy over the course of the year and up to 14% less during the summer (ibid). Gabe et al. (2019) explore whether efficiency split incentives (ESI) in the commercial sector may be a significant impediment to energy efficiency investment in the Australian office market. Despite finding that certified properties are more likely to have net lease arrangements, these leases are associated with significantly higher total occupancy costs, which outweigh any savings traded away to tenants in net lease arrangements.

Information, Feedback Loops, and Norms

Human behaviour is often modelled using standard economic theory, which has shown to be a useful predictor of choice in a wide range of applications (Darnton, 2008). Its fundamental assumptions are that people act primarily out of self-interest and have access to all information necessary to make decisions. In reality, however, even if incentives are completely aligned, users frequently lack information on their energy consumption and thus miss out on energy-saving opportunities. The problem is that energy, unlike most economic goods, is abstract and invisible (Fischer, 2008). Without understanding the consequences of their actions on energy consumption, individuals may be more prone to cognitive biases and resort to gratifying but inefficient choices (Casal et al., 2017; Erev & Haruvy, 2016). Information deficit models assume that the primary cause of inefficient behaviour and attitudes is the lack of understanding caused by information deficiency (Blake, 2020). These models suppose that information influences knowledge that affects attitudes, while attitudes lead to behaviour (Kollmuss & Agyeman, 2002). However, models of behaviour based on feedback adopt a fundamentally different view of behaviour to the linear (consequentialist) models (Darnton, 2008). Feedback models account for continuous self-monitoring of one's behaviour and its effect on the surroundings, enabling users to implement corrective actions to their subsequent behaviour and minimise the gap between the desired and observed outcomes (Carver & Scheier, 1981). Because permanent changes require frequent reinforcement and learning (Bandura, 1974; Clayton et al., 2021), literature in psychology and behavioural economics also strongly suggests that self-monitoring via the means of frequent and accurate measurement is essential to altering habitual behaviour (Tetlow et al., 2015). Empirically, human ability to respond to feedback has been shown to lead to favourable outcomes (Granovskiy et al., 2015; Jonsson et al., 2015), at least in the short term (Darby, 2006). Many studies report that feedback has successfully delivered energy savings of 5–14% (Faruqui et al., 2010), being the most potent when given frequently (Abrahamse et al., 2005).

Norms present another important avenue for information to influence energy consumption (Alberts et al., 2016). If information is received in the absence of a framework to interpret it, users may struggle to make valuable inferences from it. Enabling comparisons between one's own and others' behaviour has been shown to effectively change human behaviour (Cialdini et al., 1976; Festinger, 1954). Studies that employ the principles of gamification and social interaction also stress the importance of having relevant comparators or benchmarks to guide users towards the desired energy-saving behaviour (Bos et al., 2012; Paone & Bacher, 2018; Petkov et al., 2011). For instance, Allcott and Rogers (2014) find that customers who were given feedback on their energy consumption, which included social comparisons, significantly reduced their usage, while the frequency of the reports made the effect persistent. Therefore, benchmarks may serve as valuable reference points and catalysts for driving feedback mechanisms, where negative feedback loops reduce the discrepancy between benchmark energy consumption and action (Weiner et al., 2012).

Misaligned Incentives, Risk, and Lease Pricing

In real estate leases, the difference between a higher gross rent when the landlord pays for energy expenses and a lower net rent when this responsibility falls to the tenant reflects a value exchange between these parties in terms of uncertainty in future energy costs (Grenadier, 2003; Wiley et al., 2014). As per principal-agent theory, both risk and uncertainty come into play. With respect to risk, the principal cannot monitor the agent's actions and thus runs the risk that the agent will not act in the principal's best interest. The principal can manage this risk by establishing incentives for the agent to behave as desired, or by investing in monitoring technologies or practices. Uncertainty in future energy costs arises because it depends on both exogenous factors and the actions of parties influencing the outcome. For example, energy consumption could be high because of an unprecedented heat wave, or because the tenant's employees have to work overtime due to some economic shock. Heterogeneity in risk and uncertainty preferences of the landlord and the tenant makes such an exchange plausible, with one party agreeing to take on the risk of the other in exchange for a premium. If a gross rent contract is offered, the landlord's compensation would at least cover the present value of cost services, operating expenses, and a risk premium as reimbursement for the uncertainty of future expenses (Wiley et al., 2014). By allowing for more accurate budgeting of expenses, gross leases would appeal to risk-averse tenants (Formigle, 2017). In contrast, triple net leases often appeal to risk-averse landlords who are reluctant to be exposed to risk due to the variation in a building's operational performance (Halvitigala et al., 2011; Mattson-Teig, 2000; Rowland, 1996, 2002; Sanderson & Edwards, 2013).

Much of previous work explores the impact of operational uncertainty on rents from a theoretical perspective. Economic theory indicates that landlords should extract equal value from a property independently of lease structure (Ambrose et al., 2002; Booth & Walsh, 2001; Gabe et al., 2019; Grenadier, 1995, 1996). This idea is rooted in the work of Grenadier (1995), who asserts that occupancy costs are traded in a competitive market. However, many lease theory predictions are generally not empirically supported (Bond et al., 2008; Gabe et al., 2019). One study undertaken by Wiley et al. (2014) empirically tests the determinants of a services markup, defined as the difference between gross and net rents of a comparable building. The authors report that, in addition to being influenced by building expenses, the markup appears sensitive to market conditions and significantly increases for out-of-state owners, who are likely to be significantly more risk averse than local owners.

The influential body of research by Arrow (1963), Pauly (1968, 1974), and Rothschild and Stiglitz (1976) demonstrates that competitive markets may be inefficient in the presence of asymmetric information. Among the main sources of information asymmetry in real estate contractual agreements are the problems of differing information access (adverse selection) and incentives (moral hazard) (Benjamin et al., 1998; Eisenhardt, 1989). Adverse selection is characterised by "precontractual opportunism" (Molho, 1997, p. 8), occurring when it is advantageous for one party to disguise information about their type, or expected energy efficiency. This problem leads to a lemons market, which is comprised of high-usage occupants, to which landlords respond by raising rents (Henderson & Ioannides, 1983). In contrast, the problem of moral hazard arises when the party who is not responsible for energy expenses has zero incentive to exert energy-saving effort ex-post. If the contractual provisions of a lease do not effectively internalise the incentive to conserve energy, the landlord anticipates the expected loss from opportunistic behaviour in the form of space over-utilisation, which is reflected via increasing the rental premium (Benjamin et al., 1998). Alternatively, the landlord and the tenant can agree on contract terms that mandate the monitoring of energy-related behaviour and sharing of information. According to Smith and Wakeman (1985), "if it is relatively inexpensive to measure the intensity of use of the asset, metering can be effective in controlling use intensity" (Benjamin et al., 1995, p. 902).

3.3. Theoretical Framework and Hypotheses

This section presents the impact of sub-metering on two types of outcome randomness, uncertainty and risk, for the two primary lease participants: the landlord ("she") and the tenant ("he"). Ambiguity or Knightian uncertainty are often used to refer to situations where the outcomes and/or their probabilities are unknown and cannot be quantified (Park and Shapira, 2017). Meanwhile, risk captures heterogeneity or variability of true values typically as a function of time or space (Begg et al., 2014). Broadly construed, the concept of risk pertains to scenarios wherein the decision-making process is guided by a quantifiable probability measure. Conversely, Knightian uncertainty denotes circumstances where the decision-maker faces uncertainty regarding the precise probability measure itself, typically as a consequence of cognitive limitations or information insufficiencies.

Firstly, this section demonstrates how a situation of high uncertainty in energy expenses may result in a sub-optimal distribution of incentives via a chosen lease contract and the ways in which sub-metering may alleviate the adverse selection conundrum. Next, a behaviour change model is presented featuring a (negative) feedback loop, a central construct of the theory of control (Carver & Scheier, 1982; Darnton, 2008). This set-up demonstrates how sub-metering enables decision-makers to engage continuously in energy efficiency measures aiming to reduce the mean and risk associated with energy usage. Finally, the outlined mechanisms are linked to this study's hypotheses.

The "Cost" of Uncertainty

As a solution to the St Petersburg paradox, Bernoulli proposed in 1713 that in situations involving unexpected outcomes, individuals act on the basis of expected utility theory rather than expected value (Peterson, 2019). Since energy consumption depends on many factors, it is often associated with a forecast error, or a deviation between actual and projected usage. This theory would therefore suggest that risk-averse parties would be better off lowering their exposure to an unpredictable outcome, in addition to minimising their expected energy costs. However, ex ante lease arrangement, these parties may have insufficient information to assign probabilities of future energy consumption outcomes. Accurate prediction of operational expenses is critical for minimising cash flow uncertainty and ensuring that everyday business needs are met. For instance, without sufficient data on typical tenant usage rates, it may be difficult for a landlord to distinguish between a prospective tenant with low space utilisation and one with excessive usage before engaging in a gross lease. The lack of sufficient information on a building's historical energy consumption may also induce lease signatories to overweight the probability of extreme events, resulting in higher tail risk. Meanwhile, the lack of control over other occupants' actions would be a concern for a tenant considering a net lease in a multi-tenant property. This means that in addition to risk-aversion, lease signatories may suffer from ambiguity aversion due to having a preference for known risks over unknown risks.

Detailed information provided by sub-meters can reduce uncertainty tied to lack of knowledge about the prospective lease party's energy use patterns. Without such data, the landlord (tenant) might not know how much energy is being used at different times of day or in different parts of the building, thus not have the means of differentiating between base energy usage of a building and the tenant's contribution. Thanks to this information, the landlord (tenant) can more accurately predict how high energy consumption should be in a given month, thus a proportion of uncertainty turns into risk – a measure that can be quantified and managed by the landlord through contractual arrangements and incentives. As uncertainty is diminished, the uncertainty premium is set to decrease.

Following Laffont and Tirole's framework (1993), the total energy-related costs arising from the expected joint energy consumption level, uncertainty and uncertainty premium, and cost of energy-saving effort are presented as follows:

$$t_n = q(e_0, e_1) + \frac{1}{2}\sigma^2\tau_n + c(e_n) \tag{1}$$

where q is the quantity of total energy consumption, and e is the energy-saving effort of the two lease signatories. An additional unit of energy-saving effort is assumed to decrease energy consumption at a decreasing rate. Meanwhile, τ is the ambiguity aversion coefficient of the party in control of expenses, n, and σ^2 is the uncertainty of energy consumption. Exponential utility functions are assumed, meaning that these parties exhibit constant absolute risk aversion (CARA). If responsibility for energy falls with the landlord (tenant) in a gross (net) lease, then $n = 0$ ($n = 1$). Finally, the cost of energy-saving effort of this party is represented by $c(e_n)$, which is assumed to increase at an increasing rate.

The optimum contract type, β, is determined by solving the following joint minimisation problem[1]:

[1] Other parameters that constitute the final rent estimate, such as base rent and non-energy expenses, are omitted from this equation. When maximising the joint certain equivalent of the landlord and the tenant to determine the optimum contract type, these parameters cancel out.

$$\beta\left(q(e_0,e_1)+\frac{1}{2}\tau_0\sigma^2\right)+c(e_0)+(1-\beta)\left(q(e_0,e_1)+\frac{1}{2}\tau_0\sigma^2\right)+c(e_1) \tag{2}$$

Where $\beta = 0$ if the landlord is responsible for energy costs (gross lease), and $\beta = 1$ if the tenant is liable (net lease). Equation (2) is solved subject to these parties' incentive compatibility constraints that are determined by solving the following equations:

$$\min_{e_0}\beta\left(q(e_0,e_1)+\frac{1}{2}\tau_0\sigma^2\right)+c(e_0) \tag{3}$$

$$\min_{e_1}(1-\beta)\left(q(e_0,e_1)+\frac{1}{2}\tau_1\sigma^2\right)+c(e_1) \tag{4}$$

Because energy-saving action is costly in terms of attention and time spent exerting effort, the cost of effort is traded off against the cost resulting from lack of effort. These constraints determine the parties' individual responsiveness to incentives. Solving for the optimum effort levels yields the following incentive compatibility constraints:

$$\beta = -\frac{c'(e_0)}{q'(e_0)} \tag{5}$$

$$(1-\beta) = -\frac{c'(e_1)}{q'(e_1)} \tag{6}$$

A solution to the above joint cost-minimisation problem is shown in Appendix C.1, where specific functional forms of $q(.)$ and $c(.)$ for each party are assumed. In the presented example, the landlord's cost of effort function is assumed to be steeper than the tenant's (the landlord is assumed to be less efficient), ceteris paribus. The solution demonstrates that in the absence of ambiguity, it would be optimal to give greater incentives to the tenant to induce him to exert more effort. In a binary lease contract involving only gross and net leases, a net lease contract would be signed. Therefore, moral hazard would be eliminated for the more energy efficient party – the tenant (in this particular example).

However, when both parties are ambiguity averse and face unknown outcomes, the optimum contract choice may not necessarily be the one that yields the best energy-saving result, as also shown in Appendix C.1. In such a situation, the cost of ambiguity-bearing, in addition to the expected energy efficiency, becomes part of these parties' hidden information, inhibiting the revelation mechanism of the more energy efficient firm. With ambiguity, it may thus not be the more efficient party who would assume responsibility for energy use but the one who has a lower cost of ambiguity-bearing. If, for instance, the tenant is significantly more ambiguity averse, his willingness to pay to avoid uncertainty would be higher than the landlord's willingness to accept uncertainty. In such a case, the tenant would be willing to pay a higher premium to avoid uncertainty, even if the landlord is relatively more inefficient. Overall, the ensuing lease contract would not only reflect these parties' relative energy efficiency but also their relative cost of uncertainty-bearing.

Figure 3.1 provides an illustrative example of how a dispersion in landlord-tenant ambiguity aversions may lead to sub-optimal energy usage outcomes, and the potential of sub-metering to reduce the arising inefficiency[2]. The left-hand side presents a scenario of high ambiguity, implied in the absence of sub-metering, where the tenant is substantially more ambiguity-averse than the landlord. The diagram shows that the tenant's relatively higher cost of ambiguity-bearing results in him requiring a higher payoff to choose an unknown outcome. The difference between these parties' willingness to pay (accept) to avoid (assume) ambiguity represents the scope for the landlord to be more inefficient, while still satisfying the tenant's participation constraint to sign a gross lease. With sub-metering, as shown on the right-hand side of Figure 3.1, the link between effort, agent type, and output is hypothesised to become more deterministic. If energy consumption costs become more attributable and predictable, the optimum contract choice would more likely involve granting incentives to the more energy efficient party rather than the one with a lower uncertainty premium. In the presence of sub-metering, the extent to which the landlord's efficiency can be lower in a gross lease is reduced. Although this scenario supposes a reduction in the uncertainty premium for both parties, the tenant would experience a greater decrease, for he is assumed to be more uncertainty averse. And by decreasing the uncertainty premium required to compensate the landlord, the difference between gross and net lease rents would be reduced.

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[2] The absolute ambiguity aversion coefficients for the tenant and the landlord are assumed to be 0.8 and 0.2, respectively; uncertainty in the form of variance is assumed to decrease by 80% due to sub-metering.

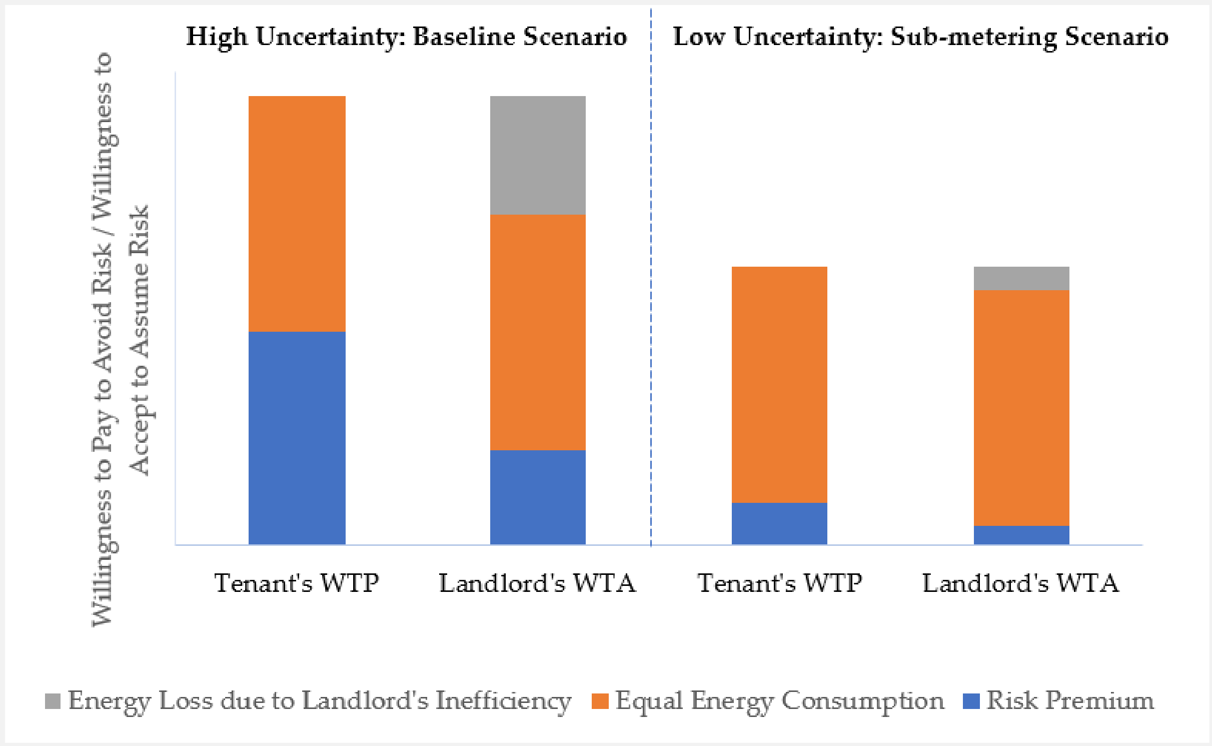

Figure 3.1: The impact of uncertainty on the landlord and tenant's payoffs in a gross lease.

Dynamic Mean-Variance Control

While the above section focuses on the mechanisms of sub-metering in influencing the reduction in uncertainty associated with energy consumption ex-ante lease arrangement, this section outlines the ways in which sub-metering can help agents to influence the distribution of energy consumption outcomes ex-post (risk). The absence of sub-metering can be viewed as a situation of incomplete information, where information needed to make energy-saving decisions is partly missing, or costly to obtain with current technology (Giraudet, 2018). When energy consumption costs are not observed in (near) real-time via sub-metering displays, information can be incomplete in at least two aspects: 1) it is provided infrequently; 2) it is aggregated for numerous building usages (ibid). With sub-metering providing disaggregated user feedback for each tenant on a granular time scale, typically every half hour, users can observe the impact of their own energy-saving actions in real time (Clark, 2013). These actions comprise a mix of energy efficiency measures (EEMs) aimed at influencing certain distribution parameters of energy consumption (Carver & Scheier, 1981). A decrease in energy consumption would imply a shift in the outcome distribution to the left in the sense of first-order stochastic dominance (Meth, 1996). The mechanism via which this shift occurs is assumed to mirror one of a merit good in the presence of imperfect information. With incomplete information, individuals are unable to decide optimally, and therefore under-invest in energy-saving practices. However, owing to the information provided by sub-metering, the marginal (private) benefit function of energy-saving shifts outwards, leading to a higher equilibrium quantity of energy-saving effort and an increase in allocative efficiency. The decision-makers can attain this optimum level of usage by identifying and curtailing those energy-consuming activities that are running unnecessarily in a given time period. For instance, by detecting high average energy consumption levels during unoccupied periods, they may be prompted to switch off appliances (such as desktops and printers), which are often left in stand-by mode overnight and during weekends. Simultaneously, one can choose to implement EEMs that would concentrate the outcome distribution around the mean in the sense of second-order stochastic dominance (Meth, 1996). The incentive to exert risk-reduction (as opposed to mean-reduction) effort would be greater for more risk-averse parties. This parameter can be reduced by detecting instances where energy consumption substantially deviates from the (historical) baseline.

Since sub-metering facilitates information processing as part of an ongoing flow of activity, in which both internal and external factors affect behaviour, it is useful to envisage its effect on energy consumption through the lens of control theory. Despite its roots in the calibration of engineering systems, control theory has informed various interventions in psychology (Mansell, 2020). Its foundational concept posits what is called a negative feedback loop, which involves a continuous comparison of the existing state of the output variable to the reference value. While a traditional (monthly) utility bill may also be considered a form of feedback, Gaskell et al. (1982) claim its feedback loop is too far removed from the use of inputs to provide any information benefit (Darby, 2006). To illustrate the impact of sub-metering feedback on energy consumption in a given time period, $q(t)$, the Ornstein-Uhlenbeck stochastic process is employed:

$$dq_t = u(\alpha b - q_t)dt + \sigma dW_t \tag{7}$$

where instantaneous volatility, or the randomness entering the system, is represented by σ, while dW_t is the increment of a stochastic process W, which obeys a Wiener process. For a Wiener process and for any partition of the time interval, the random variables, $W(t_1) - W(t_0)$, $W(t_2) - W(t_1)$,… are independently and randomly distributed with mean zero and variances $t_1 - t_0$, $t_2 - t_1$,…, respectively (Kamien & Schwartz, 1991). The presence of a stochastic disturbance term implies that the prevailing state cannot be known in advance. Therefore, the control term, u, is computed in "feedback form", or in terms of the state itself, rather than time alone (ibid). The historical baseline average energy consumption level is represented by b; meanwhile, α captures the degree to which the baseline consumption level is reduced post-sub-metering. The magnitude of the control term guides the dispersion of the process sample paths, or the difference between the new long-term mean (αb) and energy consumption in a given period. The implication of this process is that over time, the long-term mean and variance of energy consumption converge to αb and $\frac{\sigma^2}{2u}$, respectively. A yardstick scenario, the absence of sub-metering, supposes minimal mean-reversion control. The reason is that with a large window between measurements, there are relatively scarce possibilities to detect when the system is operating abnormally.

Research Questions and Hypotheses

This paper's analysis begins by comparing the mean and variability of energy consumption in the absence of sub-metering for two types of misaligned incentives: usage split incentives (USI) and efficiency split incentives (ESI). The former split incentives are present in gross leases and caused by moral hazard in tenant's energy-saving actions, while the latter split incentives occur in net leases, which presume a reverse distribution in incentives and effort. Research suggests that behavioural factors contribute significantly to the energy performance gap (Liang et al., 2019; Menezes et al., 2012), implying that the tenant may have greater influence over the mean of energy consumption than the landlord. It has also been theoretically demonstrated in the previous sections that with uncertainty and dispersion in ambiguity aversions between the tenant and the landlord, the revelation mechanism may not be effective in ensuring that the more efficient party assumes liability over energy costs. If tenants are systematically more ambiguity averse than the landlord group, and therefore prefer to engage in gross lease contacts despite being more energy efficient (having a lower marginal cost of energy-saving effort), the average energy consumption with usage split incentives would be more substantive compared to efficiency split incentives. The following hypothesis would be accepted if the average energy consumption level is higher in gross leases compared to net lease arrangements in the absence of sub-metering, ceteris paribus:

H1a: The average energy consumption is greater in the presence of usage vs efficiency split incentives.

Without sub-metering, however, neither party is expected to have superior control over energy consumption variability. The rationale is that without insight into their historical energy consumption on a granular basis, these parties are not able to identify instances when usage abnormalities would occur and implement mean-reverting EEMs. The next hypothesis would therefore be accepted if no significant difference is uncovered in the energy consumption variability between gross and net leases in the absence of sub-metering, ceteris paribus:

H1b: The variability of energy consumption does not vary between net and gross lease contracts in the absence of sub-metering.

If sub-metering lowers uncertainty of future energy expenses, the likelihood is decreased that the more efficient party outsources liability over energy consumption expenses to the less efficient one on the basis of being relatively more ambiguity averse. In addition, via frequent feedback facilitated by sub-metering, the party in control of energy may also choose to engage in EEMs that would reduce the mean and variability of energy consumption. The following hypotheses would be accepted if the mean energy and variability of consumption of properties with sub-metering are lower compared to the baseline scenario (no sub-metering) in all lease types:

H2a: Sub-metering reduces the average energy consumption in all lease types.

H2b: Sub-metering reduces the variability of energy consumption in all lease types.

However, the effect of tenant sub-metering on energy consumption may vary for different lease types. Since tenants are on average likely to be more risk averse with respect to future energy costs than landlords, tenants are expected to expend more resources on variability-reduction. And if tenants' mean energy consumption in net leases is lower than in comparative gross leases in the absence of sub-metering, they are likely to reap a lower benefit from an additional mean-reduction effort than landlords, and therefore devote fewer resources to such activities. The next set of hypotheses would be accepted if, in a sub-metered building, the change in the average energy consumption in gross leases is greater than in net leases, while the reverse relative effects are uncovered with respect to the variability:

H3a: Sub-metering influences the mean energy consumption to a greater extent in gross vs net leases.

H3b: Sub-metering influences the variability of energy consumption to a greater extent in net vs gross leases.

In the final stage of this paper's analysis, the goal is to understand whether the magnitude of the uncertainty premium, driven by uncertainty in energy expenses, decreases in the presence of sub-metering. A lower difference between gross and net lease rents would indicate a decrease in certainty equivalent due to lower implied uncertainty of future energy-related costs (while controlling for energy usage). The following two hypotheses would be empirically corroborated if, in the presence of sub-metering, gross lease premiums decline while net lease premiums increase, all else equal:

H4a: Sub-metering reduces the uncertainty premium in gross leases.

H4b: Sub-metering reduces the uncertainty premium in net leases.

In summary, ex-ante lease arrangement, sub-metering—owing to its provision of more accurate and detailed information—is hypothesised to reduce uncertainty by enhancing *knowledge* of the distribution parameters, such as the mean, variance, or the overall form of the probability density function. This reduction in uncertainty allows the more energy-efficient party, should be relatively more ambiguity-averse, to be less hesitant in assuming responsibility for future energy consumption costs. Consequently, both a decrease in uncertainty and an expectation of lower energy consumption contribute to a narrowing of the gross-net lease rent markup. Ex-post lease arrangement, the party responsible for energy payments, armed with regular and precise information provided by sub-metering, attains greater *control* over these distribution parameters. This information allows the party to identify discrepancies between actual and desired energy consumption levels, thereby facilitating energy-saving actions aimed at reducing the mean. Likewise, this party can also discern deviations between current and historical energy consumption, , thereby facilitating energy-saving actions aimed at reducing the variability. This process of mean-variance optimisation aligns with the parties' utility preferences. In particular, parties with a higher degree of risk aversion may prioritize reducing variability (variance) over average energy use (mean) compared to their less risk-averse counterparts. Consequently, this sequence of chosen actions leads to lower average energy consumption and/or reduced variability in energy use. Figure 3.2 illustrates the relationship between the proposed transition mechanisms outlined and this study's hypotheses.

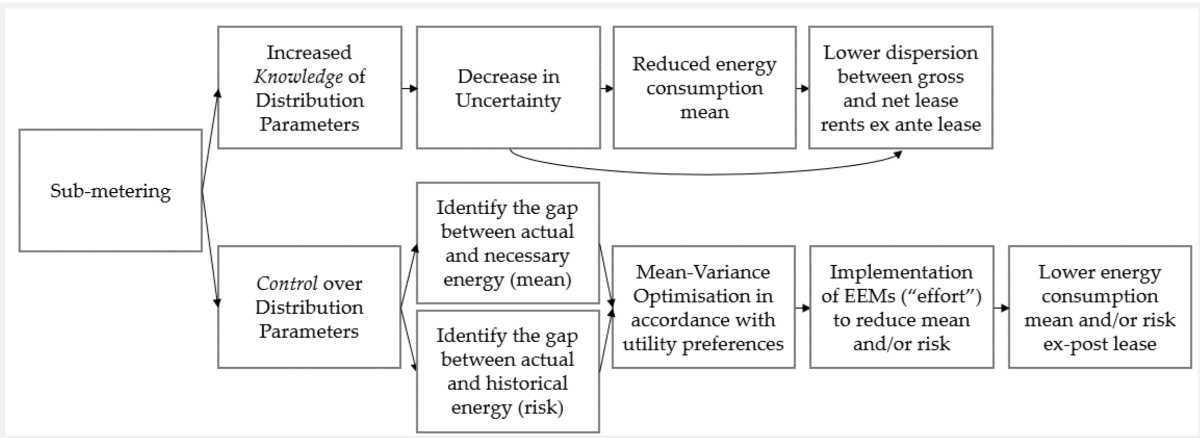

Figure 3.2: Proposed transmission mechanisms.

3.4. Data and Methods

This section details the data retrieval and matching steps of this study. Information from four datasets is combined to form a panel of observations of 246 buildings in seven US cities. The full list of this study's variables is presented in Table C.2.1 (Appendix C.2), while the city-wide distribution of observations can be found in Table C.2.2 (Appendix C.2). Data structure motivates this paper's chosen econometric approach – a multilevel model with inverse probability weights on the propensity of a net lease.

Data Gathering and Matching

Contested discussions around the problem of split incentives and the energy performance gap have triggered leading certification bodies to integrate the components of energy-aligned leases into their scoring methodologies. Leadership in Energy and Environmental Design (LEED) is one of those certification bodies. This study utilises the USGBC's (2021) publicly available scorecard data from LEED Commercial Interiors (LEED-CI) and LEED Core and Shell (LEED-CS) labels, as they allow project owners to earn credits for strategically placing sub-meters to monitor specific loads of tenants and facilitating ongoing accountability over energy use (FacilitiesNet, 2010). However, there are differences between these labels that should be pointed out. The LEED-CI label is awarded to tenant spaces that may constitute a proportion of a building. Meanwhile, LEED-CS is targeted at the whole building, enabling project owners to earn points for having a centrally monitored metering network to which tenants can easily connect.

For all datasets, data is first pre-processed (cleaned) using the "StandardizeAddresses" function in Python (van Rossum, 2020), which converts address strings to lowercase, removes extra spacing and corrects spelling errors. Next, an Excel add-in (YAddress, 2022) is used to cross-reference the list of addresses with an authoritative address database (USPS) and convert them to standardised address formats and geocodes (Placekey, 2021). Standardisation of addresses enables this study to conduct exact building-level matching in Excel of the address data across all employed datasets.

Firstly, the USGBC's project-level data is collected on seven US cities which mandate commercial buildings to publicly disclose their energy consumption: Washington DC, Chicago, New York City, San Francisco, Los Angeles, Seattle, and Cambridge. Apart from providing address data, the USGBC reports on many auxiliary variables, such as project name, LEED version, number of points achieved, certification level (Certified, Silver, Gold, or Platinum), certification and registration date, gross floor area, owner type, total property area, project type, and project owner. The manner in which the relevant credit information is extracted for each version of the above-mentioned grading systems is presented in Table C.2.3 (Appendix C.2). Where project-level data do not report whether the tenant assumes responsibility for energy costs, CompStak's (2021) contract data allows to fill the gap. For all projects during 2010–2020, CompStak provides information on individual lease transactions, including achieved starting rent, lease term, tenant identity, occupied floor, transaction type, among others. Building-level address matching is undertaken for LEES-CS projects. Meanwhile, more granular matching is conducted for LEED-CI projects by considering the following variables: tenant and landlord name, floor occupied, and project size. In addition to attributing records according to the similarity of address text strings, the temporal dimension is also considered by accounting for lease execution, lease end, and project certification dates.

Energy performance data (source energy use intensity) are obtained for the period 2011–2020 from the energy disclosure websites of the aforementioned cities (City and County of San Francisco, 2021; City of Cambridge, 2021; DC Department of Energy & Environment, 2021; Los Angeles Department of Building and Safety, 2021; NYC Mayor's Office of Sustainability, 2021; Seattle Office of Sustainability & Environment, 2021; The City of Chicago, 2021). Since project owners would begin implementing LEED measures prior to the stated project certification date, this study assumes a one-year lead period for these measures to begin affecting energy consumption. Because LEED-CI projects have a natural expiry that coincides with the tenant's move-out date, Compstak's lease end date information is used to ensure that energy records are linked in line with the USGBC's timeframes.

In the final stage, CoStar (2021) provides information on the following hedonic variables: number of storeys, year of construction or last renovation, and amenities.

Study Design

Lease structure decisions are known to vary according to hedonic and market characteristics (Gabe et al., 2019; Wiley et al., 2014). Failure to account for a tendency to select a certain lease type based on these attributes may result in a selection bias in the regression estimates (Gabe et al., 2019). Table 3.2 explores whether hedonic and lease characteristics systematically vary between gross and net leases in this study's sample, and whether certain lease types are more prevalent in some cities. This table demonstrates that sub-metering is more likely to occur in net lease structures, and a t-test confirms this is the case. It is also clear that net leases are associated with greater tenant allowances (work value) and longer lease terms. Meanwhile, subleases are more likely to occur in gross lease arrangements. Variation in lease type probability is also observed geographically. For example, gross leases are more prevalent in cities with large commercial space presence, such as New York and San Francisco.

Table 3.2: Hedonic and locational characteristics in gross and net lease buildings.

	Gross Leases		**Net Leases**	
	Mean	SD	Mean	SD
Submetering	0.49	0.50	0.71	0.45
Building size (log)	12.94	0.84	12.85	0.98
Class B	0.12	0.33	0.08	0.27
Storeys	24.07	18.42	22.29	19.86
Built/renovated	13.62	18.00	13.83	18.88
Transaction size (log)	9.58	1.35	9.61	1.35
Lease Term	8.78	4.10	9.21	3.85
Sublease	0.10	0.30	0.04	0.20
Work Value	50.98	36.67	59.80	40.40
Chicago	0.23	0.42	0.21	0.40
DC	0.34	0.47	0.39	0.49

	Gross Leases		Net Leases	
Los Angeles	0.04	0.20	0.03	0.17
New York	0.22	0.42	0.12	0.33
Seattle	0.02	0.14	0.08	0.28
San Francisco	0.14	0.35	0.07	0.25

Propensity score weighting is employed to mitigate the selection bias and ensure that gross lease observations resemble those with net lease structures (Chegut et al., 2010). This procedure ensures that the unexposed (gross lease) units that are dissimilar to the treated (net lease) ones have a near-zero probability of receiving treatment (Lee et al., 2011). The conditional probability of adopting a net lease is estimated using a logistic model by regressing this dummy variable on a range of pre-treatment characteristics expected to influence the probability of assignment (Bergstra et al., 2019; Imbens, 2000):

$$\Pr(Net\ Lease = 1 |\, X_i) = \phi(X_i'\gamma) \tag{8}$$

where X_i is a combined vector of hedonic variables (the logarithm of building size, number of years since the building is constructed/renovated, building class, number of storeys), lease characteristics (transaction square footage, tenant allowance, lease term and whether a sublease is signed) and geographic (city) controls. Inverse probability weights are then applied to the outcome linear regression model of the average treatment effect (ATE), where the type of lease acts as a predictor alongside these covariates for a doubly robust estimation (Bang & Robins, 2005).

Modelling Considerations

Cross-sectional regressions are often criticised for debasing regression estimates with an omitted variable bias, which occurs when the effect of the missing variables is wrongly attributed to the included ones. As such, hedonic strategies based on a cross-sectional approach are criticised for yielding correlative rather than causal results (Zhu et al., 2022). More specifically to the topic of this article, environmentally conscious tenants are likely to be companies with the financial capacity to locate in pristine spaces and pursue corporate social responsibility (CSR) practices. The omission of these attributes from a cross-sectional regression would inflate the coefficients of the impact of green attributes on the rental premium and energy reduction. One of this study's main identification assumptions is that the presence of sub-metering features is not one of the key factors in determining whether to lease a building. The rationale is that in the commercial rented market, energy efficiency is not a stand-alone product (Golove & Eto, 1996): tenants are first and foremost concerned with finding a space suitable for their daily business activities. Should prospective tenants be strongly inclined to incorporate sustainability into their search criteria, rational inattentiveness would likely prevent them from looking beyond more well-known sustainability characteristics, such as the presence of a green certification label. By only including LEED-CS and LEED-CI certifications in the sample of observations, this study avoids this potential econometric pitfall.

The repeat nature of building-level observations in this study's dataset implies that traditional multiple regression methods, which assume that units of analysis are independent, are not suitable for the data at hand (Rasbash, 2006). Another distinct feature of this dataset is the hierarchical sorting of observations: leases are nested within buildings that are clustered geographically (by submarket, city, and state). Correlations within these clusters must be accounted for, motivating the use of a multilevel modelling (MLM) approach. Before conducting any exploratory analysis, Singer and Willett (2003) recommend first estimating an unconditional random effects model to explore variation within and between these levels. An intraclass coefficient, which describes the proportion of the total outcome variation between units (ibid.), enables to further assess the relevance of these random controls. A range of fixed controls is then incorporated via a conditional multilevel regression model while applying sample weights of the logistic model outlined in the previous section. The following equation represents the general multilevel model set-up employed in this research:

$$y_{it} = X_{it}'\beta + \sum_{l=2}^{L} Z_{it}'u^{(l)} + \epsilon \tag{9}$$

Where y is the vector of outcomes (the logarithm of source EUI/ starting rent), X is a matrix of covariates related to fixed regressors (time-variant and time-invariant), β represents a vector of fixed-effect regression coefficients, Z is a covariate matrix related to random regressors, and u is the vector of random effects. The superscript, l, denotes the level at which Z and u occur (Bailey et al., 2019).

Volatility of Energy Use

Volatility, the most prevalent measure of risk (Duttilo et al., 2021), is chosen to capture the statistical dispersion of energy consumption in this study. Volatility represents the average degree of dispersion of observations from their expected value (Milgrom & Roberts, 1992). The instantaneous standard deviation of energy consumption of a given building is computed relative to the building's long-term average; the long-term average is estimated during two distinct phases: before the implementation of sub-metering and after. Since standard deviation cannot be less than zero, employing ordinary least squares (OLS) estimators would likely yield biased estimates. A relevant estimation approach would bypass the assumption that observations are normally distributed. Among such econometric techniques are those that use Maximum Likelihood Estimation (MLE), such as a Tobit (Tobin, 1958) model. In addition, it allows to account for panel features and the resultant intra-building clustering. The volatility is therefore estimated via the following model:

$$y_{it}^{*} = X_{it}'\beta + Z_{it}'b_i + \varepsilon_{it}, \quad \varepsilon_{it} \sim N(0, \sigma^2)$$

$$y_{it} = \begin{cases} y_{it}^{*} \; if \; y^{*} > 0 \\ 0, otherwise \end{cases} \tag{10}$$

Where y_{it} is the observed variable, deviation of the logarithm of energy consumption from the long-term mean for building i at time t, which can only take positive values. As such, the latent variable, y_{it}^{*}, is assumed to have a left-censoring limit of zero. The error term, ε_{it}, which captures random factors of this relationship, is assumed to be normally distributed. X_{it}' and Z_{it}' represent fixed and random controls, respectively. Since a random intercepts model is adopted in this study, $Z_{it}' = 1$.

3.5. Results and Discussion

This section brings together the results of this paper, which are then discussed in the context of the outlined hypotheses. The limitations of this research to be considered by future research are also stated.

Main Results

This paper's primary analysis is preceded by a range of parametric tests to ensure that the proposed econometric approach is suitable for the data at hand. A modified Wald test for group-wise heteroscedasticity firmly rejects the null hypothesis of equal variance among panel units (buildings). Heteroscedasticity-robust standard errors, also known as Huber-White or sandwich estimators, are employed to address this issue. Furthermore, a Breusch and Pagan (1980) Lagrangian multiplier test for random effects rejects the null hypothesis of no significant difference between buildings, an outcome that reinforces control for building-level random effects via a multilevel model. The problem of cross-sectional correlation is likely to occur in macro panels where $T > N$, and a Breusch and Pagan statistic for cross-sectional independence does not find evidence for contemporaneous correlations across units. The histogram of residuals is consistent with the normal distribution, which is confirmed by a Shapiro-Wilk normality test. Finally, variance inflation factors (VIFs) in conjunction with the adjusted R2 metric are used to determine the inclusion of control variables based on their collinearity with other predictors and the models' predictive power, respectively.

The first stage of this paper's empirical analysis involves the estimation of propensity scores using a logistic model with $Net\ Lease$ as a dependent variable. The results of the logistic regression are presented in Table C.3.1 (Appendix C.3). Following this estimation, balancing statistics between the control and treatment groups are checked to ensure their compatibility (Qiu & Kahn, 2019) — no reasons for concern are uncovered. The weights generated via this model are then applied in the subsequent multilevel models, which estimate the average treatment effect of sub-metering alongside lease type on energy consumption. The results of the weighted multilevel regressions with the logarithm of energy use intensity as a dependent variable are presented in Table 3.3. The complete set of results can be found in Table C.4.1 (Appendix C.4). The first model in this table, "Energy – Benchmark", uncovers no significant effect of sub-metering on energy consumption. However, the following regression, "Energy – Main", demonstrates that the insignificant result can likely be attributed to omitting an interaction between sub-metering and lease type. In the absence of sub-metering, energy consumption is on average 8.4% lower than in gross leases. This model also shows that sub-metering influences energy consumption in the opposite direction for these leases. Sub-metering is shown to significantly decrease energy consumption in gross leases by 3.0%. Meanwhile, under net lease arrangements, energy consumption is greater by 8.1% in sub-metered spaces compared to their non-sub-metered counterparts.

Table 3.3: Energy regressions. Selected results.

Dependent Variable	The Logarithm of Energy Use Intensity	
Econometric Specification	Multilevel Model	
Variable / Model Name	Energy – Benchmark	Energy – Main
Fixed-Effects Parameters:		
Sub-metering	0.019	–0.030*
Net Lease	–0.027*	–0.083***
Sub-metering * Net Lease		0.081**
Hedonic Controls	Included	Included
Amenities	Included	Included
Year Controls	Included	Included
Random-Effects Parameters:		
City Intercepts	Included	Included
Building Intercepts	Included	Included
Number of Cities	7	7
Number of Buildings	246	246
Observations	1,245	1,245
AIC	–1,817	–1,830
BIC	–1,596	–1,605

Notes: All regressions in this table apply a Multilevel Model specification with propensity weights on the likelihood of a net lease in the period from 2011 to 2020. Estimated ICC coefficients for the applied random controls are presented in Table C.3.2 in Appendix C.3. Heteroscedasticity in the error terms is addressed by using Ecker-Huber-White standard errors. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

Table 3.4 reports the selected results for random effects Tobit models relating this paper's primary research variables, sub-metering and lease type, to annual deviation from the mean energy consumption captured before and after the rollout of sub-metering. The complete set of results is presented in

Table C.**4.2** (Appendix C.4). A negative and statistically significant time-averaged effect of sub-metering on the volatility (–2.3%) is unearthed in the "Volatility – Benchmark" model. The results of the subsequent model, "Volatility – Temporal", suggest that the effect of sub-metering on energy use volatility is, to some degree, time-heterogeneous. More precisely, a significant and moderate reduction in volatility occurs in the second and fifth years after its introduction. Meanwhile, a significant increase in this variable is observed in the final year in the sample (Year 8). However, since only 8 observations are pertaining to this year, it is possible that it is attributable to an outlier in the data. The following specification, which involves interacting the net lease and sub-metering dummy variables, shows that sub-metering reduces energy consumption volatility in net leases only (–3.2%).

Table 3.4: Energy use volatility regressions. Selected results.

Dependent Variable	Volatility of the Logarithm of Energy Use Intensity		
Econometric Approach	Correlated Random Effects Panel Tobit		
Variable / Model Name	Volatility – Benchmark	Volatility – Temporal	Volatility – Main
Key Independent Variables:			
Sub-metering	–0.023**		–0.018
Net Lease	–0.011	–0.013	0.002
Sub-metering * Net Lease			–0.032*
Years After Sub-metering:			
Year 1		–0.018	
Year 2		–0.038***	
Year 3		–0.012	
Year 4		–0.001	
Year 5		–0.030*	
Year 6		0.000	
Year 7		0.021	
Year 8		0.088***	
Hedonic Controls	Included	Included	Included
Amenities	Included	Included	Included
Year Controls	Included	Included	Included
Number of Cities	7	7	7
Number of Buildings	246	246	246
Observations	1,216	1,216	1,216
AIC	–2,094	–1,629	–1,625
BIC	–1,905	–1,414	–1,451

Notes: This table reports the Tobit correlated-random-effects models in the period from 2011 to 2020. A likelihood-ratio test rejects the null hypothesis of no panel effects, and ~40% of the total source energy use intensity volatility is attributed to the panel component. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

As a robustness check, the impact on the mean and volatility is investigated using a Fixed Effects estimation. This investigation does not yield a significant decrease in energy consumption for gross leases upon the introduction of sub-metering. However, it also uncovers an increase in energy consumption for net leases when sub-metering is present (9.4% increase). A decrease in volatility is also observed (4.7%) when sub-metering is in place for net lease contracts only (Table C.4.4; Appendix C.4).

This paper's analysis is finalised by exploring whether sub-metering influences the dispersion between gross and net lease rents. The selected results of regressions that investigate this link are presented in Table 3.5, with propensity weights of a net lease applied. Complete results can be found in Table C.4.3 (Appendix C.4). While the first model in this table is presented for reference only, the following one, "Rent – Main", provides insights into this paper's primary research questions. The results of this model show that net leases are associated with a 8.9% discount relative to gross leases under the baseline scenario. However, with sub-metering in place, the difference between gross and net lease rents is reduced by 5.0%. The results also indicate that the reduction in rental dispersion between these lease types is entirely driven by net leases, as the sub-metering coefficient is negligible and insignificant.

Table 3.5: Rent regressions. Selected results.

Dependent Variable	The Logarithm of Starting Rent per Square Foot	
Econometric Specification	Multilevel Model	
Variable / Model Name	Rent – Benchmark	Rent – Main
Fixed-Effects Parameters:		
Sub-metering	0.040**	0.019
Net Lease	–0.057	–0.089*
Sub-metering * Net Lease		0.050*
Hedonic Controls	Included	Included
Lease Controls	Included	Included
Quarterly Controls	Included	Included
Random-Effects Parameters:		
City Intercepts	Included	Included
Submarket Intercepts	Included	Included
Building Intercepts	Included	Included
Number of Cities	7	7
Number of Submarkets	42	42
Number of Buildings	246	246
Observations	1,101	1,101
AIC	–267	–264
BIC	144	141

Notes: All regressions presented in this table apply a Multilevel Model specification with propensity weights on the likelihood of a net lease in the period from 2010 to 2020. Estimated ICC coefficients are presented in Table C.3.3 in Appendix C.3. Heteroscedasticity in the error terms is dealt with by employing Ecker-Huber-White standard errors. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

Discussion

The misalignment between landlord and tenant financial incentives is theoretically expected to lead to over-consumption of energy, resulting in excessive greenhouse gas emissions. But which party's inactions are more detrimental? A comparable study by Jessoe et al. (2020) finds that tenants who pay for their own utilities consume 14% less energy compared to those whose energy consumption costs are included in their lease contracts. The uncovered direction of the split incentive problem in this study suggests that, as advocated by Hypothesis 1a, energy consumption is higher in gross leases — a scenario where the tenant is not motivated to save energy. Precisely, usage split incentives are 8.4% more detrimental than efficiency ones in terms of the amount of energy wasted. Since in the office leasing market gross lease structures prevail (Mooradian & Yang, 2002), the aggregate environmental damage from usage split incentives in this market is alarming. The finding that, in the absence of sub-metering, variability of energy consumption does not statistically significantly vary between gross and net leases is also in line with this paper's expectation, which is formulated in Hypothesis 1b. In concert, these results suggest that in the scenario of incomplete information supposed by the lack of sub-metering, the tenant may have a superior ability to influence the mean, but neither party is better at controlling the dispersion.

Next to emerge in this paper's findings is a dichotomy in the impact of sub-metering on mean energy use between the two lease types. While sub-metering favourably influences average energy consumption in gross leases, it has an adverse effect on this variable in net lease arrangements. These findings lead to rejection of Hypothesis 2a and acceptance of Hypothesis 3a. An increase in the average energy use in net leases could be attributed to rebound effects: after learning that their energy bills have become lower during the initial months of sub-metering, tenants may start using energy services more (Berkhout et al., 2000; Brookes, 1990; Khazzoom, 1980; Qiu & Kahn, 2019; Sun, 2018). Alternatively, after exerting energy-saving effort for a period of time, thanks to the provided feedback, tenants could lose motivation to decrease the mean after failing to observe a substantial reduction in their total business costs. In the language of principal-agent theory, tenants would discover that the marginal benefit of their energy-saving effort is negligible. Further attestation to this supposition may be attained by viewing the energy-reduction problem through a two-task principal-agent problem, whereby tenants decide to allocate their resources to energy reduction or their primary business activities. Since the returns on these two activities are likely to be highly asymmetric (being significantly higher for tenants' primary activities), theory predicts that the tenant would always choose a task with a higher marginal benefit of effort. For the landlord, whose operational costs are expected to have a more substantial bottom line influence, the marginal benefit of her energy-reduction effort is likely to be higher than the tenant's. Additionally, since the landlord is likely to enjoy considerable economies of scale in operational activities due to managing energy consumption across multiple leases and properties, her marginal cost of energy-reduction effort is likely to be lower compared to the tenant (Mooradian & Yang, 2002).

Hypothesis 2b cannot be empirically corroborated, as a favourable effect of sub-metering on energy use variability is not observed for both lease types. The findings show, however, that sub-metering may be an effective tool in stabilising energy expenses in net leases, leading to the acceptance of Hypothesis 3b. It may be beneficial to analyse this study's mean and variability findings in tandem to gain better insight into the reasons for the uncovered effects. Owing to the feedback delivered by sub-metering, tenants may discover that their expected utility is greater through a combination of lower variability at the expense of higher average energy consumption. Since tenants are likely to be significantly risk averse with respect to uncertain energy expenses, they would incur a higher marginal benefit of lower variability compared to the marginal benefit of lower mean energy consumption.

This paper's final analysis investigates whether the uncovered changes in variability and mean are priced into lease contracts. As the dispersion between gross and net lease rents is noticeably narrowed (while controlling for energy consumption), the results of this study suggest the magnitude of the combined risk premium is lowered in buildings with sub-metering features. Interestingly, this effect seems entirely driven by net lease contracts, serving as evidence to reject Hypothesis 4a and accept Hypothesis 4b. The lack of a significant decrease in the gross rent premium could be attributed to various factors. As indicated, landlords' likely low risk aversion to future energy expenses implies they derive a low marginal benefit from uncertainty reduction. Additionally, since the incentive to conserve is still missing for tenants in gross leases (in sub-metered premises), their energy-conservation inactions may continue to expose the landlord to substantive exogenous risk. Even if landlords enjoy a lower degree of uncertainty in tenants' actions with sub-metering, the monetary costs of landlords' ex-post variability-reduction activities may completely negate any such benefits. Another plausible explanation is that a decrease in gross rents, implied by a decrease in operational risk, is fairly improbable in a market of upward-only rent reviews (Wyatt, 2013).

Despite the discernible increase in both energy usage and rent in net leases with sub-metering, it is unclear if these changes can be entirely accounted for by these factors. An analysis using multinomial logistic regression indicates that Class B buildings are least likely to fall into this category, which is also characterised by the highest number of floors. Introducing these variables into the analysis does not markedly alter the coefficients of interest, suggesting the possibility of an omitted variable bias from unknown factors in the study. Given that net leases with sub-metering might behave similarly to multi-tenant properties, it would be beneficial to run a robustness test excluding multi-tenant properties. However, given that single-tenant properties make up only 1.4% of the observations, such a test is not feasible. Meanwhile, after excluding single-tenant properties from the sample set, no significant alterations in the relevant coefficients were found.

Limitations and Future Research Guidance

There are several empirical limitations of this study that need to be pointed out as a guide for future research. Firstly, the study omits variables related to tenant type, such as tenant credit quality, earnings, industry type, and other tenant-related characteristics. There may be selection bias in the types of businesses that prefer net leases versus gross leases (Wiley et al., 2014). While CompStak's rent measure represents the actual rent paid during the first year of the lease, there are several omitted contractual elements known to influence rental premia, such as escalation or cancellation clauses (ibid). Although these variables are available in CompStak, they are not as prevalent as key lease indicators, leading to their exclusion in this paper. The sample of observations is also limited to certified buildings mandated to report on their energy consumption. Since only buildings above a certain size threshold are required to disclose in accordance with the benchmarking rules of their respective cities, the generalisability of this paper's findings is limited to larger properties. Further concerns in estimating energy consumption effects stem from data-matching assumptions of LEED-CI and LEED-CS certifications to energy observations. Precisely, LEED-CI applies to a proportion of a building rather than the whole building, as assumed by this study when estimating the effect of sub-metering on energy use intensity and its variability. Secondly, the sub-metering credit embedded in the LEED-CS scorecard signifies that the building has the infrastructure necessary for its occupants to easily sub-meter their spaces. If only a proportion of a given building with LEED-CS certification is sub-metered, a downward bias of energy estimates may occur. Finally, it remains uncertain whether submetering is absent in the counterfactual. Consequently, this study's estimates lean towards the conservative side, providing lower boundary values.

3.6. Conclusions

In recent years, the real estate industry has begun to redirect its focus away from hard energy efficiency measures to "soft" interventions that can address the energy performance gap. This study considers the impact of one such measure, sub-metering, combined with responsibility for utilities payments, on energy consumption and rental premiums in US commercial buildings. The principles of control theory, value theory of leasing provisions and utility maximisation of an uncertain outcome lay the theoretical groundwork for the effect of sub-metering on the mean and variability of energy consumption under gross and net lease contracts. A multilevel model combined with a propensity score matching procedure shows that sub-metering reduces energy consumption in gross leases, while having an adverse effect on mean energy usage in net lease contracts. However, a favourable variability-reduction effect of sub-metering is only uncovered in net leases. These effects are likely attributed to tenants being more risk averse than the landlord group, thus preferring to undertake energy efficiency measures that stabilise energy consumption over the long-term mean instead of focusing their effort on decreasing the mean. Overall, these findings should give impetus to further studies to fill a critical research gap in understanding the role of risk in decision-making to undertake energy efficiency projects.

Another important contribution of this study is the testing of the impact of sub-metering on the rental dispersion between gross and net leases, which, from a theoretical standpoint, consists of the expected energy consumption costs and a risk exchange with respect to energy consumption uncertainty between the tenant and the landlord. This paper demonstrates empirically a decrease in rental dispersal between gross and net leases in buildings with sub-metering, corroborating that sub-metering may reduce the uncertainty associated with future energy consumption expenses. The fact that a decrease in the risk premium is only observed for net lease contracts further attests to this paper's findings regarding the variability-reduction benefits derived by tenants in the presence of sub-metering. For commercial real estate owners, these findings provide insight into the financial benefits of sub-metering vis-à-vis increased net lease premiums and lower operational costs in gross leases. For policymakers, this analysis provides a possible way to reduce emissions arising from usage split incentives.

Appendix C.1

Assuming the following functional forms:

$$q(e_0, e_1) = -e_0 - e_1$$

$$c(e_0) = e_0^2$$

$$c(e_1) = \frac{1}{2}e_1^2$$

Resulting in the following incentive compatibility constraints:

$$\beta = 2e_0$$

$$1 - \beta = e_1$$

The combined cost-minimisation problem for the landlord and the tenant becomes:

$$\beta\left(-e_0 - e_1 + \frac{1}{2}\tau_0\sigma^2\right) + e_0^2 + (1-\beta)\left(-e_0 - e_1 + \frac{1}{2}\tau_1\sigma^2\right) + \frac{1}{2}e_1^2$$

Simplifying to:

$$-e_0 - e_1 + \frac{1}{2}\tau_0\sigma^2\beta^2 + e_0^2 + \frac{1}{2}\tau_1\sigma^2(1-\beta)^2 + \frac{1}{2}e_1^2$$

In the absence of risk, the above equation becomes:

$$-e_0 - e_1 + e_0^2 + \frac{1}{2}e_1^2$$

Plugging in the combined incentive compatibility constraint, $e_1 = 1 - 2e_0$, into the above equation:

$$-e_0 - (1 - 2e_0) + e_0^2 + \frac{1}{2}(1 - 2e_0)^2$$

Minimising with respect to e_0

$$\min_{e_0} -e_0 - (1 - 2e_0) + e_0^2 + \frac{1}{2}(1 - 2e_0)^2$$

$$6e_0 = 1$$

$$e_0 = \frac{1}{6}$$

Therefore,

$$\beta = \frac{1}{3}$$

$$e_1 = \frac{2}{3}$$

The above results demonstrate that greater incentives would be given to the more energy efficient party, the tenant, who has a lower marginal cost of energy-saving effort compared to the landlord (in this particular example).

In the presence of risk, the joint cost-minimisation problem is computed as follows:

$$-e_0 - e_1 + \frac{1}{2}\tau_0\sigma^2\beta^2 + e_0^2 + \frac{1}{2}\tau_1\sigma^2(1-\beta)^2 + \frac{1}{2}e_1^2$$

Plugging in the incentive compatibility constraints: $\beta = 2e_0$; $1 - \beta = e_1$

$$-e_0 - e_1 + 2\tau_0\sigma^2 e_0^2 + \frac{1}{2}\tau_1\sigma^2 e_1^2 + e_0^2 + \frac{1}{2}e_1^2$$

Substituting in $e_1 = 1 - 2e_0$

$$-e_0 - (1-2e_0) + 2\tau_0\sigma^2 e_0^2 + \frac{1}{2}\tau_1\sigma^2(1-2e_0)^2 + e_0^2 + \frac{1}{2}(1-2e_0)^2$$

Minimising with respect to e_0

$$\min_{e_0} -e_0 - (1-2e_0) + 2\tau_0\sigma^2 e_0^2 + \frac{1}{2}\tau_1\sigma^2(1-2e_0)^2 + e_0^2 + \frac{1}{2}(1-2e_0)^2$$

$$e_0 = \frac{2\tau_1\sigma^2 + 1}{6 + 4\sigma^2(\tau_0 + \tau_1)}$$

Since $\tau_0 + \tau_1 = 1$

$$e_0 = \frac{2\tau_1\sigma^2 + 1}{6 + 4\sigma^2}$$

Therefore,

$$\beta = \frac{4\tau_1\sigma^2 + 2}{6 + 4\sigma^2}$$

$$e_1 = 1 - \frac{2\tau_1\sigma^2 + 1}{6 + 4\sigma^2} = \frac{5 + 2\sigma^2(2 - \tau_1)}{6 + 4\sigma^2}$$

As such, the landlord is likely to assume greater liability over expenses (implying a higher β) for greater values of σ^2, when the tenant is more risk averse so that $\tau_1 > \tau_0$.

Appendix C.2

Table C.2.1: Description of variables and summary statistics.

Variable Name	Variable Description	N	μ	σ^2	Min	Max
Key Research Variables:						
Sub-metering	Dummy variable is 1 for buildings with sub-metering	1,245	0.39	0.49	0.00	1.00
Net Lease	Dummy variable is 1 for leases where the tenant is responsible for energy expenses	1,245	0.33	0.47	0.00	1.00
Dependent Variables:						
Source EUI	The logarithm of weather normalised source energy use intensity per square foot	1,245	4.96	0.46	2.36	7.23
Volatility	The annual standard deviation of the logarithm of energy use intensity from the long-term mean	1,216	0.12	0.12	0.00	1.09
Starting rent	The logarithm of actual rent per square foot received by the landlord for the first lease period	1,101	3.76	0.69	0.38	6.11
Hedonic Variables:						
Building Size	The logarithm of building size in square feet	1,245	12.98	0.90	10.67	15.33
Class B	Dummy variable is 1 for Class B properties	1,245	0.15	0.35	0.00	1.00
Vacancy	Percentage of space vacant in a building at the time of transaction	1,245	0.10	0.13	0.00	1.00
Age	Number of years since the building was built/last renovated at the time of the transaction	1,245	18.36	18.58	0.00	110.00
Data Centre	Dummy variable is 1 for buildings with a data centre	1,245	0.06	0.23	0.00	1.00
Storeys	Total number of floors in the building	1,245	23.87	16.64	2.00	110.00
Percent Leased	Percentage of the building that is leased	1,245	89.30	12.60	22.74	100.00
CS Certified	Dummy variable is 1 for buildings with a LEED Core + Shell (CS) certification	1,245	0.22	0.41	0.00	1.00
Single Tenant	Dummy variable is 1 for single-tenant buildings	1,245	0.01	0.12	0.00	1.00
Lease Variables:						
Renewal	Dummy variable is 1 for renewal leases	1,101	0.16	0.37	0.00	1.00
Other Lease	Dummy variable is 1 for expansion, extension or restructuring lease types	1,101	0.11	0.31	0.00	1.00
Lease Term	Length of the lease (years)	1,101	8.90	4.01	0.21	32.33
Transaction size	The logarithm of the total amount of space leased by the tenant in the transaction (in square feet)	1,101	9.59	1.34	6.28	13.71
Work Value	Negotiated allowance given back to the tenant to renovate or improve the space leased ($)	1,101	53.56	38.15	0.00	250.00
Sublease	Dummy variable is 1 for subleases	1,101	0.09	0.28	0.00	1.00

Notes: Amenities, submarket, and time control variables are excluded from this table. The reference category comprises new lease transactions obliging the landlord to pay for utilities (gross leases) signed in Class A buildings in the city of Cambridge.

Table C.2.2: Distribution of observations by city.

City	% of Observations
Washington DC	31.08%
New York	22.73%
San Francisco	20.16%
Chicago	13.01%
Los Angeles	5.7%
Seattle	4.9%
Cambridge	2.41%

Table C.2.3: LEED Certification credits employed in this study.

Type	Version	Credit	Requirements	Data Extraction
LEED-CI	2.0	Energy use, measurement and payment accountability	– Install sub-metering equipment to measure and record energy use within tenant space (1 point) – Negotiate a lease where energy costs are paid by the tenant and not included in the base rent (1 point)	For projects that score 1 point, CompStak's information on lease type is supplemented to deduce the breakdown of points
LEED-CI	v3 2008	Measurement and Verification	– Install sub-metering equipment to measure and record energy use within tenant space (2 points) – Negotiate a lease where energy costs are paid by the tenant and not included in the base rent (3 points)	Information provided in the scorecard is sufficient to determine the presence of sub-metering
LEED-CI	v3 2009	Advanced Energy Metering	– Option 1: Install tenant-level meters (1 point) – Option 2: install advanced metering to track a) all energy sources in the tenant space; b) any individual energy and uses that represent 10% or more of the total annual consumption in the tenant space	– Earning 1 point or more signifies the presence of sub-metering – Responsibility for utilities payments is supplemented using CompStak
LEED-CS	v2	Measurement and Verification	– Base building sub-metering (1 point) – Tenant sub-metering (1 point)	Scorecard data is sufficient
LEED-CS	v3	Measurement and Verification	– Base building (3 points) – Tenant sub-metering (3 points)	Scorecard data is sufficient
LEED-CS	v4	Advanced Energy Metering	– Tenant sub-metering and advanced base building metering (1 point)	– Scorecard data is sufficient to determine the presence of sub-metering – Responsibility for utilities is determined using CompStak data

Source: USGBC (2021)

Appendix C.3

Table C.3.1: Logistic model results.

Dependent Variable	Net Lease
Econometric Specification	Logistic Regression
Variable / Model Name	Propensity Score Matching
Sub-metering	–0.169
CS Certified	0.196
Annual Vacancy	–0.475
Class B	–2.824***
Age	0.000
Storeys	0.018**
Percent leased	0.016*
Building Size	–0.266*
Chicago	1.707***
Washington DC	–0.739
Los Angeles	–0.022
New York	–2.397***
Seattle	–0.467
San Francisco	–2.298***
Air Conditioning	0.035
All-day Access	0.070
Atrium	–0.250
Balcony	0.337
Concierge	0.055
Fitness Centre	–0.781***
Manager	–0.189
Restaurant	–0.174
Roof Terrace	–0.235
Data centre	–0.204
Constant	2.679
Observations	1,245
Pseudo R2	0.232

Notes: Results of a logistic regression on the likelihood of the lease being net. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The model is estimated in STATA.

Table C.3.2: Intraclass Correlation Coefficients for an unconditional variance model with the logarithm of source energy use intensity as a dependent variable.

Level	ICC	Standard Error	[95% conf. interval]
City	0.545	0.140	0.283 – 0.784
Building ǀ City	0.883	0.036	0.791 – 0.938

Table C.3.3: Intraclass Correlation Coefficients for an unconditional variance model with the logarithm of starting rent as a dependent variable.

Level	ICC	Standard Error	[95% conf. interval]
City	0.843	0.070	0.656 – 0.938
Submarket ǀ City	0.881	0.052	0.737 – 0.951
Building ǀ Submarket ǀ City	0.929	0.031	0.839 – 0.970

Appendix C.4

Table C.4.1: Energy Regressions. Complete results.

Dependent Variable	The Logarithm of Annual Energy Use Intensity	
Econometric Specification	Multilevel Model	
Model Name	Energy – Benchmark	Energy – Main
Fixed-Effects Parameters:		
Sub-metering	0.019	–0.030*
Net Lease	–0.027*	–0.083***
Sub-metering * Net Lease		0.081**
Annual Vacancy	–0.710***	–0.715***
Class B	–0.066	–0.074
Age	–0.001**	–0.001**
Storeys	–0.002	–0.002
Building Size	0.022	0.016
Percent Leased	–0.003	–0.003
CS Certified	0.173	0.210**
Single Tenant	0.156	0.161
LEED Silver	–0.049	–0.072**
LEED Gold	–0.034	–0.050*
LEED Platinum	–0.084*	–0.097**
Amenities:		
Air Conditioning	0.051	0.049
All-day Access	–0.007	–0.007
Atrium	–0.056	–0.052
Balcony	0.041	0.054
Concierge	–0.083**	–0.088**
Fitness Centre	–0.007	0.002
Manager	0.054***	0.050***
Restaurant	–0.020	–0.015
Roof Terrace	0.005	0.005
High Ceilings	0.119	0.128*
Daylight	–0.089	–0.087
Open Plan	–0.066	–0.059
Data centre	0.023	0.023
2012	–0.070	–0.064
2013	–0.153***	–0.144***
2014	–0.204***	–0.195***
2015	–0.255***	–0.246***
2016	–0.271***	–0.264***
2017	–0.264***	–0.256***
2018	–0.381***	–0.375***
2019	–0.408***	–0.400***
2020	–0.562***	–0.553***
Constant	5.410***	5.492***

(continued on the next page)

Table C.4.1 *(continued)*

Dependent Variable	The Logarithm of Annual Energy Use Intensity	
Econometric Specification	Multilevel Model	
Model Name	Energy – Benchmark	Energy – Main
Random-Effects Parameters:		
City Intercept	0.125	0.126
Building Intercept	0.094	0.094
Residual Intercept	0.021	0.021
Number of Cities	7	7
Number of Buildings	246	246
Observations	1,245	1,245
AIC	–1,817	–1,830
BIC	–1,596	–1,605

Notes: All regressions in this table apply propensity weights on the likelihood of a net lease in the period from 2011 to 2020. Heteroscedasticity in the error terms is addressed by using Ecker-Huber-White standard errors. Random-effects parameters are significant at the 5% significance level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

Table C.4.2: Energy use volatility regressions. Complete results.

Dependent Variable	Volatility of the Logarithm of Energy Use Intensity		
Econometric Approach	Correlated Random Effects Panel Tobit		
Variable / Model Name	Volatility – Benchmark	Volatility – Temporal	Volatility – Main
Key Independent Variables:			
Sub-metering	–0.025**		–0.018
Net Lease	–0.011	–0.002	–0.012
Sub-metering * Net Lease			–0.032*
Sub-metering Years:			
Year 1		–0.018	
Year 2		–0.038***	
Year 3		–0.012	
Year 4		–0.001	
Year 5		–0.029*	
Year 6		0.000	
Year 7		0.021	
Year 8		0.088***	
Hedonic Controls:			
Annual Vacancy	0.105***	0.103***	0.107***
Class B	–0.002	–0.002	–0.002
Age	0.000*	0.000	0.000*
Storeys	0.000	0.000	0.000
Building Size	–0.010	–0.010	–0.010
Percent Leased	0.000	0.000	0.000
CS Certified	0.026*	0.023	0.026*

Table C.4.2 *(continued)*

Dependent Variable	Volatility of the Logarithm of Energy Use Intensity		
Econometric Approach	Correlated Random Effects Panel Tobit		
Variable / Model Name	Volatility – Benchmark	Volatility – Temporal	Volatility – Main
Amenities:			
Air Conditioning	0.029*	0.029*	0.029*
All-day Access	–0.008	–0.008	–0.008
Atrium	–0.006	–0.006	–0.005
Balcony	0.015	0.014	0.014
Concierge	–0.019	–0.018	–0.019
Fitness Centre	–0.022	–0.021	–0.022
Manager	–0.002	–0.001	–0.002
Restaurant	0.001	0.000	0.002
Roof Terrace	–0.001	–0.001	–0.003
Data centre	–0.003	–0.005	–0.002
Time Controls:			
2012	0.048*	0.051*	0.046*
2013	–0.036	–0.031	–0.038
2014	–0.043*	–0.041*	–0.046*
2015	–0.050**	–0.048*	–0.052**
2016	–0.045*	–0.041*	–0.047*
2017	–0.066***	–0.063***	–0.068***
2018	–0.055**	–0.056**	–0.057**
2019	–0.027	–0.028	–0.029
2020	0.063**	0.060**	0.060**
City Controls:			
Chicago	0.027	0.025	0.035
Washington DC	0.008	0.006	0.017
Los Angeles	0.003	0.006	0.006
New York	–0.014	–0.016	–0.009
Seattle	0.004	0.002	0.014
San Francisco	–0.001	–0.002	0.005
Constant	0.280**	0.283**	0.269**
Number of Cities	7	7	7
Number of Buildings	246	246	246
Observations	1,216	1,216	1,216
AIC	–2,094	–1,629	–1,625
BIC	–1,905	–1,414	–1,451

Notes: This table reports the Tobit correlated-random-effects models in the period from 2011 to 2020. A likelihood-ratio test rejects the null hypothesis of no panel effects, and ~40% of the total source energy use intensity volatility is attributed to the panel component. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. All models are estimated in STATA.

Table C.4.3: Rent Regressions. Complete results.

Dependent Variable	The Logarithm of Starting Rent per Square Foot	
Econometric Specification	Multilevel Model	
Variable / Model Name	Rent – Benchmark	Rent – Main
Key Independent Variables:		
Sub-metering	0.040**	0.019
Net Lease	–0.057	–0.089*
Sub-metering * Net Lease		0.050*
Lease Controls:		
Transaction Size	0.006	0.006
Work Value	–0.000	–0.000
Lease Term	0.003	0.003
Sublease	–0.037	–0.038
Renewal	0.034**	0.031*
Expansion/Extension/Restructure	0.088***	0.089***
Retail	0.235*	0.241*
Other	0.013	0.017
Hedonic Controls:		
Source EUI	0.102***	0.103***
Quarterly Vacancy	0.152**	0.150**
Class B	0.007	0.006
Age	–0.002***	–0.002***
Building Size	–0.044	–0.043
Percent Leased	0.002	0.002
CS Certified	0.118***	0.121**
LEED Silver	0.034	0.032
LEED Gold	–0.028	–0.029
LEED Platinum	0.098**	0.100**
Amenities:		
Air Conditioning	0.017	0.019
All-day Access	0.019	0.023
Atrium	–0.020	–0.022
Balcony	0.053***	0.052***
Concierge	0.001	0.002
Fitness Centre	0.098**	0.096*
Manager	0.026	0.027
Restaurant	0.082	0.080
Roof Terrace	0.056	0.057
Data centre	0.017	0.019
Single	–0.042	–0.042
Time Controls:		
2010 – Q2	0.073	0.078
2010 – Q3	0.113	0.123
2010 – Q4	0.233**	0.235**
2011 – Q1	0.189***	0.190***
2011 – Q2	0.326***	0.334***
2011 – Q3	0.092	0.103
2011 – Q4	0.165	0.168
2012 – Q1	0.036	0.042
2012 – Q2	0.147**	0.151**
2012 – Q3	0.312**	0.319**
2012 – Q4	0.396***	0.397***

(continued on the next page)

Table C.4.3 *(continued)*

Dependent Variable	The Logarithm of Starting Rent per Square Foot	
Econometric Specification	Multilevel Model	
Variable / Model Name	Rent – Benchmark	Rent – Benchmark
2013 – Q1	0.319***	0.320***
2013 – Q2	0.501**	0.504**
2013 – Q3	0.284*	0.296**
2013 – Q4	0.232*	0.245*
2014 – Q1	0.287**	0.291**
2014 – Q2	0.273**	0.275**
2014 – Q3	0.336***	0.346***
2014 – Q4	0.332***	0.349***
2015 – Q1	0.270***	0.274***
2015 – Q2	0.407***	0.413***
2015 – Q3	0.417***	0.418***
2015 – Q4	0.318***	0.327***
2016 – Q1	0.310***	0.314***
2016 – Q2	0.389**	0.392**
2016 – Q3	0.343***	0.344***
2016 – Q4	0.379***	0.376***
2017 – Q1	0.316***	0.332***
2017 – Q3	0.487***	0.483***
2017 – Q4	0.414***	0.415***
2018 – Q1	0.591***	0.600***
2018 – Q2	0.410***	0.414***
2018 – Q4	0.338**	0.323**
2019 – Q2	0.670***	0.666***
2019 – Q3	0.700***	0.705***
2020 – Q3	0.233**	0.242**
Constant	2.811***	2.796***
Random-Effects Parameters:		
City Intercept	0.745	0.744
Submarket Intercept	0.042	0.044
Building Intercept	0.027	0.027
Residual	0.043	0.042
Number of Cities	7	7
Number of Submarkets	42	42
Number of Buildings	246	246
Observations	1,101	1,101
AIC	–267	–264
BIC	144	141

Notes: All regressions presented in this table apply a Multilevel Model specification with propensity weights on the likelihood of a net lease in the period from 2010 to 2020. Heteroscedasticity in the error terms is dealt with by employing Ecker-Huber-White standard errors. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The models are estimated in STATA.

Table C.4.4: Energy and Volatility Regressions. Robustness Checks.

Dependent Variable	The Logarithm of Energy Use Intensity	Volatility of the Logarithm of Energy Use Intensity
Econometric Specification	Fixed Effects	
Variable / Model Name	Volatility – Robustness	Energy Mean – Robustness
Sub-metering	0.009	–0.010
Net Lease	0.026	–0.079**
Sub-metering * Net Lease	–0.045*	0.094**
Annual Vacancy	0.125***	–0.691***
Age	0.000	–0.000
Storeys	0.001	–0.009
Building Size	0.074	–0.269
LEED Silver	0.037	–0.054
LEED Gold	0.032	–0.048
LEED Platinum	0.039	–0.051
Data centre	–0.006	–0.005
2012	0.027	–0.008
2013	–0.053**	–0.079*
2014	–0.063**	–0.127***
2015	–0.070***	–0.152***
2016	–0.067***	–0.181***
2017	–0.087***	–0.199***
2018	–0.073***	–0.302***
2019	–0.044*	–0.339***
2020	0.048*	–0.496***
Constant	–0.825	8.862*
Number of buildings	246	246
Observations	1,227	1,227

Notes: All regressions presented in this table apply a Fixed Effects specification. Heteroscedasticity in the error terms is dealt with by employing Ecker-Huber-White standard errors. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. The models are estimated in STATA.

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4 Conclusions

Given that the supply of energy is still primarily reliant on fossil sources, the carbon emissions due to electricity usage remain at a substantially high level. The commercial sector is a significant driver of electricity consumption due to the type of services it relies on. Reducing this sector's vast emissions is a critical step for the UK and US to successfully reach their net zero targets by 2050. Despite the financial benefits presented by energy-saving opportunities, various barriers hinder this sector's decision-makers from realising economically optimal energy savings. The lack of visibility of energy efficiency characteristics in a building is one of the main barriers in explaining why these opportunities are overlooked. However, the fact remains that design intentions for energy efficient buildings are not always met in practice; moreover, there exists a performance gap between calculated and measured energy use. In the rented sector, split incentives in the landlord-tenant relationship are some of the most prominent contributors to the energy performance gap.

Energy savings in buildings can be realised through various channels, which can emanate from "hard" (Paper 1) and "soft" (Paper 3) interventions, or a mixture of both (Paper 2). Paper 1 examines the extent to which the UK's introduction of the Minimum Energy Efficiency Standards (MEES) has effectively facilitated market transformation towards more efficient building stock. Paper 2 explores whether energy management can reduce actual energy consumption and thus bridge the gap between the predicted and actual energy usage. Furthermore, Paper 2 investigates the extent to which operational activities that promote occupant productivity further widen the energy performance gap. Finally, Paper 3 questions whether feedback delivered by sub-metering can reduce energy losses arising due to the split incentive problem, and whether this effect is stronger under a given lease arrangement. In addition, this paper explores whether sub-metering reduces the variability of energy consumption. The rental impact of energy management and productivity-enhancing features, as well as sub-metering, is also explored in Paper 2 and Paper 3.

This conclusion synthesises the main empirical findings from the three papers, linking them to the original research questions outlined in the introduction. Consequently, it presents the implications for policy and the commercial real estate industry. Finally, the limitations of this research are highlighted, and recommendations for future work are proposed.

4.1. Key findings

Rent Premium

The first key result of Paper 1 suggests that during the transitional window into MEES (1 January 2012–31 March 2018), substandard (soon to become non-compliant) buildings undergo a significant rental decrease compared to the compliant building stock, as demonstrated in Figure 4.1. More precisely, using a Fixed Effects specification on repeat EPC units where leases are signed before and after the announcement of MEES – this study's preferred econometric approach – the rental value of units with F–G ratings decreases by 7.6% relative to those with A–C ratings during this period. However, this result seems to be entirely driven by F-rated properties. While a statistically significant and sizeable decrease in rents of 27.8% is uncovered for the F–G EPC group after the official enactment of this policy using a Difference-in-Differences method, this result cannot be empirically verified using Fixed Effects. Data shortage is the reason: only 0.2% of leases in the sample set are signed in F–G units after the enactment period of MEES (after 1 April 2018), and no leases signed prior to the announcement could be attributed to these remaining EPCs in the sample. Nevertheless, insufficient leases signed in units with F–G ratings during the post-enactment period is a sign that the primary aim of this policy has been achieved, as most energy inefficient buildings are successfully eliminated from the London commercial rented market. This research also uncovers that this mandatory minimum energy performance standards programme has a weak negative impact (–5.4%) on rents of the new de facto substandard building stock comprised of E-rated EPC units.

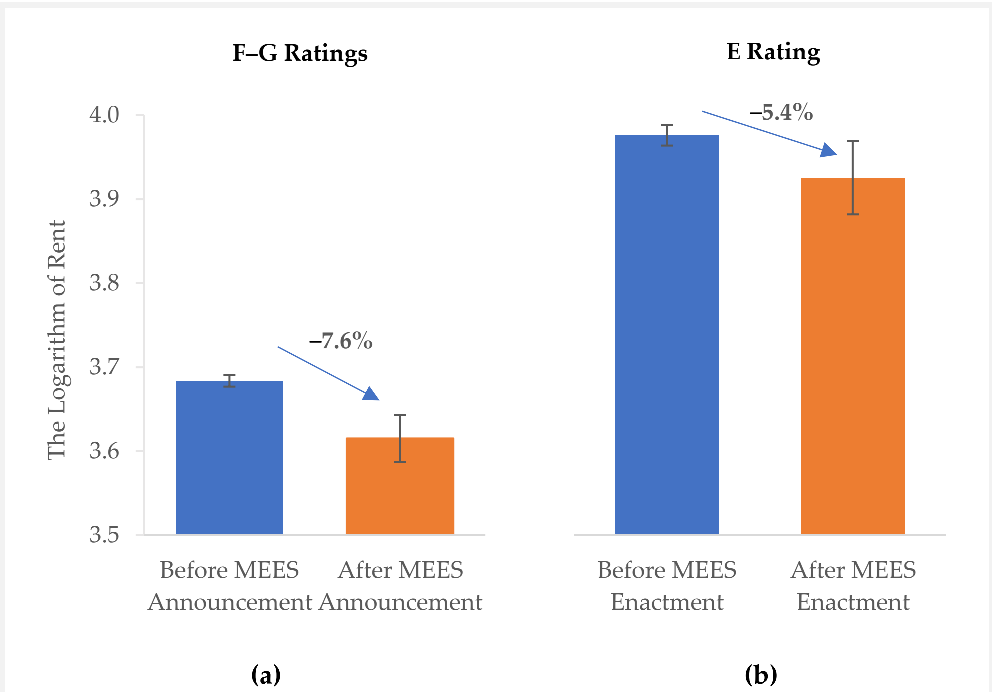

Figure 4.1: The rental effect of a) MEES announcement on F–G units; b) MEES enactment on E-rated units.

Paper 2 shifts focus to operational measures implemented in the commercial rented market in the US. Using a multilevel modelling (MLM) approach, this paper unveils that, in the eyes of the tenant, the LEED EBOM certificate brings about both productivity and energy-saving benefits. This assertion is grounded in uncovering a varying premium level for gross (2.1%) and net (6.6%) lease contracts for this type of certification (Figure 4.2). However, an attempt to find out whether some underlying features drive the uncovered gross and net rent premia of this certificate yields less informative results. Specifically, the findings suggest that tenants do not recognise the benefits of this label's energy management and productivity-enhancing features. One exception is the Enhanced Ventilation credit — one of the building blocks of the indoor environment category of the LEED EBOM label — that brings about a 4.1% rental premium.

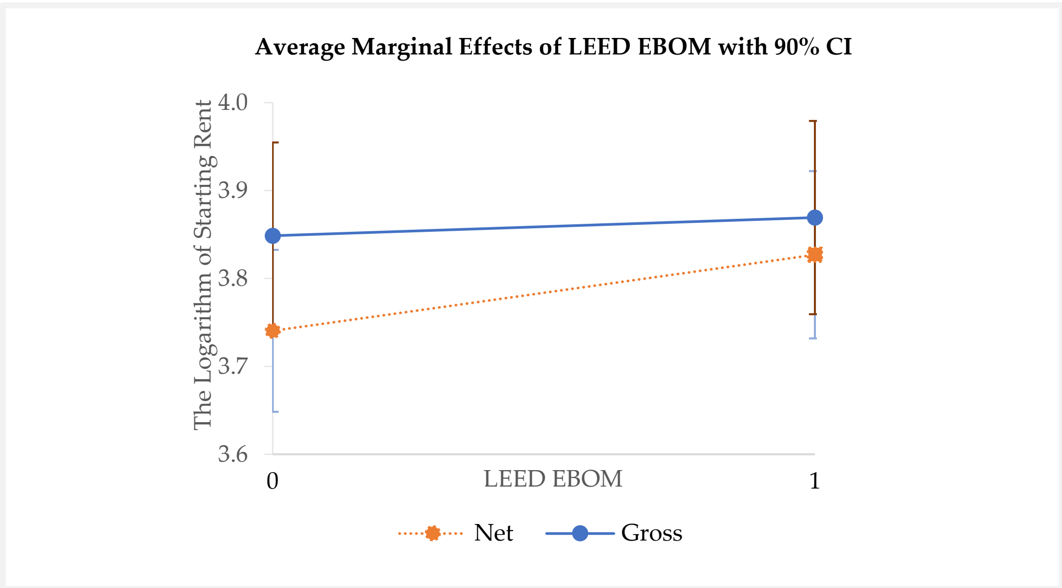

Figure 4.2: The impact of LEED EBOM on the logarithm of starting rent of gross and net leases.

Nevertheless, Paper 3 shows that tenants do pay heed to sub-metering, a measurement technology that allows for nearly immediate and disaggregated feedback on their energy consumption. A multilevel model demonstrates that this feature reaps a 5.0% rental premium in a contract where the tenant assumes responsibility for energy costs. The hypothesis that sub-metering reduces the uncertainty premium of the party responsible for energy costs is also empirically supported, as the difference between gross and net lease rents decreases in the presence of this feature (Figure 4.3). However, this uncertainty reduction effect apparently stems entirely from the tenant as no significant change in rents of gross leases is observed.

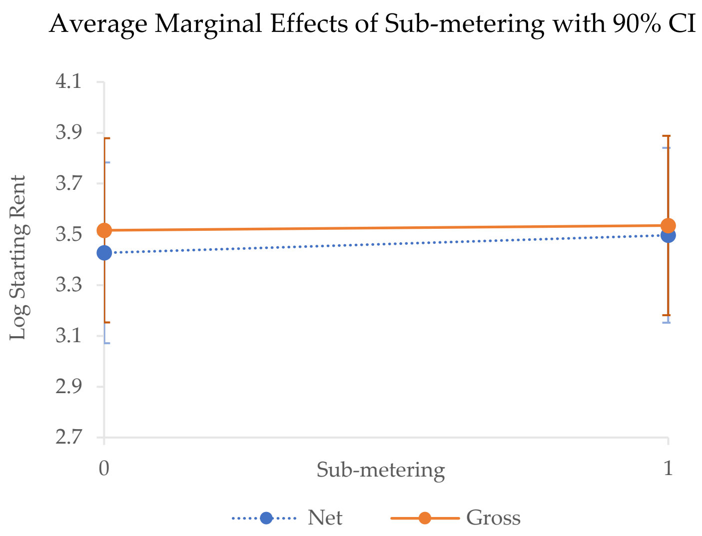

Figure 4.3: The impact of sub-metering on the logarithm of starting rent of gross and net leases.

Energy Consumption

Using actual energy consumption data (site energy use intensity), Paper 2 uncovers that energy consumption of LEED EBOM buildings decreases during the performance period by 2.6%. Meanwhile, the decline in energy consumption intensifies during the first two years of certification, reaching the maximum of 4.8% relative to the pre-registration phase (Figure 4.4).

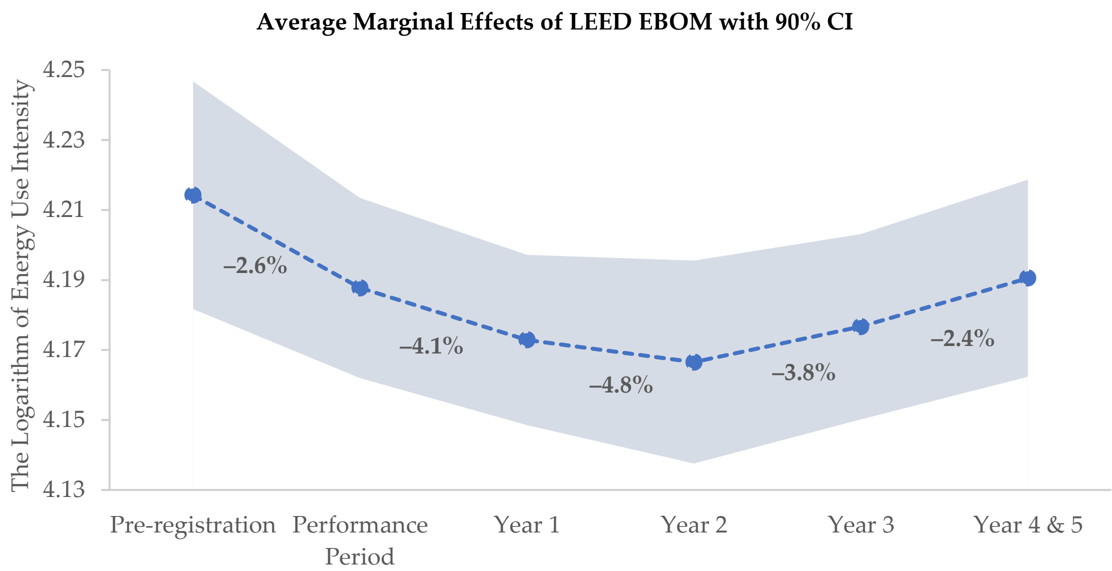

Figure 4.4: The impact of LEED EBOM on the logarithm of energy use intensity during the performance and certification years.

The answers to which (if any) energy management features deliver energy savings, and whether productivity-enhancing ones (if any) affect energy consumption adversely, are also provided in this paper. The findings confirm the anticipated direction of the relationships in question. While ongoing commissioning delivers a 4.4% reduction in energy, the presence of building automation systems (BAS) reduces energy consumption by 2.9%. Meanwhile, outdoor air delivery monitoring, a productivity-enhancing feature, increases energy usage by 11.0% (Figure 4.5).

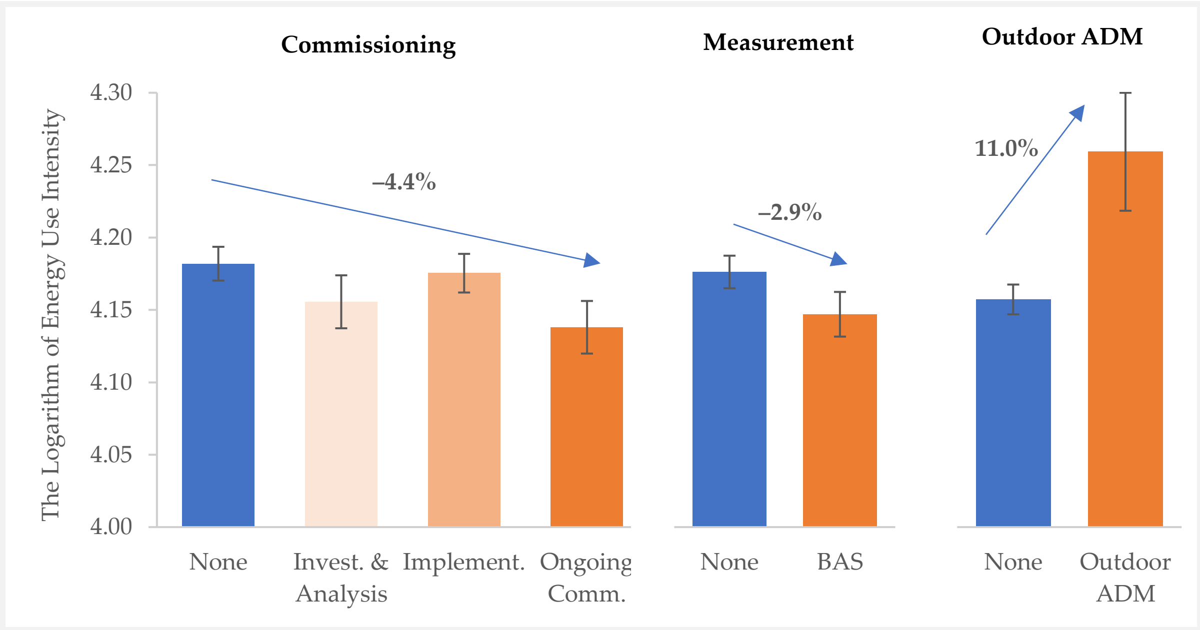

Figure 4.5: The impact of commissioning stages, increased ventilation, and outdoor air delivery monitoring on the logarithm of energy use intensity (90% CI).

Finally, the results of Paper 3 are mixed with respect to whether sub-metering can effectively negate energy losses caused by split incentives. On the one hand, sub-metering reduces the amount of energy wasted due to *usage* split incentives, as the average energy consumption decreases by 3.0% in gross leases when this feature is present. On the other hand, a statistically significant increase of 8.1% in the average energy consumption level is uncovered in a scenario when the tenant is liable for utilities, as demonstrated in Figure 4.6. Nevertheless, as shown in Figure 4.6, sub-metering is also associated with lower volatility of energy use intensity in net leases (–3.2%). A decrease in the volatility of gross leases, however, is not found to be statistically significant.

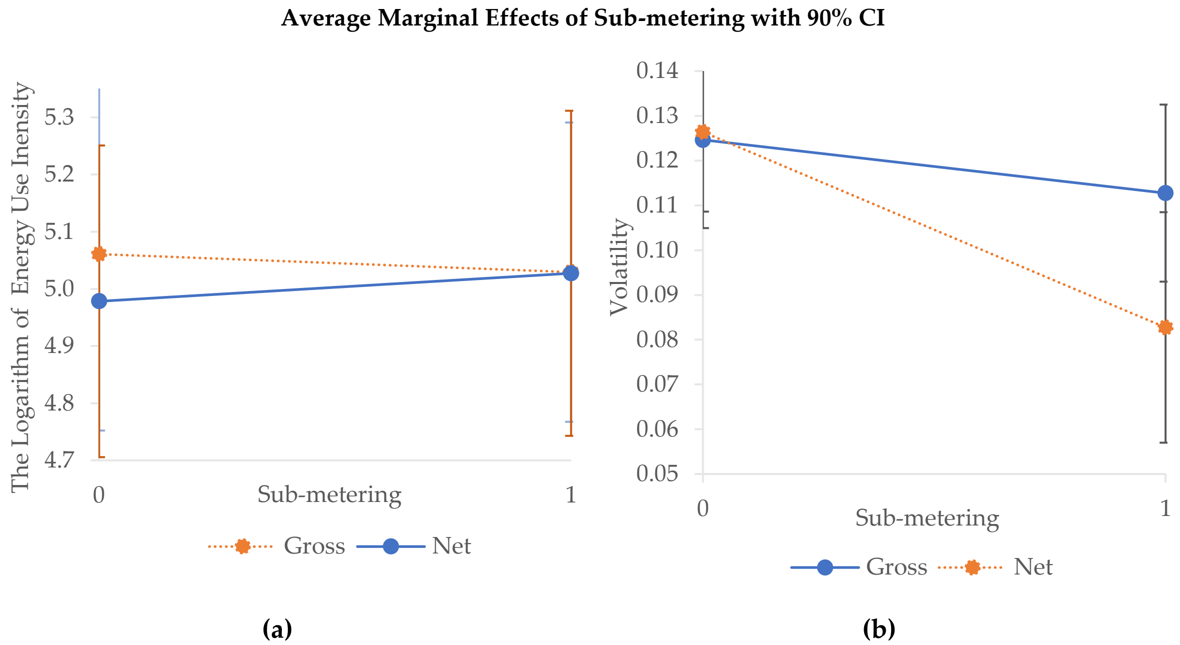

Figure 4.6: The effect of sub-metering on a) the mean and b) volatility of energy use intensity.

4.2. Implications for Policy

In recent years, information programmes that aim to increase the adoption of energy efficiency measures and reduce energy consumption have gained significant popularity in the mandatory and voluntary context. While this research uncovers a significant adverse rental impact of the MEES policy on the substandard building stock, it is important to consider whether this programme can effectively contribute towards the UK's objective of net zero emissions. On the one hand, considering that the majority of commercial leases in the UK are full repairing and insurance leases (Davies, 2019) where efficiency split incentives occur, MEES may be a suitable mechanism to address the arising inefficiencies. However, the lack of confidence in the ability of EPC ratings to impact in-use energy consumption arguably creates a so-called design-for-compliance culture (BBP, 2019) dominated by perverse incentives, wherein owners of real estate do the bare minimum to comply with the upcoming regulations instead of focusing on the core objective of making their properties more operationally efficient. Mandatory disclosure of energy consumption data of commercial properties in the UK (akin to the US market) is one way to quash such doubts. Moreover, this would help establish if the MEES policy leads to the most efficient allocation of resources in delivering the necessary energy reductions in this sector. While these barriers are gradually being shattered in the UK's residential sector due to the recent availability of high-resolution energy data merged with occupant and property characteristics (SERL, 2022), the costs of inaction in taking similar steps in the commercial sector should not be understated.

The findings of Paper 2 bring to the surface that energy management activities are not priced into rent premiums of net leases, despite having a statistically significant positive impact on energy savings. In the absence of price signals for these features, landlords would lack the incentive to invest in energy management practices in the first place. The lack of awareness and market recognition of energy management may serve as a justifiable pretext for government intervention. Some jurisdictions in the US have already begun incorporating energy management measures into their policy mandates. For instance, in Reno, Nevada, in lieu of meeting the energy performance criteria set by the jurisdiction, buildings are given the option to adopt a range of prescriptive measures, one of which involves performing ongoing commissioning of electrical and mechanical systems (Nadel & Hinge, 2020). This approach would be particularly beneficial for building owners that do not have sufficient resources to invest in high-capex energy efficiency retrofits and upgrades or receive certification under LEED for Existing Buildings.

Another key finding to interest policymakers relates to the uncovered trade-off between certain productivity-enhancing measures and operational energy efficiency. Firstly, this result questions the fundamental purpose of LEED EBOM to guarantee environmental performance. This result corroborates one of the most heeded criticisms of green certification labels: the ever-increasing demand for energy-intensive services/amenities may significantly outweigh any energy efficiency improvements of these properties. Secondly, this finding raises a fundamental question of whether energy use intensity (energy consumption normalised for square footage) is a suitable metric for commercial real estate properties to be benchmarked on. Shifting the focus on the primary purpose of commercial buildings – their productive output – may offer a more valuable lens through which their energy efficiency can be viewed and henceforth compared. While this idea is relatively refined in the manufacturing sector, where energy consumption and product output can be linked with a relatively low degree of obscurity, such attribution cannot be made with equal ease for office occupants. For instance, Newsham et al. (2018) propose evaluating productivity in white-collar workplaces using a basket of metrics. However, evaluating energy consumption using multiple measures may be cumbersome and complex, thus hindering effective decision-making. Bupo Happold's consulting arm proposes a more straightforward approach of indexing the economic contribution of a building according to its tenant types (Baumgartner, 2013). The resulting metric enables to quantify the relative economic contribution of a building per one unit of source energy consumed. In summary, although the disclosure of energy use across many US jurisdictions is arguably a step in the right direction, there is significant scope to devise measures that would enable more meaningful insight into, and comparison between, the energy efficiency of commercial buildings. In turn, this would help establish more relevant benchmarks for the commercial sector participants to strive towards.

In contrast to the inconclusive result of the energy management variable, sub-metering appears financially relevant to commercial market participants in net leases. This finding alludes to the efficient functioning of the market, as tenants apparently recognise the benefits of a better ability to control their energy consumption. The less encouraging finding is that average energy consumption is higher upon the introduction of sub-metering in net leases. One takeaway is that pecuniary feedback may not always be able to bring about a reduction in energy consumption, possibly because office tenants' expected marginal product with respect to energy-saving effort might be low. Therefore, it might not be the most effective tool at the disposal of policymakers in this lease context. However, the fact that the variability of energy consumption decreases under this contract is encouraging, considering the intermittent nature of the future low-carbon energy supply. Additionally, the uncovered reduction of energy consumption in gross leases means this feature could be a promising solution to the usage split incentive problem. While the city of New York already recognises the importance of tenant sub-metering, the uncovered reduction in energy consumption in gross leases owing to this technology, and future studies' support of this, may propel other jurisdictions around the world to follow suit in mandating these practices.

4.3. Implications for Industry

For owners of commercial real estate in the UK, one key finding relates to the risk of MEES intensifying in the future. Specifically, the uncovered discount for units with E EPC rating indicates their owners are better off future-proofing their assets to achieve ratings beyond the compliance threshold. The emerging evidence of brown discounting as a consequence of MEES legislation also has implications for owners of units with other EPC ratings. As such, to mitigate the risk of an EPC rating being lowered, landlords may benefit from incorporating green clauses to prevent tenants from undertaking modifications that could cause the current EPC to change. In addition, real estate owners could include clauses that allow them to gain access to undertake works in relation to MEES (Sayce & Hossain, 2020). The heightening risk of owning properties close to the compliance threshold could also be on the radar of lenders, who may integrate EPCs into their assessment criteria.

The finding that LEED EBOM delivers a significant premium in net leases, while its underlying energy management credits do not, alludes that this label successfully addresses tenants' rational inattentiveness with respect to energy-related features. More precisely, tenants seem to recognise the energy-saving benefits of the LEED EBOM certificate but may not have the knowledge or time to learn about the benefits of this label's energy-saving constituents. Since LEED EBOM is indeed associated with lower energy consumption, it could be an effective tool for property owners to signal their buildings' cost-effectiveness. However, the opposing effect of energy management and indoor environment features on energy consumption casts doubt on whether LEED EBOM can consistently deliver energy savings in practice. Two buildings that attain LEED certification could therefore end up with varying energy consumption if their credit allocation between energy management and indoor environment categories also varies. Such variation questions whether LEED EBOM acts as an accurate representation of a building's energy performance. To account for this issue, the USGBC and other certification bodies may consider issuing separate grades to distinguish between the environmental (energy, water, etc.) and productivity (indoor environment) attributes of certified buildings.

Despite the insignificant impact of energy management features on rent, landlords under gross lease arrangements would benefit from higher net operating income due to lower energy consumption achieved in the presence of ongoing commissioning. Another notable finding to the investor group is that tenants recognise LEED EBOM's aggregate productivity-enhancing benefits and are willing to pay a premium to occupy buildings with increased ventilation. It is also possible the effect of improved ventilation on rent would have been more prominent had this research encompassed a period beyond year 2020. The explanation is that as the world was undergoing the COVID pandemic, the value of this feature in commercial real estate space became more salient (Isle, 2020). Although increased ventilation is also associated with a significant increase in energy consumption, the benefits of higher rent would likely outweigh the associated energy costs. Given the indisputable link between increased ventilation and improved health outcomes (Loftness et al., 2006), the associated increase in energy consumption should not necessarily result in this feature being discarded. One would not want energy savings to be at the expense of occupants' ability to effectively perform their work. Instead, landlords could consider undertaking precautionary energy-saving measures to offset the rise in energy demand.

Finally, this research uncovers that sub-metering has the potential to be a win-win solution for property owners offering both net and lease contract types. Under a gross lease, landlords clearly benefit from increased net operating income due to lower energy consumption. Given the low costs of investment associated with sub-metering installation and the magnitude of savings that this research uncovers, the payback period of sub-metering would likely be quick, especially compared to implementing high-capex energy efficiency investments to offset inefficiencies due to usage split incentives. Should a net lease be signed, landlords benefit from higher rent in exchange for offering tenants increased certainty of energy bills. As discussed, the problem with offering submetered spaces to tenants in net leases is that expected energy consumption is found to increase. Although this would not directly impact the bottom line of property owners, due to the proliferation of energy disclosure and benchmarking policies across the US, a possibility of decreased marketability of high energy-consuming properties in the future ought to be considered.

4.4. Limitations and Future Work

Several limitations of this thesis must be acknowledged. Considering that the London market receives significant investor attention and regulatory oversight, the uncovered magnitude of the MEES effect may not be as sizeable in other parts of England and Wales. It may therefore be fruitful for future research to resurface this study's primary questions using data from other regions in England and Wales where MEES compliance levels are likely to be lower. Furthermore, from the standpoint of policy evaluation, the experiences of other markets such as the Netherlands and Scotland, which exhibit divergences in their MEES policy design in a number of aspects (McAllister & Nase, 2019), can also be compared. Since the MEES will extend to all existing commercial leases by April 2023 and eventually rise to a minimum grade C (Booker, 2019), further rental shifts are expected in other EPC ratings that are due to become substandard. Since the timeliness of this research limits its analysis to the first official phase of MEES, these results could serve as a point of reference for future studies aiming to understand the long-term implications of this policy. Additionally, the lack of publicly available energy data for commercial properties in the UK prevents this research from evaluating the extent to which MEES has been effective in curbing the emissions of the commercial building stock — unquestionably a key outcome in assessing the efficacy of this programme.

By relying on secondary data, a limitation of Paper 2 and Paper 3 depicts the innumerable factors that influence energy consumption, making the results vulnerable to an omitted variable bias. For example, factors that can impact energy consumption significantly (such as mechanical systems design, plant and equipment) are not accounted for in these studies. Another concern is the assumption that the features collected from the LEED scorecards (such as sub-metering, energy management and indoor environment) are introduced at the same time as a building certification. Should these features exist prior to the certification period, the magnitude of the uncovered effects would be underestimated. Given these limitations, the results documenting the energy consumption outcomes of these papers are intended to lay the groundwork for studies involving larger and more frequent energy datasets, using, for instance, half-hourly energy data on commercial tenants and more granular information on tenant types and lease terms. The results of Paper 3 may motivate future studies to undertake experimental research into sub-metering in terms of its potential to reduce both the mean and variability of energy consumption. Since minute changes to the energy monitoring display design have been shown to influence energy use behaviour in the residential sector (Krishnamurti et al., 2013), randomised control trials (RCTs) can help establish the most effective ways of delivering information feedback for commercial tenants. Alternatively, future work may consider using panel datasets that are representative of the whole population. Unfortunately, the Commercial Building Energy Consumption Survey (CBECS) — the existing national database produced by the US Department of Energy — can only be used for cross-sectional analysis, which is vulnerable to omitted variable bias (Qiu & Kahn, 2019). Future studies would also benefit from undertaking longitudinal occupant-level analysis to account for the possible endogeneity associated with tenants choosing to locate in buildings with energy conservation attributes.

The hedonic price regression applied throughout this research is criticised for lacking transparency and failing to reveal the underlying theoretical relationships (Mullainathan & Spiess, 2017). The conceptual nature of energy management and productivity makes these variables suitable candidates to be explored via Structural Equation Modelling (SEM), a method that would enable the investigation of a series of complex inter-relationships between these variables and their fundamental components. Instead of parameter estimation, the primary means of most economic applications, there is also scope for real estate research to employ prediction methods that form the basis of machine learning models.

Finally, reducing energy consumption is not the only means of lowering energy expenses at the disposal of investors. An alternative or complementary strategy could be for property owners to shift their energy consumption from peak to off-peak periods when energy prices are lower. Levelling off energy demand, also known as peak shaving, could bring a plethora of climate change mitigation benefits by lowering the maximum power requirements that the grid needs to provide at one time. By reducing total system demand during peak events, commercial energy consumers can thus help accelerate the replacement of fossil fuels with renewable energy resources. While the topic of demand-side management falls outside of the scope of this research, it presents a promising avenue for future work.

4.5. Concluding Remarks

To date, the topic of energy conservation in real estate has received little attention in at least three aspects. Firstly, previous studies have been largely myopic towards energy consumption in residential buildings, as data paucity has hindered research efforts in the commercial sector, especially in the UK market. Secondly, over-consumption of energy is often addressed from a technical standpoint, with existing solutions largely omitting the impact of humans on the building environment. Thirdly, little evidence exists of the solutions to the misalignment between tenant and landlord incentives that results in the over-consumption of energy. This research aims to fill these gaps by examining the effectiveness of various energy conservation measures in commercial real estate. The UK's Minimum Energy Efficiency Standards (MEES) regulation is found to under-price units with substandard energy performance certificates and eliminate non-compliant properties from the market following this policy's enactment. Since this regulation aims to reduce hypothetical energy consumption predicated on buildings' energy efficiency characteristics, the findings of this paper allude to a narrowed energy efficiency gap due to efficiency split incentives in the UK commercial market. The results of this thesis also show that energy management practices, such as ongoing commissioning, can reduce the energy performance gap. In contrast, indoor environment features, such as improved ventilation and air delivery monitoring, may increase it. Finally, sub-metering has the potential to reduce the energy performance gap by lowering energy consumption arising from usage split incentives. While facilitating lower variability of energy usage, however, this feedback technology is found to generate undesired outcomes in tackling energy consumption in net lease arrangements.

Minimising energy consumption is an important opportunity for both business competitiveness and national carbon dioxide emission targets. Energy cost fluctuation is also a significant risk factor for businesses. The ensuing energy crisis is throwing many organisations into disarray by exposing them to soaring energy prices and volatility. Yet the turmoil in energy markets presents a unique opportunity for businesses that occupy, manage and own real estate to devise long-term strategies around energy demand reduction. Alongside short-term measures to shield businesses from the impacts of this crisis, governments need to step up their policy initiatives to guide commercial real estate towards this objective. Companies that take action now will be better equipped for the next big challenge in line – the push for net zero. In line with the above, energy efficiency and savings are set to become more valuable than ever. The present work provides a novel set of findings around "soft", "hard" and "hybrid" energy conservation interventions, which can aid commercial real estate participants in making the necessary leap towards decarbonisation at this critical point in history. Yet further research of this kind should be encouraged in order to verify and extend the presented results. More research is needed to understand how to extract the most value from every Joule of energy consumed to help drive informed action. Solutions around better building management and occupant engagement are the promising agents of change for commercial real estate in decoupling this sector's economic growth from energy consumption in preparation for the unavoidable low-carbon future.

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