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Essays on Economic Mechanisms of the UK Housing Market

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Declaration of Ownership

I confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Abstract

This thesis examines how three interconnected economic mechanisms impact the UK housing market. At its foundation lies the valuation mechanism - how market participants assess future housing benefits through discount rates. This valuation process then influences how policy interventions affect market behavior and ultimately determines how housing investments generate returns.

The research begins by examining the fundamental valuation mechanism, analyzing leasehold and freehold price differences using a unique dataset combining HM Land Registry property transaction dataset with detailed property characteristics in the Registered Lease dataset. This analysis provides new evidence on the term structure of discount rates over very long time, addressing measurement challenges that have limited previous research while providing insights into how market participants value future benefits. This valuation mechanism act as the foundation to understand both the housing policy transmission and housing return generation. Building on this valuation framework, the second analysis examines how policy interventions affect market behavior through the study of the 2016 Buy-to-Let (BTL) 3% tax surcharge. Using a difference-in-differences methodology, the second analysis examine the policy impacts based on the comprehensive transaction data and leasing data. The findings show that the policy led to a 6% increase in rent and a 25% increase in time-on-market (TOM) for rental properties. The research reveals evidence of speculative behavior before policy implementation and demonstrates how tax burden is transferred to tenants through multiple channels. The findings indicate how market participants react

to the policy change based on their valuation about the future costs and benefits. The third analysis shows how the valuation and policy responses ultimately reflect in the total housing returns. Using matched rental and price data for 265,052 properties across England to examine return generation in residential rental housing. The study finds England average annualized capital gains of 2.2% and net income yields of 3.0%, with significant regional variations. London shows the lowest total returns at 4.5%, while higher-priced properties demonstrate stronger capital appreciation but lower rental yields. These patterns reflect the interaction between fundamental valuation decisions and policy induced market changes.

The thesis makes several significant contributions to both academic literature and practical application. It provides new empirical evidence on long-term discount rates, extending previous theoretical work on housing market valuation. It demonstrates how policy transmission depends on the underlying valuation of the market participants. It develops new methodological approaches for measuring housing returns, addressing measurement challenges identified in recent literature. Most importantly, it shows how these mechanisms work together: valuation patterns shape policy responses, while policy interventions and valuation of market participants affect the total return generation of housing. The research has substantial practical implications, informing current policy debates on the leasehold reform and investment practices especially in residential and rental property. The findings regarding unintended consequences, speculative behaviours, and market adjustment patterns provide valuable guidance for policy design. In short, this comprehensive examination of housing market mechanisms contributes to both theoretical understanding and practical application, offering insights for policy design and investment strategy while suggesting new approaches to analyzing housing market dynamics.

Impact Statement

This thesis examines three key economic mechanisms in housing markets: valuation, policy transmission, and return generation. The research provides important insights for both academic understanding and practical applications in housing policy and investment.

The research connects three important aspects of housing markets, showing how they work together to influence housing market. This comprehensive approach improves the understanding in several key areas of academic research. This thesis begins with the valuation mechanism as its foundation, addressing a fundamental gap in the understanding of long-term discount rates, which serves as the foundation for both policy transmission and return generation. While theory has shown that discount rates are important (Weitzman, 1998; Stern et al., 2006), there has been little real-world evidence about very long-term rates (Groom et al., 2005). By leveraging the unique UK leasehold system, this research provides new evidence about how market participants value housing benefits over very long periods. The research methods build on recent work in leasehold valuation (Giglio et al., 2015; Bracke et al., 2018) and propose novel method, establishing a new understanding of long-term decision-making in the UK housing markets. The methodological approach developed for the term structure of discount rate estimation provides a framework that future researchers can apply to other markets and contexts. Building on this valuation foundation, the thesis examines how policy interventions interact with market participants' valuation decisions through the transmission mechanism. While extensive research exists on rent control policies (Turner & Malpezzi, 2003; Kholodilin, 2024), the impact of transaction taxes specifically targeting the Buy-to-Let (BTL) sector remains understudied. The research demonstrates how policy effectiveness is linked to underlying valuation patterns, with market participants adjusting their valuations in response to policy changes. The findings extend recent work on market responses to policy interventions (Best & Kleven, 2017) and contribute to the understanding of policy transmission mechanisms in the UK housing markets (Han et al., 2022). The thesis finally shows how both valuation patterns and policy interventions ultimately affect the housing market returns through the return generation mechanism. Previous studies have typically looked at either rental income (Campbell et al., 2009; Clark & Lomax, 2020) or price appreciation (Dusanskyl & Koç, 2007; Bhatia & Mitchell, 2016) in isolation. This research demonstrates how returns emerge from both capital gain and net rental income. The innovative matching of rental and price data at the property level addresses measurement issues identified in previous studies by Chambers et al. (2021). This methodological contribution provides a robust foundation for future research on housing market returns.

Apart from the contribution in academic, this thesis has substantial implications beyond academic knowledge, offering practical value for policymakers, investors, and market participants in the current and future housing market challenges and policy reforms. The analysis of the term structure of discount rates provides guidance for policy design, particularly relevant to recent housing market reforms. For example, the findings contribute to the ongoing implementation of the Leasehold Reform (Ground Rent) Act 2022, which aims to make leasehold properties more comparable in value to freeholds. The research's insights into how market participants value future benefits can help policymakers refine the implementation of this reform and design future leasehold reforms more effectively. The examination of the Buy-to-Let (BTL) tax surcharge's effects is particularly relevant given recent updated of housing policy on tax surcharge. The research findings regarding speculative behavior and market responses to the original 3% tax surcharge are especially relevant to the recent increase to 5% announced by UK Chancellor Rachel Reeves's Autumn Budget in October 2024. The immediate implementation of this increase, with only one day's notice, appears to reflect the findings about speculative behavior identified in this research. The estimation of the housing returns also offers practical guidance to the implementation of the new Consumer Duty regulations by the Financial Conduct Authority (FCA), particularly regarding the assessment of fair value in mortgage and property investment products. The documented regional variations in returns suggest the need for nuanced approaches to these regulatory requirements.

In short, this thesis demonstrates the importance of understanding the valuation, policy transmission, and return generation mechanisms in housing market. In addition, this thesis also demonstrates the connections between these mechanisms and how they impact both academic knowledge and practical decision-making in the housing markets.

Table of Contents

List of Tables

List of Figure

Chapter 1 General introduction

The housing market fundamentally operates through the interaction of supply and demand, where prices adjust to balance the quantity of housing demanded by potential buyers and renters with the supply offered by sellers and landlords (DiPasquale & Wheaton, 1992). In a basic framework, housing demand is driven by factors such as household income, population growth, and financing costs, while supply responds to construction costs, land availability, and regulatory constraints. However, this basic framework becomes significantly more complex when considering the unique characteristics of housing as both a consumption good and an investment asset. This thesis examines three critical economic mechanisms that extend beyond the basic supply-demand framework: the valuation mechanism, the policy transmission mechanism, and the return generation mechanism. These mechanisms help explain how market participants make decisions, how policies affect market outcomes, and how investment returns are generated in the housing market. The first economic mechanism explores how market participants value future housing benefits, particularly over long-time horizons. Based on the basic supply and demand framework, property values should reflect the intersection of willingness to pay (demand) and willingness to accept (supply). However, the dual role of housing as both consumption good and investment asset means current prices must incorporate expectations of future benefits. The research examines how these expectations, expressed through discount rates, vary across different market segments and time horizons (Giglio et al., 2015; Bracke et al., 2018). The second mechanism examines how policy interventions like the Buy-to-Let (BTL) tax surcharge affect supply and demand conditions. However, the research shows that transmission occurs through multiple channels beyond simple price adjustments. For example, the tax changes landlords' willingness to supply rental properties (supply-side effect) while simultaneously affecting tenants' ability to save for homeownership (demand-side effect) (Han et al., 2022). The third mechanism investigates how housing generates returns through both rental income and capital appreciation. Returns in the housing market emerge from the interaction of supply and demand in both the rental and sales markets. This mechanism reveals how different components of returns vary across market segments and respond to market conditions (Jordà et al., 2019; Chambers et al., 2021). These three economic mechanisms in fact are interconnected. The valuation mechanism is fundamental to understanding both investment decisions and policy effectiveness. The term structure of discount rates shows important implications on how households value future costs and benefits. This valuation patterns explain the behaviour of market participants and the transmission of tax surcharge policy effects. Furthermore, the discount rates and policy effectiveness commonly shape patterns of housing returns. The valuation pattern serve as the fundamental factors of returns and the transmission of policy effect shows how market participants would change on their valuation, which commonly lead to varying returns in different regions.

This thesis makes several significant contributions to the existing research gaps. Despite extensive theoretical work on discount rates and the importance of discount rates for policy evaluation is widely recognized (Weitzman, 1998;

Stern et al., 2006), empirical evidence on long-term discount rates remains scarce due to the limited availability of assets with very long maturities (Groom et al., 2005). The UK housing market, with its system of leaseholds and freeholds, provides a unique opportunity to examine how market participants value future housing benefits over centuries rather than decades. This research leverages the unique institutional features of the UK housing market, particularly its leasehold system, to provide new evidence on long-term discount rates. Following methodological advances by Gautier & van Vuuren (2014) and Giglio et al. (2015), the approach exploits price differences between properties with different lease lengths to reveal how market participants value future housing benefits. This study makes several important contributions to the understanding of valuation mechanisms. First, it provides new empirical evidence on long-term discount rates derived from actual market transactions, contributing to both the descriptive and prescriptive approaches to discount rate estimation (Baum, 2009). Second, it offers methodological innovations in the estimation of long-term discount rates, building on previous work by Bracke et al. (2018) and Fesselmeyer et al. (2021), providing a framework that could be applied in other contexts. These contributions have significant implications for both policy design and market analysis, particularly regarding the evaluation of long-term infrastructure investments and housing market interventions.

The private rental sector plays a crucial role in housing provision, particularly for lower-income households (Kemp, 2011; Rubaszek, 2019). This sector serves as a vital alternative to homeownership, especially during periods of market stress, as demonstrated during the 2008 financial crisis (Arce & Lopez-Salido, 2011; Rubaszek & Rubio, 2020). However, recent policy interventions in the UK housing market have increasingly focused on promoting homeownership through regulations affecting the rental sector (Kettunen & Ruonavaara, 2020). Despite extensive research on housing market policy, several gaps remain unsolved. First, while the impact of rent control policies has been extensively studied (Turner & Malpezzi, 2003; Kholodilin, 2024), Second, the effects of transaction tax policies specifically targeting the BTL sector remain understudied. This represents a significant gap given the increasing use of tax policy to influence housing market outcomes. the potential unintended consequences of policies aimed at promoting homeownership, particularly their effects on rental market efficiency and tenant welfare, require more detailed examination (Breidenbach et al., 2021; Mense et al., 2022). This is especially important given evidence that homeownership policies can contribute to community development and crime reduction (Disney et al., 2023) while potentially affecting tenants' ability to accumulate wealth (Lersch & Dewilde, 2018). This research employs a difference-in-differences (DID) methodology to examine the impact of the UK's 3% tax surcharge on BTL properties. Following methodological approaches developed in recent studies (Han et al., 2022; Hahn et al., 2022), this approach offers several results in identifying causal effects and analyzing market responses. This study makes several contributions to the understanding of housing policy transmission mechanism. First, it provides new evidence on how transaction tax policies affect both rental and owner-occupied market segments, extending recent work on market responses to policy interventions

(Best & Kleven, 2017). Second, it demonstrates how policy interventions can have unintended consequences, particularly regarding rental market efficiency and tenant welfare. This research provides important insights for policymakers considering housing market interventions, particularly in understanding how different market participants respond to policy changes and how unintended consequences might arise from well-intentioned regulations.

Residential real estate represents the largest asset class globally, yet our understanding of its return characteristics remains incomplete. This context has become particularly significant given the rapid expansion of housing investment interest, especially following the Great Recession (Chambers et al., 2021). The return generation mechanism in housing markets operates through multiple channels: rental income generation, capital appreciation, and the interaction between these components across different market segments. Traditional approaches to measuring housing returns have often focused on single components. Many studies have concentrated solely on income yields through rent-price ratios (Campbell et al., 2009; Clark & Lomax, 2020) or examined capital gains in isolation (Dusanskyl & Koç, 2007; Bhatia & Mitchell, 2016). Comprehensive analysis of total returns using matched rental and price data for the same properties remains scarce (Chambers et al., 2021; Eichholtz et al., 2021). This represents a significant gap in our understanding of how different return components interact. Second, the relationship between property values and return components across different market segments remains incompletely understood. Previous research has typically relied on aggregate measures or estimated rents (Eisfeldt & Demers, 2022), potentially missing important variations in return. This research employs an innovative methodology combining detailed property-level data on both rents and prices to provide more accurate estimates of housing returns. Unlike previous studies that relied on estimated rent prices using hedonic regression models (Eisfeldt & Demers, 2022) or housing price indices from external sources (Chambers et al., 2021), our approach utilizes actual matched rental and price data at the property level. This study makes several important contributions to the understanding of return generation mechanism. First, it provides new evidence on total housing returns using matched property-level data, extending recent work by Jordà et al. (2019) and addressing measurement concerns raised by Chambers et al. (2021). Second, it demonstrates how property values influence the balance between capital gains and rental yields, building on findings from studies of city-level variations in returns (Eisfeldt & Demers, 2022).

The thesis thus provides a comprehensive examination of how these interconnected economic mechanisms influence housing market outcomes, offering important insights for both policy design and market analysis. Understanding these relationships is crucial for developing more effective housing market interventions and investment strategies.

1.1 Research outline

Chapter 2 Long-run discount rates: evidence from UK repeat sales housing – Chapter 2 presents the analysis and results for the first research question of estimating the term structure of discount rate based on evidence from UK housing market and shows the difference of discount rates used by households across different areas, such as poor and rich neighborhoods or between London and Non-London regions to provide direct evidence and reference for the need of corresponding policy design andinvestment considerations should take into account regional differences.

Chapter 3 Buy-to-Let Market Responses to Transaction Tax Surcharge – Chapter 3 presents the analysis and results for the second research question of estimating the effect of 3% transaction tax surcharge on Buy-to-Let properties and shows the redistributional effects of the policy, with improving the affordability for homeowners at the expense of tenants.

Chapter 4 Total Returns to Residential Rental Housings – Chapter 4 presents the analysis and results for the total rate of returns estimation for the England residential rental housings and shows geographical dispersion at regional level. London region exhibits the lowest investment performance.

Chapter 5 General Conclusion – Chapter 5 marks the end of this doctoral thesis, and it synthesizes the findings discovered.

1.3 Aim and objectives

The research aims to investigate the economic mechanisms of the UK housing market. The research has the following objectives:

a) To propose an estimation on the term structure of very long-run discount rates (over 100 years) which can be used to more accurate value assets with long investment horizons such as housing, climate change, infrastructure.

b) To analyze the effect of government interventions to taxation of property transactions on the rental market and associated spillover effects to owner-occupied housing.

c) To examine the total rate of returns of the England residential rental housings.

1.4 Research questions

With the stated aims, the corresponding research questions are:

a) What is the term structure of very long-run discount rates based on evidence from the English housing market?

b) What is the effect of a 3% transaction tax surcharge on buy-to-let properties?

c) What is the total rate of returns of the England residential rental housings?

1.5 Ethical consideration

The data collection of housing transactions and rental information in the UK was approved by the UCL Research Ethics Committee. The data collection in this research was registered with the UCL Research Ethics Committee under a project ID of 21349/002. This research only conducts the secondary data analysis and confirmed that there was no potential harm to any individuals, and no identifying information exists that can be used to identify specific individuals. There would be no personal information of households exists and any information that could be used in tracking the households would be excluded from any published document.

1.6 Data protection consideration

Any data would only be accessible by the researcher and would only be used in this research. Data could potentially be published or made public in journals, conference papers, and this research. All data was securely stored following the UCL Code of Conduct. The storage was password-protected and fully encrypted, where the researcher would be the only individual with and access. Any copy made were stored in approved storage spaces and were password-protected.

Chapter 2

Long-run discount rates: evidence from UK repeat sales housing

2.1 Introduction

The term structure of discount rates plays a crucial role in the evaluation of long-term projects, particularly in the context of intergenerational investment and policy design. This is particularly relevant in the current landscape, where there is a growing emphasis on environmental, social, and governance (ESG) considerations. Recent events such as climate change issues and the COVID-19 pandemic have heightened the importance of sustainable governance and the need to address societal inequalities, energy transition, and air pollution.

ESG goals require not only government attention but also the active participation of corporations, ranging from multinational enterprises to small and medium-sized enterprises. In response to these imperatives, the UK government released the "Greening Finance" roadmap in October 2021. This roadmap outlines the government's commitment to attracting green and sustainable investment and includes measures such as mandatory Climate-Related Financial Disclosures across the entire UK economy by 2025 and the implementation of a Green Taxonomy to assess corporate environmental behavior. These initiatives have significant implications for the UK financial sector, compelling them to transform their portfolios and consider long-term investments with cash flows extending into the distant future.

In line with these developments, Xie and Milcheva (2022) conducted a study and found that local greenness and sustainable development policies have a significant influence on private equity firms' intention to invest in ESG-related projects. This highlights the interconnectedness between policy frameworks, investment decisions, and the term structure of discount rates in the context of ESG. In the valuation of long-term projects, such as those related to climate change mitigation, pollution management, water scarcity, and biodiversity recovery, there are different approaches to determining the appropriate discount rate for cost-benefit analysis. Two main branches can be observed: the use of a constant discount rate schedule or a declining discount rate schedule.

The government of the United States generally favors the use of a constant discount rate schedule in cost-benefit analysis. The Office of Management and Budget (OMB) recommends using a constant exponential discount rate of 3 percent and 7 percent for such analysis. The former is based on the real rate of return on Treasury bonds, while the latter is based on the pretax average return on private investments. As a sensitivity analysis, OMB suggests applying a lower but positive discount rate to account for policies or regulations that may have an impact on future generations. However, this approach has been criticized for introducing inconsistency in cost-benefit analysis between intragenerational and intergenerational projects, even if they occur in the same year (Arrow et al., 2013).

An alternative approach is to apply a declining discount rate schedule in cost-benefit analysis, irrespective of whether the project affects future generations.

Countries such as the UK, France, Norway, and Denmark adopt this approach, gradually reducing the discount rate over time in policy appraisals. This acknowledges the notion that the impacts of projects extend beyond the immediate timeframe and assigns greater weight to future welfare.

The choice between a constant and declining discount rate schedule in cost-benefit analysis has implications for the evaluation of long-term projects and the trade-off between present and future costs and benefits. It involves considering ethical considerations, the distribution of benefits and costs across different generations, and the intergenerational equity of policies and regulations. Different countries have adopted varying approaches based on their policy priorities and societal values.

Governments worldwide have encountered the challenge of determining appropriate discount rates for the valuation of long-term projects, highlighting the significance of this issue in research and policymaking. Emmerling et al. (2019) conducted a study on the impact of discount rates on emission policies and advocated for the use of lower discount rates in assessment models. Their findings demonstrated the influence of discount rates on climate mitigation indicators and the global timeline for achieving zero-emissions targets. This highlights the importance of selecting appropriate discount rates to optimize policy outcomes, as evidenced by debates surrounding the Stern review (Stern, 2006; Nordhaus, 2007; Weitzman, 2007).

However, there is limited empirical evidence on how households discount cash flows in an intergenerational setting due to a lack of data on long-lasting assets. Existing literature has leveraged the unique characteristics of housing markets in the U.K. and Amsterdam, where leaseholds with tradable ownership for a specified period provide a basis for estimating the term structure of discount rates (Wong et al., 2008; Gautier & van Vuuren, 2014; Giglio et al., 2014; Bracke et al., 2017). Transaction prices of leaseholds contain valuable information on how households perceive the value of owning property over time. The term structure of discount rates is thus inferred by examining how households evaluate the future time value of housing. For example, the price difference between 100-year leaseholds and otherwise identical 999-year leaseholds reflects the value of owning the property for 899 years, discounted 100 years into the future. This provides insights into the implied discount rate underlying households' payment decisions.

Existing studies in this field have either relied on historical datasets from the 1990s or overlooked unobserved heterogeneity among different properties. Consequently, these studies may not capture the implied discount rate in recent payment decisions and may suffer from potential misestimation. In this chapter, I focus on repeat sales of leasehold properties in the U.K. housing market, allowing for better control of housing attributes and more precise estimation of price discounts resulting from differences in ownership time. The analysis is based on two comprehensive and novel datasets: one containing information on all registered residential property transactions in England and Wales from 2004 to 2020, and the other containing registered leasehold information for the same period. By employing a conservative matching strategy that retains only exact matches, I obtain a sample of 290,240 matched repeat sales housing pairs. I contribute to the existing literature by examining the implied discount rate through a repeat-sales model, addressing issues related to selection bias and omitted variables that may arise in hedonic price models. Additionally, I provide a comparative analysis of the repeat-sales model, the hedonic model, and the findings of previous literature, highlighting differences in estimation outcomes after accounting for unobserved factors.

After applying the Gordon Valuation Model with the estimated price discount, the analysis reveals that the term structure of discount rates exhibits a downward-sloping shape over a span of 125 years. Specifically, the implied gross discount rate at the 100-year mark amounts to 1.3% after employing the repeat-sales model for estimation. In comparison to previous academic findings, such as the results reported by Giglio et al. (2014) and Bracke et al. (2017), which indicated discount rates of 1.9% and 2%, respectively, the estimates are approximately 0.6% lower. This discrepancy suggests that households place greater emphasis on future cash flows when compared to earlier research.

While existing literature has primarily focused on the accuracy of discount rate estimation, it is important to note that Environmental, Social, and Governance (ESG) considerations encompass not only long-term environmental sustainability and governance aspects, but also social issues related to the well-being of individuals. Within the social aspect of ESG, research on wealth inequality has gained significant attention in recent years, as it represents one of the most pressing challenges faced by economies worldwide. Extensive studies have explored saving mechanisms to understand the relationship between wealth inequality and saving behavior, as well as the impact of policy reforms on these dynamics (De Nardi & Fella, 2017).

Building upon the research on saving mechanisms, Piketty and Zucman (2015) provided estimations of long-run trends in wealth inequality based on national balance sheets from 1970 to 2010 for the top eight developed economies. Moreover, Jorda and Alonso (2020) highlighted the crucial role of government intervention in mitigating wealth inequality and revealed that the severity of wealth inequality has varied across countries. While existing studies have primarily focused on understanding the mechanisms and trends of wealth inequality over time, as well as the critical role of policy reforms, they have largely overlooked the link between ESG policies and wealth inequality mitigation.

In addition to tax reforms, the recent growth of ESG policies and investments can play a significant role in addressing wealth inequality. Hence, it is essential to comprehend the term structure of discount rates that are suitable for individuals from both affluent and economically disadvantaged backgrounds. This understanding holds particular importance in the design of related ESG policies and the valuation of ESG investments. Notably, households residing in the same area tend to have similar wealth statuses due to shared factors such as educational background, income levels, and needs for public facilities like schools, hospitals, and parks. Consequently, these factors contribute to differing preferences in evaluating long-term cash flows.

Hence, in order to gain a deeper understanding of the differences in discount rates among households affected by wealth inequality, the study contributes to the existing literature by examining the term structure of discount rates specifically for poor and rich areas. This research provides valuable evidence on the discount rates used in the valuation of ESG policies and investments, taking into account regional disparities. Additionally, I explore the term structure of discount rates employed by households in London[1] compared to those in non-London areas, given the unique status of London within the U.K. The findings indicate that households residing in poor, or London areas utilize higher discount rates compared to those in rich or non-London areas. The term structure of discount rates continues to exhibit a downward-sloping trend over time, with the implied gross discount rate at the 100-year mark being 1.2%, 1.5%, 1.4%, and 1.8% in rich, poor, non-London, and London areas, respectively. These results provide evidence of divergent evaluation preferences among households residing in different areas. Taken together, the findings suggest that the term structure of discount rates used in the valuation of long-term policy design or ESG project investments should consider regional differences in order to mitigate societal inequalities.

Furthermore, this chapter contributes to the ongoing debate in the literature on the term structure of discount rates in the context of climate change abatement (Weitzman, 1998; Stern, 2006; Nordhaus, 2007; Weitzman, 2007), as well as

[1] London in this Chapter refer to the Greater London Area.

the discussion surrounding declining or constant discount rate schedules in cost-benefit analysis (Newell & Pizer, 2003; Office of Management and Budget, 2003; Arrow et al., 2013). Additionally, the analysis is relevant to a range of frontier economic issues, including real estate economics, long-term mortgage research, and the portfolio choice of ESG projects. The results of the study have practical implications for policy appraisal on long-term projects such as infrastructure projects, pensions, nuclear waste management, and climate change abatement. However, it is important to consider the relative riskiness between the real estate market and the target asset market when applying the chapter's findings.

The remainder of the chapter is structured as follows. In the next section, I provide detailed review on the relevant literatures. Section 2.3 provides a detailed description of the unique characteristics of the housing market in the U.K. Section 2.4 outlines the data sources used in the empirical analysis, explains the data integration process, and presents descriptive statistics of the dataset. Section 2.5 discusses the methods employed in the empirical analysis. In section 2.6, I present the estimation results. Section 2.7 compare the results with existing estimates. Section 2.8 discusses the short-term leases comparison. Section 2.9 presents the implied discount rates. Section 2.10 discusses the threats to identification and in Section 2.11, I offer concluding remarks.

2.2 Literature Review

2.2.1 Discount rate estimation

Cost-benefit analysis for public policy requires an assumption of discount rate in the economic model to get the target result of whether the total benefit of the policy intervention surpasses the total cost (Koster & Pinchbeck, 2022). The discount rate represents how human make decisions relating to the future at present cost by discounting the future benefits and costs to the present. But how do economic agents evaluate and discount cash flows in the far distant future remains an uncertain but critical question in many economic studies, which is not only essential in finance but also in climate change, energy, natural resources, etc. (Weitzman, 1998; Stern et al., 2006; Badarinza & Ramadorai, 2014).

The Ramsey model lies at the heart of the discount rates estimation (Ramsey, 1928). This model was originally designed to explore the saving scheme for a country (Rezaei, 2021). Later, it was applied for investigation on practical economy (Cass, 1965; Koopmans, 1965). More recently, it's been used in long-term discount rate estimation for cost-benefit analysis of public policy (Tamai, 2023; Cohen, 2024). The standard economics model developed by Frank Ramsey that determines the discount rates to be used over time is called Ramsey Model. The Ramsey model has been presented by Frank Ramsey, originally it is to answer the question of how much a nation should save and invest in order to maximize benefits over time (Ramsey, 1928). It is about how society should weight current versus future benefits, in other words, what rate should the future benefits be discounted. The standard Ramsey model looks like this, $R_t = \rho + \eta g_t$, where R is the discount rate, ρ is the rate of pure time preference, η is the elasticity parameter of marginal welfare (measure the relative welfare change from additional unit of consumption) and g is the expected annual growth rate of consumption between time 0 and time t.[2]

Prescriptive or descriptive approach are two schools of thought on estimating the appropriate discount rate for intergenerational project or government regulation (Arrow et al., 1996). Although they both employ the Ramsey equation, prescriptive approach applies ethical principles to set the rate of pure time preference ρ and the elasticity parameter η to estimate the discount rate r (Broome, 1992; Cline, 1992; Stern, 2006). Based on the ethical principles, future generation should claim on same well-being level as the current one, hence the ρ is usually set as 0, η is usually set as positive number.[3] Meanwhile, descriptive approach prefers directly to get the discount rates from observable rates of return or real interest rate on actual economy. As long as the setting of discount rate meets the descriptivist requirement, the value of ρ and η can be flexible (Baum, 2009).

The main distinction between prescriptive and descriptive approaches is how they measure the discount rate base on present data and recognition. The prescriptive approach considers the well-being of both present and future generations, but the descriptive approach decides the social discount rate

[2] η sometime can be seen as the “rate of relative risk aversion”.

[3] The value of η has no common agreement, for example, Stern (2006) prefers to set $\eta = 1$, meanwhile, Dasgupta (2008) prefers higher values. Higher value of η means that the marginal welfare declines more significantly as consumption increases.

based on the observable behaviors of the present generation. A criticism of the prescriptive approach usually comes from descriptivist, who states that the ethical principal of some philosophers or economists cannot represent the views of the citizens, and being undemocratic (Nordhaus, 2007; Weitzman, 2007). Conversely, the descriptive approach supports that the decision of the discount rate should be made based on how the real society would make and the result should represent the society's actual preference, i.e., the rates of return on investment, household saving rates or the real interest rate (Baum, 2009). The estimated discount rate should purely represent how the society or household discounts, without any subjective assessment by economists or philosophers.

Economists' opinion on the prescriptive or descriptive approach is contrary. Some of them support adopting the ethical view to decide how to optimize the well-being of present and future generations (Polasky & Dampha, 2021). However, many of them prefer the democratic view to get the discount rate from the actual economy of how the present households make the decisions (Laibson et al., 2024). Apart from prescriptive and descriptive conflicts, there is also an uncertain view on which form of discount rates should be implemented in public policy, constant discount rate or declining discount rate schedule.

In practical, there are two branches of the representative for the form of discount rate that should be used in cost-benefit analysis, constant exponential discount rate and declining discount rate schedule (Costanza et al., 2021; Strulik, 2021). The government of the United States prefer the former option. The Office of Management and Budget (OMB) recommends using a constant exponential discount rate of 3 percent and 7 percent in cost-benefits analysis. The former number is measured by the real rate of return on Treasury bonds, while the latter is measured by the pretax average return on private investments. OMB (2003) also suggests that cost-benefit analysis might consider applying lower but positive rate as a sensitivity analysis if it is for policy or regulation that will affect the future generation. However, this suggestion has been criticized on creating inconsistency in intrageneration and intergeneration cost-benefit analysis even if they happen in the same year (Arrow et al., 2013). It is clear that the OMB doesn't have exact discount rate recommendations for public policies or projects affecting intergeneration.

An alternative approach is to apply a declining discount rate (DDR) schedule in cost-benefit analysis to all policies and government regulations. The United Kingdom and France government prefer to use the DDR schedule in their discounting guidance. DDR schedule requires a regularly update if more information or new data is available (Newell & Pizer, 2003). However, the UK discount rate schedule has not been updated since 2003, making it less instructive and reliable for recent policy appraisal (Treasure, 2003).

Despite the importance of long-term discount rate, empirical work in this research area is rare due to the lack of long-run maturities markets or assets, the available longest government bond normally last around 40 years[4], which is not enough to estimate discount rates over centuries (Groom et al., 2005). Hence, real estate market with maturities over centuries is an appropriate asset to conduct long-term discount rate estimation. Empirical works on the discount rate estimation includes Gautier & van Vuuren (2014), Giglio et al. (2015), Bracke et al. (2018) and Fesselmeyer et al. (2021).

Using Amsterdam land-lease contracts, Gautier & van Vuuren (2014) estimated both the short-run and long-run discount rates. They found the long-run discount rate at 2.79% and the short-run discount rate at 18.12%. Giglio et al. (2014) groups housing transactions of similar remaining leases into lease groups, for example, 80-99 years, 100-124, 125-149, 150-300, 700-999 years and the freehold, then adopt the hedonic regression method to estimate relative discount of various lease groups to the freehold in UK and Singapore, and then back out the long-term discount rate. They found that households use a net discount rate of 1.9% for cash flows more than 100 years in the future. Bracke et al. (2018) use a historical dataset in prime central London from 1987 to 1992 to avoid UK lease extension and lease enfranchisement reform in 1993. Based on this historical setting, they find the term structure of net discount rate declines from 5-6% for nearly expired leases to around 3% for 100 years remaining lease. To avoid the historical data distortion, they also compare regression in London using the same sample period 2004-2013 as Giglio et al. (2014) and find the net discount rates are around 2% for 100 years

[4] Although US Treasury start thinking about the "ultra-long" Treasury bonds, which last for 50 or 100 years from the date of issuance, it is still not available and not enough for discount rate estimation over centuries. Available from: https://fortune.com/2019/08/23/ultra-long-century-bonds/.

of remaining lease. Fesselmeyer et al. (2021) provide empirical support for using a declining discount rate schedule for public policy that affects intergeneration. The net discount rate falls to 1% by year 300 and 0.5% by year 400.

Some empirical work focuses on the rate of return on housing rather than directly estimating the implied discount rate. These results can also reference the applied discount rate in public policy appraisal. Such works include Jordà et al. (2019), Eichholtz et al. (2021) and Giacoletti (2021). Jordà et al. (2019) estimate the total rate of return of housing and compare it with the equity market around the world. Eichholtz et al. (2021) estimate the real total return of housing by real transaction price and rent in Paris and Amsterdam, and they find that the rate of return almost comes fully from rental yields. Piazzesi et al. (2020b) point out that house price fluctuation during the housing boom and bust is different for more and less expensive houses. Giacoletti (2021) found the yields are significantly different across low- and high-income regions. The yield’s difference comes from difference in property characteristics and local factors, households tend to live in same area if they have similar education background, income level and needs of public facilities including schools, hospitals, park, etc. Hence, this leads to different investment recognition and opinion on future cash flows in poor and rich region. Eichholtz et al. (2021) also found that a higher rate of return has been discovered in the poor region. Households living in rich and poor neighborhoods differ in their recognition of the time value of money (discount rates), environmental concerns and investment opportunities. This different recognition comes from various reasons, including educational background, professional experience, income level, investment experience, influence from neighbors, awareness of future uncertainty, consideration of heritage distribution, consideration for future generations and tradeoff between consuming now or saving for the future. These reasons form the household's investment choice on choosing their living area, which leads to a phenomenon that households with similar background and recognition tend to live in the same or nearby street. Hence, poor households and rich households have different investment preference and recognition on the time value of money. It is worth investigating them separately to provide better evidence for policy design.

The Law Commission Report (2020) indicates some problems in current property valuation, specifically an unsuitable valuation of properties with high and low value. High value properties tend to locate in the same area, and it is called rich area in this research, likewise, low value properties tend to locate in a poor region. Current housing policy mainly targets at the entire country but without a granular policy design considering the difference in various regions. Even in the most developed countries like UK, there is an inequality exists in different regions. Researching poor and rich regions individually is helpful to better know the difference in both regions and is helpful to provide academic evidence on more accurate policy design in both regions.

Johnson (2015) reviews the UK Consumer Price Statistics and find the consumer price inflation rates experienced by rich and poor households are different. This means the increase in prices of goods and services, spending for welfare and actual cash outlay for consumption is different for rich and poor households in the same period. Johnson (2015) finds in most of the time poor households experienced higher inflation than rich households. Although the consumer price statistics mainly focus on the cost of living, such as food and energy, it shows poor and rich households have different resilience when they experience same situation of same period. Gillard et al. (2017) try to improve the energy justice in the UK for household encounters energy vulnerability and try to improve the energy efficiency level for them by promoting retrofit policy advice. This is especially helpful for low-income households live in poor quality housing and has negative effect for their physical and mental well-being.

In summary, the long-term discount rate estimation needs more empirical work and evidence to pinpoint which type should be used, constant or declining discount rate schedule? What is the difference in terms of discount rate in rich and poor region? The last but not least, academic research needs a more accurate estimation on the term structure of discount rates for public policy appraisal and these questions will be addressed in this research.

2.2.2 Reform on lease extension and enfranchisement

Leaseholds and freeholds are two main forms of owning property in the UK. The most significant difference among them is that leaseholders can only own the property for a certain period, whereas the freeholders can own perpetuity. Apart from this, leaseholders need to pay annual ground rent to the landlord as agreed.

Leaseholders now have the right of collective enfranchisement to purchase the right of freehold as a group and the right to extend their lease. However, it has been through several leasehold reforms and lengthy discussions in history. There are more than 20 Bills have been introduced to explain the principle of enfranchisement and lease extension since 1884, and the Reform targets leasehold houses first. However, it wasn't until the 1967 Leasehold Reform Act legally confirms that leaseholders in houses have been given the right of collective enfranchisement and lease extension. According to this Act, leaseholders in houses can buy the freehold as a group or extend 50 years of leases after the date on which the existing term is due to expire (Barnes, 1968).

The 1967 Leasehold Act targets Reform on leasehold houses, but the leasehold flats remain an unsolved problem in giving leaseholders the right to purchase the freehold and lease extension. It seems like a straightforward legal process to conduct a similar reform in leasehold flats as in leasehold houses. However, this process has lasted over decades after the 1967 leasehold reform. In 1982, HMSO (1982) presented a report to show evidence that landlords have financially exploited leaseholders and recommended giving leasehold in flats the right to collectively purchase the freehold. However, this report is not a legal reform, although it did accelerate the reform process. In 1987, the Landlord and Tenant Act was introduced to confirm that leaseholders have the right to pre-emption on purchasing the freehold under market value if the landlord wants to sell their property. However, the lack of legislation and formal rules makes it difficult for leaseholds to pursue this pre-emption right (Cole & Smith, 1994).

It was not until the 1993 Leasehold Reform, Housing and Urban Development Act legally gave the similar right of leaseholds in flats compared to leaseholds in houses. The 1993 Leasehold Reform provides the collectively enfranchisement right for leaseholders in flats. After the enfranchisement process, the freehold would be owned by a nominee purchaser. In addition, the Reform also gives leaseholds in flats the right to extend 90 years of leases after the existing term is due to expire. In this way, it tackles the mortgage problem since it becomes difficult to secure a mortgage as the remaining lease diminishes (Cole & Robinson, 2000).

After leaseholders are given the right of collective enfranchisement and lease extension, if they want to make these actions, the first two questions would be what the procedures are and how much they will cost. Currently, the collective enfranchisement and lease extension procedure is complex and depends on whether leaseholders and freeholders can make an agreement. Leaseholders are highly recommended to use a specialist solicitor and surveyor to conduct the whole process. Two scenarios can happen. One is an agreement has been made between leaseholders and freeholders in terms of the detail of enfranchisement and lease extension, such as how much it costs, what terms would it be, and who is the nominee purchaser, etc. The second scenario is no agreement has been made between leaseholders and freeholders. In this case, the First-tier Tribunal will have the legal power to make the final decision based on a series of evidence and valuation processes.

In the majority of cases, the price is the main conflict between leaseholders and freeholders, and surveyors play an essential role in the determination of the price of lease enfranchisement and lease extension. The surveyor needs to follow a set of standards when conducting the valuation task. In the UK, the RICS Valuation Global Standards (RICS, 2020) are the principal standards which follow the International Valuation Standards (IVS, 2020). There are several different approaches and methods in the valuation of different markets. In the UK, the lease extension and enfranchisement valuation mainly adopt the implicit valuation model (French, 2013).

The implicit valuation model contains two main parts and one additional part, which constitute the majority of prices. The term value – the total ground rent the landlord would expect to receive over the life of the existing lease. For example, if the existing lease is 68 years, the total ground rent of 68 years is the value that the landlord should have received without the enfranchisement and lease extension. Then is the reversion value – the eventual value of the property at the end of the lease when ownership transfers back to the landlord. The reversion value relies highly on the appropriate discount rate used to represent the time value of money. The additional part is the marriage value, which would be considered if the remaining lease term is below 80 years at the point of enfranchisement and lease extension. The marriage value represents the increased value of the leasehold property after the completion of enfranchisement or lease extension. The marriage value also relies heavily on the valuation of time value since the only difference of a housing before and after the lease extension and enfranchisement is the remaining ownership time.

Current valuation standards and procedures of collective enfranchisement and lease extension face much criticism. In 2017, the UK government asked the Law Commission to review and make plans for legislation to improve the valuation standard and procedure of leasehold enfranchisement and extension. Law Commission report (2020) finds several problems in the current valuation process for lease extension and buying the freehold. The main criticism is the valuation process is too complex and not transparent for leaseholders, which mainly determined by the experience of surveyors.

As the Secretary of State for Housing, Communities and Local Government, Jenrick (2021) propose that a series of leasehold reforms is under review, and legislation of setting future ground rents to zero would be the first reform. On 8 February 2022, the Leasehold Reform (Ground Rent) Act 2022 formally entered the statute books in the UK, making it one of the most significant changes to property law in a generation. This Act's aim is to solidify the homeownership of leaseholders and to make leasehold properties similar value to otherwise similar freeholds; to make the valuation process of lease enfranchisement and lease extension easier by prohibiting the landlord from charging ground rents, the amount of ground rent the new leaseholds need to pay for the landlord is zero. Hence, this leasehold reform will lead to changes in the valuation process, the calculation of premium that freeholds compared to leaseholds and further affect buyer's perception of leaseholds and freeholds and finally changes the overall housing markets in the UK. According to Jenrick (2021), the Ground Rent Reform is just the first step of the leasehold reform plan. Future legislation will reform the calculating valuation process of enfranchisement and lease extension, abolish the marriage value, and introduce different valuation methods for low-value properties.

In this research, the focus is not on reviewing the valuation process in the UK housing market as Gabrielli and French (2020). Instead, the focus is on to what extent does the household's perception on the time value of money, which can give direct empirical evidence for further leasehold reforms, such as enfranchisement and lease extension valuation criteria, marriage value abolishment and low-value properties valuation method.

2.3 Housing market in the United Kingdom

2.3.1 Institutional background

The property market in the UK possesses a distinctive characteristic, namely the existence of two forms of property ownership in England and Wales: freehold and leasehold. Scotland has a different system of property ownership, while Northern Ireland shares similarities with England and Wales but with some variations. For the purpose of this chapter, the focus is on the residential property market in England and Wales.

The key distinction between freehold and leasehold lies in their respective ownership rights. Freehold represents the permanent and outright ownership of both the property and the land it stands on. On the other hand, leasehold signifies a time-limited ownership of the property without ownership of the land. Leasehold ownership is tradable, similar to the perpetual ownership of freehold properties. The remaining duration of the leasehold can be traded in an open market. Leasehold ownership is granted to property buyers, referred to as leaseholders, through a contract with the freeholder, which is documented in a lease. The lease contains detailed terms outlining the rights and responsibilities of the leaseholder, who has the ability to rent, sell, and mortgage the property as if they were the freeholder. The initial lease term can vary, ranging from 99, 125, or 250 years to as long as 999 years, although it can also be as short as 10, 30, or 40 years.

In terms of leasehold registration, the Land Registration Act 2002 mandates that leasehold transactions must be registered with the appropriate authority if the lease maturity exceeds seven years and has been transferred or granted. To ensure more reliable leasehold data, I only include leasehold data from 2004 onwards, as prior to the implementation of the Act 2002, registration was not legally required. Additionally, given that leasehold tenures can span over long-term periods, leaseholders typically possess the right to make non-structural changes to the property, such as minor improvements. However, structural changes can only be made with the consent of the freeholder. To avoid price distortions arising from freeholder-induced structural changes, I focus solely on leaseholds in the main empirical analysis.

Upon purchasing a leasehold property, buyers inherit all the responsibilities associated with the remaining lease term, and the ownership must eventually be returned to the freeholder unless a lease extension or collective enfranchisement occurs[5]. The property ownership reverts to the freeholder unless the leaseholder negotiates with the freeholder for a lease term extension. Leaseholders have the legal right to formally request a lease extension under the Housing and Urban Development Act 1993 and the Commonhold and Leasehold Reform Act 2002. The terms for lease extension differ depending on whether the property is a house or a flat. For flat owners, leaseholders have the right to request a lease extension of up to 90 years beyond the remaining lease maturity, provided they have held the lease for more than two years. A premium payment for the lease extension is required. In the case of house owners, the two-year holding requirement still applies, but they can only extend the lease by 50 years beyond the remaining lease term, and no extension fee is needed, except for the possibility of an increase in ground rent. Due to the divergent provisions in lease contracts for flats and houses, the analysis primarily focuses on the flat market to avoid potential unobserved heterogeneity.

2.3.2 Valuation of lease extension and collective enfranchisement

To exercise the right of lease extension and enfranchisement, leaseholders are required to reach an agreement with the freeholders regarding the lease extension fee, also known as the premium. This fee is determined through negotiations between the leaseholders and freeholders. In the event that no agreement is reached on the price, the valuation process may be taken to the

[5] Lease extension and collective enfranchisement are two ways for leaseholders to extend the current lease based on the terms of the Leasehold Reform Act. I discuss this in detail at Section 2.2.2.

Leasehold Valuation Tribunal (LVT), which serves as a UK First-Tier Tribunal responsible for making the final decision on the lease extension fee. However, engaging in this legal process can be time-consuming and costly for leaseholders, as they have to cover expenses related to lawyers' fees and property valuer fees, while facing the uncertainty of the court's final decision.

The lease extension fee, or premium, is paid by leaseholders to compensate the landlords. This compensation reflects the legitimate property value and ground rent income that landlords would have received before the extension and enfranchisement, considering that leaseholders will possess a longer lease term and will no longer need to pay ground rent (zero ground rent) to the landlords. By extending the lease, leaseholders effectively reduce the annual ground rent revenue received by the landlords, putting them at a disadvantage. Thus, the premium serves as a compensation to landlords from leaseholders, reflecting the property's legitimate value and the ground rent income prior to the extension and enfranchisement. The premium calculation in the UK currently consists of three components: the term, the reversion, and half of the marriage value.

The term and the reversion represent the value of the property that landlords would legitimately own. The term represents the value of the right of the landlord to receive ground rent over the existing leases before the extension and enfranchisement. The reversion represents the value of the right of the landlord to regain full ownership of the property once the lease expires. In essence, the term and the reversion together represent the original value that landlords could have received from leaseholders and the property itself before the lease extension and enfranchisement. These two components form two out of the three parts of the compensation owed to landlords.

The marriage value is an additional component of compensation that applies only when the remaining lease term is below 80 years at the time of leaseholders applying for extension and enfranchisement. The marriage value reflects the additional value generated by the property as a result of the lease extension and enfranchisement. For instance, if a flat in London had an existing lease of 70 years, and the leaseholder applied for a new lease under the terms of the Leasehold Reform Act, which allows for a 90-year extension, the new lease term would be 160 years. The property value would significantly increase following the new lease, benefiting both landlords and leaseholders. Therefore, the marriage value reflects the additional market value resulting from owning a longer lease, and the Act stipulates that both landlords and leaseholders should contribute to paying the marriage value. In the premium calculation, leaseholders and landlords share the marriage value in a 50:50 split. The inclusion of half of the marriage value constitutes the third part of the compensation paid to landlords.

However, it is worth noting that the valuation of the marriage value is currently reliant on the subjective opinions of valuers, which may lack reliability and depend on subjective judgments or limited data evidence used by the First-tier tribunal. The results obtained in this study, particularly the relative discounts observed between short-term and very long-term leaseholds, can provide direct empirical evidence on the valuation of the marriage value, and contribute to the overall calculation of the premium in lease extension and enfranchisement cases.

2.4 Data

2.4.1 Data source

This study does not involve direct data collection from individuals, but rather relies on publicly available data obtained from UK government institutions and other primary sources. I utilize five datasets sourced from two data sources: HM Land Registry (LR) and National Statistics. These datasets include transaction data from the HM LR Price Paid Data (PPD), registered lease data from the HM Land Registry, UK house price index from the HM Land Registry, indices of deprivation from National Statistics, and the postcode lookup directory (PLD) from National Statistics.

The LR PPD data encompasses all registered residential property transactions in England and Wales from 1995 onwards. Each transaction record contains information such as the transaction price, transaction date, locational details (postcode, full address), and property characteristics (apartment or house, old or new, freehold or leasehold)[6]. The registered lease data comprises information on all registered leaseholds in England and Wales from 1995 onwards. Each leasehold record includes lease contract information (registration date, lease start date, lease term) and locational information (postcode, full address). It should be noted that leasehold registration was not

[6] Available at: https://use-land-property-data.service.gov.uk (HM Land Registry).

mandatory until the enactment of the Land Registry Act 2002, which required leaseholders to register leasehold transactions within two months of completion starting from October 2003. Consequently, transactions that occurred prior to October 2003 may not have matched leasehold information. To mitigate this potential distortion, this study focuses on the period from 2004 to 2020. By utilizing these publicly available datasets, I ensure the integrity and reliability of the data while maintaining compliance with ethical standards and privacy regulations.

The UK House Price Index data provides monthly updated house price indices for all local authorities in England and Wales. It represents the general level of property transaction prices and enables the analysis of price trends over time. This data is crucial for conducting repeat-sales analysis, which helps control for price trends between the first and second transactions of the same property.

The Indices of Deprivation data comprises information on the level of deprivation for all lower-layer super output areas (LSOAs) in England and Wales. Deprivation is measured across seven domains with appropriate weights: Income (22.5%), Employment (22.5%), Education, Skills, and Training (13.5%), Health and Disability (13.5%), Crime (9.3%), Barriers to Housing and Services (9.3%), and Living Environment (9.3%). Each domain includes multiple sub-components. For example, the Barriers to Housing and Services domain includes sub-components such as homelessness, housing affordability, and the distance to essential amenities like post offices, primary schools, general practitioners (GPs), and supermarkets. It is important to note that the level of deprivation does not change significantly over time, and the most recent Indices of Deprivation data was published in 2019. For this study, I utilize the 2019 deprivation level to represent all LSOAs in England and Wales. The Postcode Lookup Directory (PLD) contains corresponding locational information. Each postcode is associated with a lower-layer super output areas (LSOA) code, local authority code, city code, and region code. By matching transaction data with the PLD, I can enrich the locational information for each transaction.

2.4.2 Data integration

To conduct the empirical analysis, it is essential to integrate all the data sources into a single dataset. This integration allows us to have both individual-level and regional-level information for each observation. The regional information can be obtained by merging the UK House Price Index data, Indices of Deprivation data, and the Postcode Lookup Directory using the locational variable, which is the postcode.

For the individual-level information, I utilize the transaction data and registered lease data. However, these two datasets do not have a common identifier to directly match the transactions. Therefore, I employ the Python record linkage toolkit to match the transactions from the LR PPD data and the registered lease data based on detailed addresses. It is important to note that addresses in different data sources may have variations in writing styles and order. To enhance the accuracy of address matching and following a conservative approach, I have set the accuracy standards to the highest level available in the record linkage toolkit. After dropping the unmatched observations and selecting properties that have been transacted more than once during the study period, I obtain a matched dataset comprising 290,240 repeat sales observations.

By creating this matched dataset, I ensure that I have reliable and consistent individual-level information that can be analyzed alongside the corresponding regional information. This integration of data sources allows for a comprehensive empirical analysis to be conducted.

2.4.3 Data summary

Table 2.1 presents the descriptive statistics for the individual data sources (transaction data and registered leases data) obtained from the HM Land Registry, as well as the matched repeat sales data. The observations in the dataset span the period from 2004 to 2020. After matching the transaction data with the registered leases data, all observations in the matched dataset pertain to properties with leasehold tenure and complete registration in the HM Land Registry.

Table 2.1 Descriptive statistics and main data sources

	Land Registry Price Paid Dataset	Land Registry Registered Lease Dataset	Matched Repeat Sales Dataset
Observations	3,861,491	2,912,639	290,240
Mean Price	238,264	.	254,316
Median Price	160,000	.	182,000
Apartment	0.76	.	0.98
New	0.19	.	0.23

Lease	1.00	1.00	1.00
Median Lease Term	.	125	150
Median Lease Start Year	.	2010	2005
Median Lease End Year	.	2143	2142

Notes. The first two columns show the original data sources, transaction data and registered lease data from the HM Land Registry (LR). The third column shows the matched repeat sales dataset after using python record linkage toolkit to match both original datasets through address to integrate all individual information into one dataset.

Table 2.1 shows the final matched repeat sales dataset is about 10% of the original Land Registry Registered Lease dataset. There are several reasons of why it is left with about 10% of the original dataset. First, the nature of repeat sales method is designed to control for unobservable property-specific by only including properties that have been transacted more than once characteristics. Hence, many properties that have only been transacted once are excluded from this analysis. Second, the matching criteria mentioned above indicate a high standard of matching between different dataset to ensure the exact same property to be match, hence, some observations have been excluded. Third, the original dataset collects the data from several real estate agencies, which results in the duplicate record in the original dataset. This has also been identified and excluded. As for the representative of the matched dataset, it covers all geographic distribution, size of the property, and different price range. This can be seen as the random sample selection procedures but for those transacted more than once. In addition, this chapter also conduct the complementary analysis, the hedonic model to include properties only transact once in the analysis to examine the gap caused by the repeat sales selection, so that the results presented in this Chapter is not only for the repeat sales samples, but also cover the other samples.

Within the matched dataset, the vast majority of observations (98%) represent apartments, which aligns with the prevailing trend in England and Wales, where a significant proportion of apartments are leasehold properties[7]. In terms of property type, only a small percentage (2%) represents houses. Additional descriptive statistics include the average transaction price, median lease term, average lease term, and average lease extension. These figures provide insights into the financial aspects and lease characteristics of the properties included in the dataset. Given the distinct differences between the apartments market and the houses market in terms of legal contracts and lease regulations, the primary focus of this analysis is on the apartments market, which constitutes the majority of the matched repeat sales data.

Table 2.2 provides a summary of the main variables present in the matched dataset. Each observation includes transactional information such as the price of the property at the first and second transactions, the date of the second transaction, and the holding period (i.e., the time duration between the first and second transactions) measured in years. The locational information consists of the postcode and the postcode district. The poverty measurement variable represents the Indices of Deprivation, which quantifies the level of deprivation for the area where the property is located. This measurement encompasses various domains, including income, employment, education, health and disability, crime, barriers to housing and services, and living environment. The leases information includes the remaining lease term of the property in years, the year in which the lease commenced (lease start year),

[7] A few apartments are in freehold tenure type. They usually lived by the freeholder, rather than a share of freehold by collective enfranchisement.

and the total term of the lease in years (lease term). In order to compute the remaining lease, data cleaning and processing were performed on the registered lease data. For example, if a property was transacted in 2020 with a lease term information of "250 years from 1 January 2017," the lease term would be recorded as 250 years, the lease start year as 2017, and the remaining lease calculated as 250 + 2017 - 2020, resulting in 247 years remaining.

Table 2.2 Summary of main variables

Variable Name	Description	Type
First Sale Price	Sale price for first transaction	Numeric
Second Sale Price	Sale price for second transaction	Numeric
Transaction date	Property transaction date	Category
Holding Period	Time between first and second transactions.	Numeric
Property Type	Type of the property, apartment or houses.	Category
Postcode	Full postcode of the property	Category
Postcode district	3-digit postcode, the first part of the postcode	Category
Indices of deprivation	Measure of poverty level of small areas	Numeric
Remaining Lease Group	Equals 1 if the remaining lease lies in one of the groups.	Category
Remaining Lease Dummy	Equals 1 for each remaining lease from 1 to 999.	Category
Lease Start Year	The first registered lease year	Numeric
Lease Term	Original lease term of the property.	Category

Notes. Table shows the summary of main variables in the final matched dataset. Description for each Numeric and category variables have been given.

Table 2.3 shows the decile distribution of the indices of deprivation in 2019. England and Wales have 32,844 lower-layer super output areas (LSOA). The decile divides them into ten equal groups. Each decile group represents their relative poverty level. In this study, I define Decile 1 and Decile 2 as the 20% most deprived area (poor area). Deciles 9 and 10 represent 20% of the least deprived area (rich area). In later analysis, I estimate discounts and the implied discount rates in the poor and rich areas to compare the difference in household living in these two areas. The Indices of Deprivation data comprises information on the level of deprivation for all lower-layer super output areas (LSOAs) in England and Wales. Deprivation is measured across seven domains with appropriate weights: Income (22.5%), Employment (22.5%), Education, Skills, and Training (13.5%), Health and Disability (13.5%), Crime (9.3%), Barriers to Housing and Services (9.3%), and Living Environment (9.3%). Hence the definition of rich or poor in this study is not solely for the income level, it stands for the overall living standard for households, generally the 20% most deprived area (poor area) means households who live in this area may have relatively low income, lack of employment opportunity, lack of suitable skill training, lower health status, higher crime rate and worse living environment, while households in rich area are opposite. This is a research angle that existing literatures have not been involved in, which enable to see the variation of investment preferences for households with different living status.

Table 2.3 Distribution of the indices of deprivation

Decile	Decile Description	Ranks
1	10% most deprived	1 to 3,284

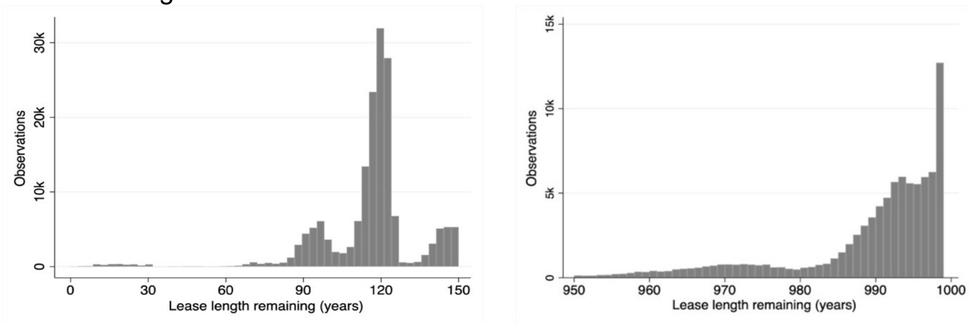
2	10% to 20%	3,385 to 6,568
3	20% to 30%	6,569 to 9,853
4	30% to 40%	9,854 to 13,137
5	40% to 50%	13,138 to 16,422
6	50% to 60%	16,423 to 19,706
7	60% to 70%	19,707 to 22,990
8	70% to 80%	22,991 to 26,275
9	80% to 90%	26,276 to 29,559
10	10% least deprived	29,560 to 32,844

Note. Table shows the deprivation ranks and decile. Deciles divide 32,844 neighbourhoods in England and Wales into 10 equal groups with decile 1 and 2 represents the 20% most deprived (poor) region and decile 9 and 10 represents the 20% least deprived (rich) region.

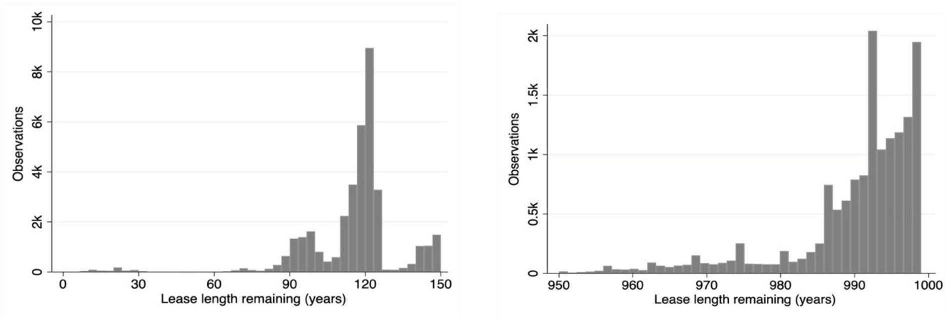
Figure 5.1 illustrates the distribution of the remaining lease length in the matched dataset at the time of sales. Panel A provides an overview of the full repeat sales sample distribution in England and Wales. This plot allows for a comprehensive understanding of the range and distribution of lease lengths across the entire dataset. To focus on the specific study of leasehold discounts in relation to poor and rich areas, Panels B and C zoom in on the range of

Figure 2.1 Repeat-sales sample distribution

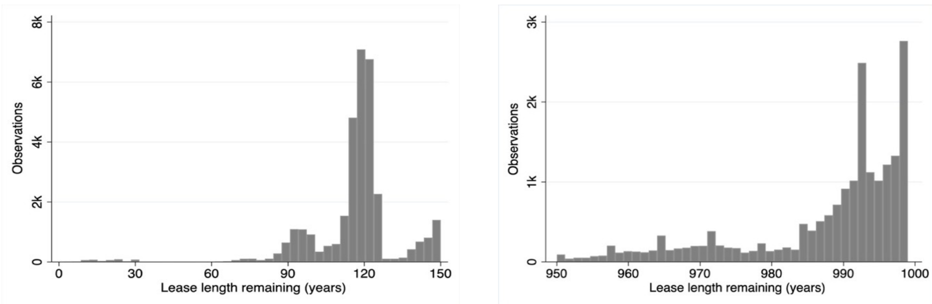
Panel A England and Wales



Panel B Poor area



Panel C Rich area



Notes. Figure shows the distribution of remaining lease length at the time of sales in the matched repeat sales pair dataset. Panel A shows the distribution in England and Wales. Panel B and Panel C shows the distribution of poor area and rich area, respectively.

lease lengths from 0 to 150 years and 950 to 999 years. These panels highlight the lease length distributions in poor areas (Panel B) and rich areas (Panel C). By narrowing the range of lease lengths, I can better analyze and compare the leasehold discounts in these specific contexts. To establish a baseline for comparison, this study adopts the conservative principle, considering leaseholds with a remaining lease length of 980 years or more as the baseline group. This baseline group provides a reference point for estimating the relative leasehold discounts for different remaining lease lengths in the range of 0 to 150 years. By comparing these discounts to the baseline group, I can infer the implied discount rates associated with various lease lengths.

Table 2.4 Summary statistics for subsample (below 80 years remaining)

		Mean	Std. dev.	P25	P50	P75	P95	P99
All	Price (£'000)	170.38	319.90	15	55	142	850	1712
	Remaining Lease	30.97	22.00	15	21	40	79	80
	Lease Term	31.23	29.08	15	20	29	99	102
	Lease Start Year	2009	11.20	2007	2013	2016	2019	2019
	Lease End Year	2040	21.46	2026	2032	2042	2087	2093
0-30	Price (£'000)	151.55	324.91	10	35	110	702	1712
	Remaining Lease	18.31	6.08	14	20	22	30	30
	Lease Term	16.61	6.54	10	15	20	25	30
	Lease Start Year	2012	5.50	2009	2014	2016	2019	2019
	Lease End Year	2029	6.36	2025	2028	2033	2040	2044
30-50	Price (£'000)	152.64	258.67	15	45	150	759	1118
	Remaining Lease	42.30	5.74	39	40	50	50	50
	Lease Term	31.45	17.11	20	25	42	51	99
	Lease Start Year	2012	11.16	2011	2016	2017	2019	2019
	Lease End Year	2043	11.73	2036	2039	2055	2067	2069
50-80	Price (£'000)	166.07	339.83	10	35	120	961	1712
	Remaining Lease	21.25	11.02	15	20	25	40	70
	Lease Term	17.49	6.64	10	15	21	30	39
	Lease Start Year	2013	4.56	2010	2014	2017	2019	2019
	Lease End Year	2030	7.58	2025	2029	2036	2043	2053

Notes. Table shows the summary statistics for subsample (below 80 years remaining) with several split (all, 0- 30, 30-50 and 50-80). Lease term represents the initial lease length in the contract.

Table 2.4 presents the summary statistics for the subsample consisting of leaseholds with a remaining lease length below 80 years. This subsample is unique due to the trigger of marriage value and the potential occurrence of lease extension and collective enfranchisement. I focus on this subsample in Section 2.8 to investigate the impact of the cutoff point (80 years) on the price discount of otherwise identical properties

2.5 Methodology

In section 2.5, I utilize two commonly employed models, namely the hedonic price model and the repeat-sales model, to estimate the relative leasehold discounts compared to the baseline group, which comprises leaseholds with 980-999 remaining leases. I employ two different methods to group the leaseholds based on their remaining lease lengths.

The first method is the group method, where leaseholds with similar remaining lease lengths are grouped together. I create four distinct groups based on the remaining lease lengths: 0-80 years, 80-100 years, 100-125 years, and 125-150 years. By categorizing the leaseholds into these groups, I can estimate the relative discounts of each group compared to the baseline group.

The second method I employ is the dummy method. Using this approach, every integer value of remaining lease length becomes a categorical variable, excluding the baseline group. By treating each remaining lease length as a separate category, I can estimate the relative discounts for each specific remaining lease length in comparison to the baseline group.

2.5.1 Hedonic price regression

The hedonic price regression method was initially developed by Waugh (1928), Court ‘s 1939 analysis, and Griliches (1971). It regresses the log-level of prices against housing characteristics over time, in which it can decompose the value of housing into the value of a series of housing characteristics and estimate each characteristic’s contribution value. The typical strength of the hedonic model is that it provides a direct estimation of the price change over time and the corresponding contributory value for each housing characteristic. In academic research, the hedonic model is commonly used in real estate economics, price index construction and the estimation of price change due to changes in a certain characteristic.

The hedonic price model with group method is expressed as:

$$P_{iht} = \alpha + \sum_{j=1}^{4} \beta_j 1_{\{T_{it} \in LeaseGroup_j\}} + \delta X_{it} + \lambda_{ht} + e_{iht} \tag{2.1}$$

where P_{iht} is the logarithm transaction price of an individual property i with a time of sale t in geographical area h. β_j capture the log-discount of leaseholds with remaining lease in group j relative to the baseline group. λ_{ht} is the interaction between three-digit postcode and time of sale (month) dummies. X_{it} is a property characteristic variable and δ is the corresponding coefficient. Standard errors are clustered at both the three-digit postcode and month level.

The hedonic price model with dummy method is expressed as:

$$P_{iht} = \alpha + \sum_{j=1}^{979} \beta_j D_j + \delta X_{it} + \lambda_{ht} + e_{iht} \tag{2.2}$$

where D_j is the integer value of remaining leases of the property, ranging from 1 to 979 and the β_j is the corresponding coefficient that capture the log-discount of leaseholds with any integer value of remaining lease relative to the baseline group.

However, the hedonic method has been criticized for a series of problems, even though it is one of the most used regression methods in economics research. Problems include: The assumption of no structural change during the sample period can lead to unrealistic distortion of estimation result (Clapp & Giaccotto, 1998); The omitted variable bias that it cannot include every single contributory characteristic (Case & Quigley, 1991; Ekeland et al., 2004); Cannot control the unobserved heterogeneity across different but similar properties. Among the problems mentioned above, the most criticized problem is the omitted variable bias. If the hedonic method omits unobserved variables that could significantly affect the housing price over time, it can lead to a huge bias in estimations.

2.5.2 Repeat-sales regression

Even though the hedonic price regression model can provide a direct estimation of the price change over time, it relies on thorough and high-quality housing characteristic information. This cannot be achieved sometime due to the restriction of data collection or the error that occurred in the raw data collections. Hence, a less data-intensive regression method has been developed, the repeat-sales regression method.

Repeat-sales regression model is a method introduced by Bailey et al. (1963) and popularized by Case & Shiller (1988). It is a commonly used approach in economically empirical analysis based on housings that transacted more than once during the sample period and regress price changes of the same property over time. The most significant assumption of the repeat sales method is that the characteristics and quality of the housing do not change during the first and second transaction, so the regression on the pure price change among the first and second transactions of the same property can provide a measure of house price dynamics (Jones, 2010). This is crucial in real estate research, as properties inherently possess unique characteristics, and it is difficult to find two properties that are exactly the same. Collecting comprehensive and detailed property characteristics data can be challenging due to missing values or discrepancies across different data sources. Case & Shiller (1988) proposes that the repeat-sales method can have more accurate control for the housing characteristics. By analyzing the price differences between repeat sales of the same property, the repeat-sales model helps mitigate omitted variable bias and specification errors that can arise in the hedonic price model. It allows researchers to capture the pure price appreciation or depreciation of properties by controlling for the property-specific unobserved factors that remain constant over time. Indeed, it is important to see the limitation of the repeat sales model. The traditional repeat sales model may overlook variables that change over time, which could lead to omitted variable bias. For example, change in property features between transactions could affect the value of property and create bias into the repeat sales model (Cheung, 2023). There are many studies try to improve the model and make adjustments, such as the suggestion of spine regression approach proposed by Melser (2023). Melser (2023) enable the housing characteristics to influence the price movement through imputing the price changes for the stock of homes and control for selection-on-observables. Yiu and Cheung (2021) use the improvement-value adjusted repeated sales method to compensate the limitation of repeat sales model. Despite them, there are a bunch of methods out there to improve the model and fix the quality movement between sales. In terms of the key concern of the model is the quality change between two sales, this study try to solve it through the comparison angle, not the model improvement as there are just too much way for it and it is unsure which one is the best. The hedonic model discussed before can be the comparison to the repeat sales model, so that in this study, the result of price difference is presented by both hedonic model and the traditional repeat sales model. In this way, the study is able to propose the comparison of results as hedonic model should be able to capture the quality change of properties over time.

The repeat-sales model with group method is given by:

$$P_{iht} = \alpha + \sum_{j=1}^{4} \beta_j 1_{\{T_{it} \in LeaseGroup_j\}} + \delta X_{it} + \lambda_{ht} + \theta_i + e_{iht} \tag{2.3}$$

For the repeat-sales model, I include θ_i, the pair fixed effect in the model[8]. X_{it} is a variable capture time-varying characteristic of the property and δ is the corresponding coefficient. The inclusion of pair fixed effects and time varying characteristic can imply that any changes in price appreciation should result from the differences in remaining lease.

The repeat-sales model with dummy method is given by:

$$P_{iht} = \alpha + \sum_{j=1}^{979} \beta_j D_j + \delta X_{it} + \lambda_{ht} + \theta_i + e_{iht} \tag{2.4}$$

[8] The θ_i is pair fixed effect in this analysis as the common accepted form in academic. It means if a property is transacted 3 times, I 'break it up' into 2 pairs, instead of the property fixed effect that treating it as 1 property. See Francke (2010) for the detailed difference.

where D_j is the integer value of remaining leases of the property, ranging from 1 to 979 and the β_j is the corresponding coefficient that capture the log-discount of leaseholds with any integer value of remaining lease relative to the baseline group, the leaseholds property with 980-999 remaining leases.

Nonetheless, repeat-sales methods are not without limitations. As mentioned above, the assumption is that housing characteristics and housing quality do not change during the sample period. Intuitively, this is hard to happen since the property's structure can depreciate over time, and some properties might have renovation during the sample period. Another limitation of the repeat-sales model is that it excludes properties that have only transacted once. This can result in a reduced sample size and potentially introduce sample selection bias. It is important to be aware of this limitation when interpreting the results of the repeat-sales model and consider potential biases associated with the sample composition. In addition, the inefficient use of information on the repeat-sales method has also been criticized. Suppose there is a significant difference in price changes for properties that transacted only once or transacted more frequently than twice. In that case, the result of the estimation cannot provide the price change of the overall actual housing market, or the result is possible to be over-represented by those frequently transacted properties (Hansen, 2009).

2.5.3 Gordon Valuation Model

To estimate the implied discount rates based on the relative leaseholds discount, I use the predictions from Gordon's (1959) simple constant discount rate model. In this model, rental income Q_t grows at rate g and discounted at constant net rate r. Nevertheless, in this study, I will test whether the gross and net discount rate is constant or varies over time as Bracke et al. (2017) did, and then construct the term structure of discount rate in the England and Wales housing market.

As in Bracke et al. (2017), very long but finite leases should be equivalent to infinite leases, which are freehold. Hence, based on the Gordon (1982) valuation for infinite assets, the prices for the baseline group (leaseholds with 980+ years) are valued at $P_t = Q_t / (r - g)$. After adjusting the infinite price for finite leaseholds price, the leaseholds with T remaining leases are valued at $P_t^T = P_t\,(1 - e^{-(r-g)\,T})$. In this way, I can have the valuation of price discount between very long-term leaseholds and shorter-term leaseholds, which is given by:

$$Disc_t^T = \frac{P_t^T}{P_t} - 1 = -e^{-(r-g)T} \tag{2.5}$$

where $Disc$ represents the relative leaseholds discount between various leaseholds and the baseline group (leaseholds with 980+ remaining leases). T represents the remaining leases of the property. Then I can infer the implied net discount rates $(r - g)$ for housing cash flows. And if I have the rental growth rate g, I can further infer the implied gross discount rate r.

Discounted cash flow (DCF) is the most used methodology for valuation of financial projects, stocks, bonds and the business entity like a corporation (Smith, 2023). The Gordon Valuation Model uses the DCF approach as the fundamental and most of the people in financial industry use it to compute the value of the stock and focuses on future cash flows from dividends. This is commonly used in the financial market and not in the analysis of housing market. However, Giglio et al. (2014) is the first to try to apply it in the housing research and treat the housing as stock, the rents of housing as dividends in stock. Some people may argue that the constant growth rate assumption in the model is not valid in the long term. Smith (2023) points out that some company managers use the weighted average cost of capital to determine the discount rate for acquiring capital to fund long-term projects. However, this approach is not directly applicable in the housing market studies as it needs anticipate returns against the risk of the investment and there is no preceding literature use it in the housing market study. In addition, the DCF approach, which is the fundamental of Gordon Valuation Model has been used and continually used in the financial valuation project. This prove the reliability and the suitable use of the assumption of Gordon Valuation Model as it fits with the most common use of valuation model in the financial industry. Hence, in this study, I will stick to the Gordon Valuation Model, and it has been proved can be used in the housing market discount rate study as in Giglio et al. (2014) and Bracke (2017) as well.

2.6 Relative Leasehold Discounts

2.6.1 Hedonic price model result

In Table 2.5, I present the regression results using the hedonic price regressions with the group method for apartments. The columns represent different samples and specifications. In column (1), I report the results using all samples in the matched dataset, which includes properties transacted only once during the study period. This provides a comprehensive analysis that incorporates the entire sample. In column (2), I exclude properties located in the London area to examine the price discounts in regions outside of London. This allows for a comparison between the relative leasehold discounts in London and other regions. In column (3), the analysis focuses specifically on properties located in the London area. This allows for a comparison of the leasehold discounts between London and other regions within the dataset. Column (4) presents the results for properties located in a poor area, representing the 20% most deprived areas in England and Wales. This provides insight into the leasehold discounts in economically disadvantaged regions. Column (5) reports the results for properties located in a rich area, representing the 20% least deprived areas in England and Wales. This allows for an examination of the leasehold discounts in economically advantaged regions.

Table 2.5 Hedonic price regressions with group method

	(1) All	(2) Excl. London	(3) London	(4) Poor area	(5) Rich area
0-80 years	-0.248***	-0.262***	-0.226***	-0.231***	-0.241***
	(0.033)	(0.021)	(0.035)	(0.036)	(0.095)
80-100 years	-0.228***	-0.240***	-0.203***	-0.182***	-0.191***
	(0.015)	(0.015)	(0.032)	(0.023)	(0.026)
100-125 years	-0.127***	-0.114***	-0.166***	-0.083***	-0.126***
	(0.018)	(0.011)	(0.036)	(0.024)	(0.019)
125-150 years	-0.108***	-0.087***	-0.120***	-0.071**	-0.091***
	(0.019)	(0.014)	(0.034)	(0.024)	(0.020)
Fixed effects	PC x M	PC x M	PC x M	PC x M	PC x M
N	572,706	386,438	187,082	114,268	114,460

Notes. The dependent variable is the log price for apartments in England and Wales between 2004 and 2020. I include three-digit postcode by month fixed effects. Standard errors in parentheses clustered by three- digit postcode and by transaction month. Significant Levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The results display the price discounts associated with leaseholds in different remaining lease length groups compared to very long-term leaseholds (leaseholds with 980+ remaining leases). The analysis employs the group method, grouping leaseholds with similar remaining lease lengths together. In this case, I have four groups: 0-80 years, 80-100 years, 100-125 years, and 125-150 years. The coefficients for the remaining lease length groups indicate the price discounts relative to the very long-term leaseholds. Higher discounts are observed for leaseholds with fewer remaining leases, indicating that properties with shorter lease terms tend to command lower prices compared to those with longer lease terms.

Column (1) of the regression results shows that leaseholds with 0-80 remaining leases have a price discount of approximately 24% compared to very long-term leaseholds. For a median-priced apartment in England and Wales, this represents a discount of £38,400. The relative price discount gradually decreases to 22% for the 80-100 remaining leases group, 12% for the 100-125 remaining leases group, and 10% for the 125-150 remaining leases group. These discounts correspond to £35,200, £19,200, and £16,000, respectively. These relative discount results provide practical insights for leasehold property valuation in the UK. When leaseholders seek a lease extension or consider collective enfranchisement, they can consult a professional valuer who will provide a valuation report. The valuer will determine the relative discount of leasehold properties with specific remaining leases compared to the freehold, which can be used as a negotiation tool with landlords. Currently, valuers rely on their experience rather than empirical analysis using extensive transaction data to make such relative discount decisions.

By focusing on different areas in England and Wales, I find that in the 0-100 remaining leases group, leaseholds located in London tend to have lower discounts compared to leasehold properties in other regions. However, in the 100-150 remaining leases group, the results are opposite, with London properties showing higher discounts. One possible explanation for this difference is the challenges associated with short lease transactions. Selling or buying a property with a lease of fewer than 100 years requires the buyer to have a higher deposit-paying power, as many mortgage companies provide mortgages of 25 years or more. However, mortgage companies have tightened their lending criteria after the financial crisis and may not lend to buyers if the property has less than 70 or 80 remaining leases. Households in London generally have greater purchasing power, investment intentions, and choices compared to households in non-London areas. Consequently, leasehold properties with shorter leases in London may be valued more and have fewer price discounts. On the other hand, households in non-London areas tend to target properties with longer remaining leases in the 100-150 years range, leading to higher value for this group and fewer price discounts. When comparing poor and rich areas, the relative discount is higher in rich areas across all remaining lease groups. This indicates that households in rich areas place greater value on owning time and are willing to pay more for properties with longer remaining leases. The differences in price discounts across different regions highlight the importance of studying location-specific dynamics and the need for diverse policies that address the unique characteristics and needs of different regions.

2.6.2 Repeat-sales model result

Table 2.6 presents the regression results using the repeat-sales regressions with the group method for apartments. Each column represents a different sample selection, with the same specifications as the hedonic price regressions except for the inclusion criteria based on the repeat-sales model. In the repeat-sales model, only properties that have transacted more than once are included in the analysis, with two transactions of the same property forming a pair. This approach allows for a focus on the price differences between repeat sales of the same property, capturing the pure price appreciation or depreciation over time. The results from the repeat-sales model exhibit a similar pattern to the hedonic price regression results. Within the repeat-sales sample, I observe a gradual decline in the relative leasehold discounts from 27% for the 0-80 remaining leases group to 12% for the 125-150 remaining leases group. This corresponds to a discount of £49,140 and £21,840 for the median apartment in England and Wales, respectively. When examining different areas, I find that the relative discounts in London versus non-London areas and in poor areas versus rich areas exhibit the same pattern as observed in the hedonic model results. This suggests that the differences in leasehold discounts based on location and economic conditions hold consistent across both modeling approaches.

Indeed, the results of the repeat-sales regression consistently exhibit higher relative discounts compared to the hedonic price regression results. This highlights the importance of employing the repeat-sales model as an alternative method to address the issues of heterogeneity, omitted variable bias, and specification errors that may arise in the hedonic price model. By focusing on the price differences within the same property over time, the repeat-sales model provides a valuable perspective on the relative discounts between various term leaseholds and very long-term leaseholds.

To the best of my knowledge, this study represents the first analysis that applies the repeat-sales model to estimate the relative discounts of leaseholds with different remaining lease lengths compared to very long-term leaseholds. By utilizing this approach, I am able to mitigate potential biases and enhance the robustness of the findings. The higher discounts observed in the repeat-sales regression results further underscore the importance of considering the repeat-sales methodology in the analysis of leasehold properties.

Table 2.6 Repeat-sales regression with group method

	(1) All	(2) Excl. London	(3) London	(4) Poor area	(5) Rich area
0-80 years	-0.278***	-0.311***	-0.254***	-0.241***	-0.252***
	(0.033)	(0.022)	(0.036)	(0.043)	(0.045)
80-100 years	-0.241***	-0.278***	-0.236***	-0.197***	-0.211***
	(0.014)	(0.015)	(0.031)	(0.026)	(0.026)
100-125 years	-0.163***	-0.138***	-0.181***	-0.102***	-0.159***
	(0.016)	(0.011)	(0.033)	(0.025)	(0.018)
125-150 years	-0.121***	-0.100***	-0.144***	-0.080**	-0.123***
	(0.018)	(0.017)	(0.030)	(0.028)	(0.022)
Fixed effects	PC x M	PC x M	PC x M	PC x M	PC x M
N	290,240	193,204	93,352	57,099	57,191

Notes. The dependent variable is the log price for apartments sold more than once in England and Wales between 2004 and 2020. I include three-digit postcode by month fixed effects. Standard errors in parentheses clustered by three-digit postcode and by transaction month. Significant Levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The informal investigation conducted by Giglio et al. (2014), which explored the opinions of shareholders in the real estate market regarding the relative discount of leasehold properties, highlighted the diverse range of opinions on this matter. This diversity of opinions underscores the limitations of relying solely on valuers' professional knowledge in practical leasehold valuation. It also emphasizes the necessity of conducting large-scale empirical analyses to obtain academic evidence on the relative discounts between leaseholds with different remaining lease lengths and very long-term leaseholds.

By employing the repeat-sales model and conducting a comprehensive analysis, this study contributes to filling the gap in the existing literature. The empirical evidence derived from the repeat-sales model offers an alternative perspective and enhances the understanding of the relative discounts in leasehold properties. Moreover, it provides valuable guidance for practical leasehold valuation, supplementing the current hedonic analysis.

Additionally, the need for further analysis of areas with different poverty levels is recognized. Understanding the dynamics and variations in leasehold discounts across different socioeconomic contexts is essential for developing targeted policies and interventions. The repeat-sales model, with its ability to capture price differences within the same property over time, can provide valuable insights for academic research and practical leasehold valuation in diverse areas.

By conducting large-scale empirical analyses and incorporating the repeat-sales model, this study aims to contribute to both academic research and practical leasehold valuation by providing robust evidence on the relative discounts between leaseholds with different remaining lease lengths and very long-term leaseholds.

2.7 Comparison to existing estimates

In this subsection, I aim to compare the results of the hedonic price model and repeat-sales model in this research with the current estimates in academic research, particularly with the findings presented in column (1) of Table III in Giglio et al. (2014). To ensure comparability, I exclude the 0-80 remaining leases group in the second and third columns of Table 2.7, as Giglio et al. (2014) also excluded leaseholds with less than 80 years remaining leases to avoid the influence of lease extensions.

Table 2.7 Comparison with Giglio et al. (2015)

	Giglio et al. (2014) *Hedonic* *(2004-2013)*	This research *Hedonic* *(2004-2020)*	This research *Repeat-Sales* *(2004-2020)*
80-100 years	-0.176***	-0.228***	-0.241***
	(0.007)	(0.015)	(0.014)
100-125 years	-0.110***	-0.127***	-0.163***
	(0.008)	(0.018)	(0.016)
125-150 years	-0.089***	-0.108***	-0.121***
	(0.008)	(0.019)	(0.018)
Fixed effects	PC x M	PC x M	PC x M

N	1,373,383	572,706	290,240

Notes. The first column of the Table shows column (1) of Table III in Giglio et al. (2014). The second column shows the result of hedonic regression in this research and the third column shows the result of repeat-sales regression in this research. All three columns focus on England and Wales, this research use transactions in 2004-2020 and Giglio et al. (2014) use transaction in 2004-2013. The baseline category in Giglio's research is freehold properties, the baseline category is 980 years + leaseholds.

Compared to the Giglio et al. (2014), the baselines estimates provided by Giglio et al. (2014) serve as the reference point for comparison is freehold properties, as they assume that leaseholds with 700+ remaining leases have similar values to freehold properties. The price difference estimation between the reference group and the varying lease group is extremely important for this type of study as it represents the time value of money for the same property. However, the chosen reference group of freehold property in Giglio et al. (2014) may lead to misestimation of the relative discount measurement as the freehold and very long-term leasehold have the fundamental difference. First, even though for the very long-term leasehold property, the leaseholders still need to pay ground rent to their freeholders, this generates the different value over time (Seagraves, 2023). Second, the leasehold system has been questioned and unsatisfied recently. The unfairness, exploitation against developers and landlords are severe as buyers were less aware of the intricacies of the leasehold system at the point of purchase (Camilla and Will, 2019), therefore even though the price difference between very long-term leasehold and freehold may seem tiny in the Giglio et al. (2014), it could be due to the less awareness of homebuyer on the leasehold system. Third, politicians and advocacy group have voiced up against the leasehold system as it allows developers and landlords to make profit at the expense of leaseholders (Harding et al., 2018). Seagraves (2023) indicates that there has been a legislation aimed at banning the leasehold system for the newly built homes in the UK. If the very long-term leaseholds truly as the same as the freehold property, then there would be no such debates going on. Hence, there is some unobserved bias if use freehold as the reference group in the analysis. In this study, I use leaseholds with 980+ remaining leases as the baseline group to ensure consistency with varying lease group, this is one of the contributions of this chapter by focusing on leasehold properties within this analysis, I aim to mitigate unobserved heterogeneity and preference differences between freehold and leasehold properties compared to the result of Giglio et al. (2014) as more accurate estimation of price discount is the key to the further discount rate estimation.

Furthermore, it is important to note that the hedonic result and repeat-sales result in Table 2.7 may have different sample sizes due to variations in data sources and the data cleaning process. Giglio et al. (2014) obtained the unpublic lease information directly from the Land Registry to add variables related to leaseholds characteristics, however, the unpublic lease information cannot been seen. Scholars cannot use those unpublic dataset to validate and justify the results. Also, their unpublic dataset cover only part of the datset as the Land Registry cannot provide all to them at that time. Luckily, the registered lease dataset has been published by the land registry recently, although there is no common identifier to match property transaction dataset and the lease dataset. This led to the second contribution of this chapter, as this chapter is the first to utilize the publicly available lease dataset to conduct a fuzzy match between the transaction and registered leases datasets based on addresses to obtain the matched dataset. Consequently, the sample sizes may be smaller in the second and third columns due to the fuzzy match high standard matching criteria.

In addition, It is crucial for governments to update discount rate guidelines regularly based on the latest available data. However, it is noteworthy that the UK discount rate guideline has not been updated since 2003. The third contribution of this study is using the newest data and provide the result of repeat sales estimation on this study as there is only hedonic estimation available on this kind of study yet. I utilize seven additional years of transaction data compared to Giglio et al. (2014) and by employing on both hedonic and repeat-sales model, as presented in the second and third column of Table 2.7, I observe a relatively higher discount compared to the Giglio's estimation. This difference in discounts may arise from the heterogeneity of different properties, the preference for freehold properties, and the presence of omitted variable bias.

In short, by comparing the results with the baseline estimates in Giglio et al. (2014), I provide valuable insights into the relative leasehold discounts in England and Wales. Despite some differences in methodology and sample sizes, this analysis contributes to the existing academic research by offering alternative estimates and shedding light on the variations in leasehold discounts. The findings of this study highlight the importance of considering these factors and conducting robust empirical analyses to estimate the relative discount, which is the base for estimating the inferred discount rates. As property characteristics and market conditions evolve over time, it is essential for governments to update their discount rate guidelines to ensure they reflect the current market dynamics and provide accurate guidance for policy decisions and valuations.

2.8 Short-term leases comparison

In Tables 2.8 and 2.9, I present the results of the short-term lease comparison, specifically focusing on leaseholds with remaining leases below 80 years, which is close to the cutoff point where the marriage value becomes relevant. This setting resembles a regression discontinuity design.

Table 2.8 Short-term leases comparison (below 80 compared to 80-90)

	(1) All	(2) Excl. London	(3) London	(4) Poor area	(5) Rich area
Panel A *Hedonic model*					
0-80 years	-0.067***	-0.078***	-0.063***	-0.070***	-0.068***
	(0.019)	(0.020)	(0.016)	(0.024)	(0.018)
N	21,838	18,272	3,566	4,506	3,694
Panel B *Repeat sales model*					
0-80 years	-0.059***	-0.068***	-0.054***	-0.062***	-0.058***
	(0.021)	(0.018)	(0.017)	(0.022)	(0.020)
N	10,846	9,066	1,766	2,175	1,788
Fixed effects	PC x M	PC x M	PC x M	PC x M	PC x M

Notes. Table shows the short-term leases comparison (below 80 years and 80-90 remaining lease). Panel A shows the regression results of hedonic model and panel B shows the results of repeat sales model. I include three-digit postcode by month fixed effects. Standard errors in parentheses clustered by three-digit postcode and by transaction month. Significant Levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

In Panel A of both tables, I compare the below 80 years lease group to otherwise identical properties with 80-90 remaining leases. I analyze this comparison using both the hedonic and repeat-sales models, as shown in Table 2.8 and Table 2.9, respectively. The results indicate that the price discount for the below 80 years lease group is approximately 6-7% compared to properties with 80-90 remaining leases in the entire sample. Panel A of both tables demonstrates that the price discounts estimated using the hedonic and repeat-sales models are similar, with the repeat-sales model yielding estimates around 1% lower than the hedonic model. These findings provide further evidence of the consistent patterns observed in the analysis and reinforce the robustness of the results.

By conducting this short-term lease comparison, I gain insights into the price discounts associated with leaseholds approaching the marriage value cutoff point. These findings contribute to the understanding of the valuation dynamics and market behavior in the context of short lease extensions or collective enfranchisement.

Overall, both the hedonic and repeat-sales models yield comparable results, highlighting the validity and reliability of the estimates. The slight variation between the models underscores the importance of utilizing different analytical approaches to validate findings and account for potential biases. The results indicate that non-London areas exhibit the highest price discount for leaseholds, suggesting that households in these areas place greater value on longer lease terms and rely on bank financing[9]. This preference for longer leases may stem from a desire for stability and the ability to secure mortgage financing more easily. The higher price discount in non-London areas reflects

[9] Properties with less than 80 years lease could have difficulty in securing the mortgage from lenders.

the importance of lease length in these regions and the impact it has on property valuations.

Table 2.9 Short-term leases comparison (below 80 compared to 90-125)

	(1)	(2)	(3)	(4)	(5)
	All	Excl. London	London	Poor area	Rich area
Panel A *Hedonic model*					
0-80 years	-0.105***	-0.118***	-0.093***	-0.098***	-0.090***
	(0.019)	(0.020)	(0.018)	(0.034)	(0.018)
N	287,164	237,734	49,430	63,456	57,362
Panel B *Repeat sales model*					
0-80 years	-0.097***	-0.129***	-0.091***	-0.082***	-0.086***
	(0.021)	(0.017)	(0.020)	(0.022)	(0.023)
N	143,545	118,827	24,701	31,680	28,641
Fixed effects	PC x M	PC x M	PC x M	PC x M	PC x M

Notes. Table shows the short-term leases comparison (below 80 years and 90-125 remaining lease). Panel A shows the regression results of hedonic model and panel B shows the results of repeat sales model. I include three-digit postcode by month fixed effects. Standard errors in parentheses clustered by three-digit postcode and by transaction month. Significant Levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

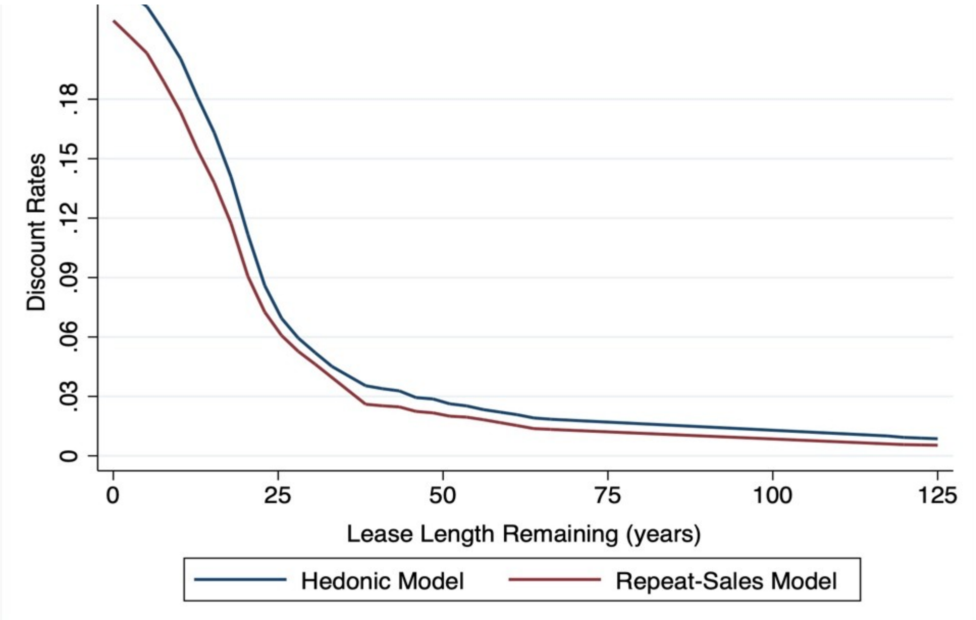
In contrast, households in London exhibit a relatively higher tolerance for properties approaching the lease cutoff point. This finding can be attributed to the intense housing price competition in London, where demand often outweighs supply. In such a competitive market, buyers may be more willing to accept properties with shorter lease terms, potentially due to the availability of alternative funding sources or a preference for riskier assets.

The results highlight the regional variations in price discounts and provide insights into the different factors influencing property valuations. Understanding these preferences and dynamics in different areas is crucial for policymakers, investors, and individuals involved in property transactions. It underscores the need to consider regional context and market conditions when assessing the value of leasehold properties and making informed decisions.

2.9 Implied discount rates

Figure 2.2 shows the term structure of net discount rate estimation using equation (2.5). The implied net discount rate ($r - g$) can be inferred from the relative leaseholds discount $Disc$ and the remaining leases of the property T. The implied net discount rate can show how households in England and Wales treat future cash flows. Using the dummy method, the relative leaseholds discount of each remaining lease using hedonic price model and repeat-sales model can result from equation (2.2) and equation (2.4), respectively. The estimated net discount rates are then fitted with a second-degree local polynomial weighted by the number of sales at each remaining lease length.

Figure 2.2 Implied net discount rates (repeat-sales and hedonic model)

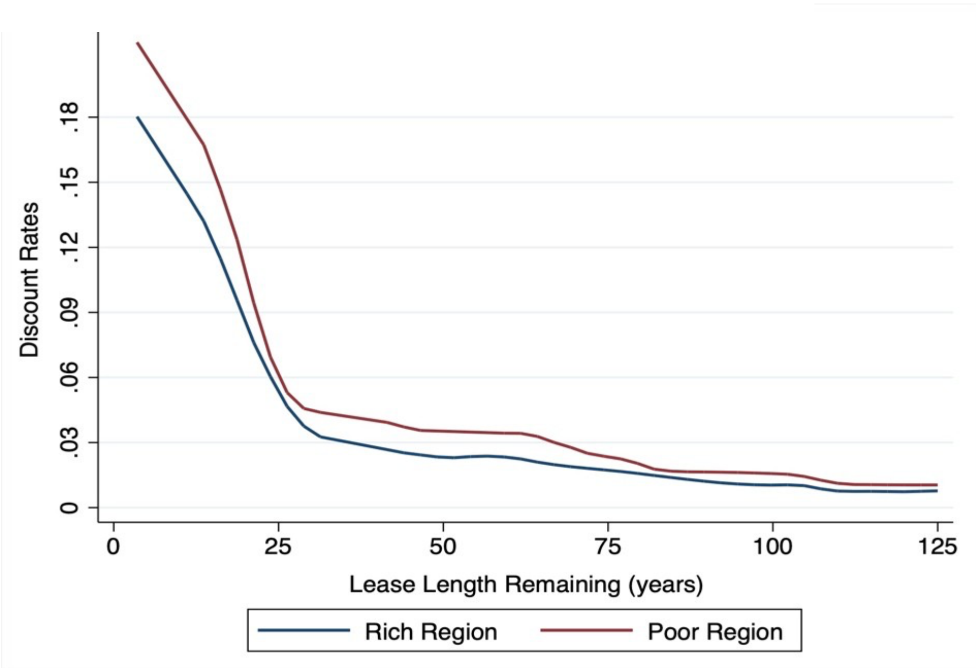


Notes. The chart shows the net discount rates implied by the relative leaseholds discount of each remaining leases length with second-degree local polynomial. The Figure shows the term structure of net discount rate using repeat-sales model and hedonic model on large-scale real transaction data.

The term structure of net discount rates observed in this analysis aligns with the declining discount rate guidelines in the UK and France, as well as the findings of Giglio et al. (2021) on real estate discount rates. I observe a downward-sloping shape, with higher discount rates for very short leases and lower discount rates for long leases with more than 100 years remaining.

The estimation of the net discount rate for housing cash flows beyond 100 years is remarkably low, with a rate of 1.3% using the hedonic model and 1.1% using the repeat-sales model. These estimates are consistent with previous studies by Giglio et al. (2014) and Bracke et al. (2017), which reported rates of 1.9% and 2% respectively. However, the estimates in this study are even lower, particularly with the repeat-sales model, underscoring the need for alternative methods to the hedonic model in discount rate estimation. There are many debates going on which model to choose, hedonic or repeat sales model. Both of them are commonly use method, especially in the housing studies. For example, Melser (2022) points out that the repeat sales method is susceptible to selection bias as price movements for these properties may not be representative of the overall properties. Lots of academic papers try to improve and solve the limitation for both hedonic and repeat sales model. Melser (2022) propose a new approach to control for selection bias in the repeat sales model. They impute the price changes for each home in the market, instead of only using the property sold twice or more. Contat and Larson (2024) develop new algorithm to ensure feasible estimation of geographically granular repeat sales model in cases of low transaction counts. In addition to these, there are many more works on how to improve the repeat sales model or the hedonic model (e.g. Oust et al., 2019; Yiu and Cheung, 2021). The key point of this study is not to compare which model is better to be used. This study is providing a new evidence of repeat sales model on the discount rate estimation as there is no such evidence of repeat sales model exists in this research area, in fact, the major paper in this area Giglio et al. (2014) and Bracke et al. (2017) are using hedonic model to examine the discount rate in housing market because of the lack of data or the unfeasible model usage in their dataset. This paper decide to provide the evidence in using the repeat sales model to estimate the implied discount rate in the UK housing market. Hence, the result can be used to compare with the result generated by the hedonic model and provide extra evidence for the policy designer to refer.

Figure 2.3 Implied net discount rates (rich and poor region)



Notes. The chart shows the term structure of net discount rates in poor and rich area, respectively. The net discount rate implied from the estimated leaseholds discount using repeat-sales model.

To examine the application of net discount rates in poor and rich areas, I conducted a regression analysis focusing on these two regions. The results, as shown in Figure 2.3 and equation (5.4) and equation (5.5), indicate that households in poor and rich areas apply different net discount rates.

Households in rich areas (20% least deprived) tend to apply a lower net discount rate of 1.0%, while households in poor areas (20% most deprived) use a net discount rate of 1.3%. As the identification strategy of rich and poor area in the study is based on various factors including income, employment, education, skills, training, health, disability, crime, barriers to housing and services and living environment. It is not simply depending on money to distinguish rich and poor area. It is the overall welfare of the region define the rich or poor area in this study. This finding suggests that households in rich areas assign greater importance to future cash flows when making investment decisions, demonstrating a willingness to invest for future returns rather than immediate consumption. There are several reasons drive this investment preference. Because the rich area defined in the study is not just about income level, hence households live in rich area enjoy better public education, abundant skills and training for work, better health care, less crime rate and better living environment. Hence, they are the beneficiary of this better living standard compared to those living in the poor area. Netuveli and Watts (2020) use the UK Household Longitudinal Study to explore whether the pro-environmental behaviours and attitudes are associated with health, wellbeing and life satisfaction. They found that the households with higher life satisfaction scores, physical health and mental health tend to have more pro-environmental behaviours and attitudes. This phenomenon has been justified in many countries apart from the UK. Capstick et al. (2022) use data obtained in Brazil, China, Denmark, India, Poland, South Africa and the UK, they have also observed the positive and reciprocal relationship between higher life satisfaction, wellbeing and the pro-environmental behaviour. The lower discount rate shown in the rich area, representing the households live in these areas have better wellbeing and life satisfaction, hence they would give more weight and consider the future generation when they make investment decision compared to those live in the poor area.

The London area holds a unique position within the UK, attracting a significant portion of households due to its abundant resources and distinct policy settings. While Bracke et al. (2017) estimated housing market discount rates specifically for nineteenth-century London using historical transaction data, this study expands beyond London to encompass a comprehensive examination of discount rate applications across various areas.

Figure 2.4 presents the term structure of net discount rates in London, non-London areas, and England and Wales as a whole. The observed trend of declining net discount rates aligns with the downward-sloping pattern found in previous analyses. Notably, households residing in non-London areas exhibit a lower net discount rate of 1.2% in comparison to those in London areas, who employ a net discount rate of 1.6% for housing cash flows extending beyond 100 years in the future. This finding suggests that households in London assign relatively less weight to future cash flows and prioritize immediate returns, while households in non-London areas are more open to slower returns in the future.

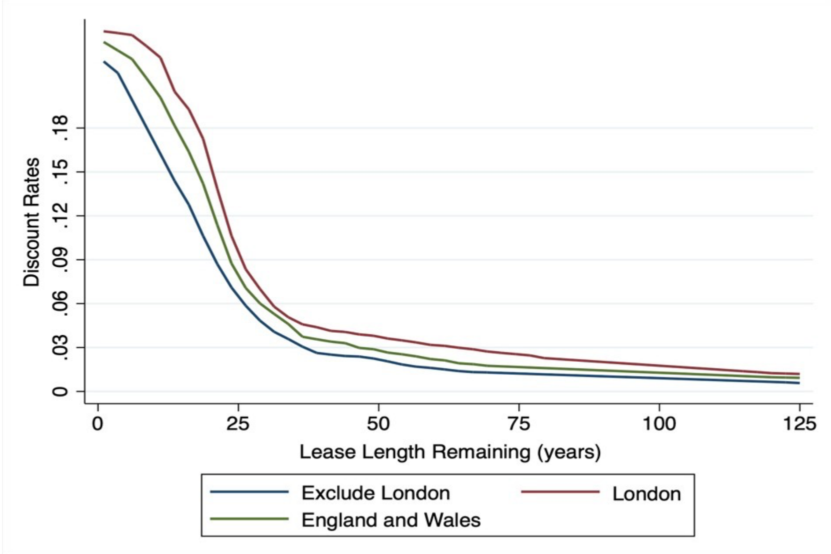
The differential net discount rates applied in London and non-London areas reflect distinct preferences and investment behaviors within these regions. Roser (2009) indicates that the idea of optimal growth models is to look for a balance between consumption and savings that maximized discounted utility over time, where it is assumed that what is saved is invested at a positive rate of return. It shows the fundamental differences of whether save more today or consume more today for the future generation. Households in London shows a preference to save more and tend to invest in the project with positive rate of return compared to the households in non-London area. There are some reasons behind why households in London tend to have more practical way of using their money. Padley et al. (2017) points out that the largest additional costs in London continue to arise as a result of more expensive housing, childcare and public transport costs compared to outside London. The unique characteristics and dynamics of London as a global city, coupled with the the high level living cost and the availability of varying investment tools to get the investing money out of financial institution, likely influence households' investment decision-making processes as they need to make sure a positive rate of return investment to repay the cost of getting loan from financial institution and pay their high level cost of living, making them less likely to invest more for the future generation like the households in non-London area. In contrast, households in non-London areas may exhibit a greater willingness to accept longer-term returns and have less eager to save more for current positive rate of return for their investment. But it doesn’t mean households in non-London area do not chase recent return, the relative higher discount rate only means the households in non-London area are giving more weight to the future when they make investment decision compared to those in London.

The different investment preference for households live in London and non-London area and different pro-environmental behaviour for households live in rich and poor area lead to the implication of tailored housing strategies for different kind of areas. Currently, most housing strategies apply to the whole country, or it only targets at certain price range or type of the property. The future housing strategies should consider how to leverage the different status of areas to design the policy that can achieve the common objectives, like the wealth equality, higher life satisfaction, or more affordable housing.

Estimating the gross discount rates by incorporating the long-run real rental growth rate provides further insights into the investment dynamics in the housing market. While previous studies such as Giglio et al. (2014) and Bracke et al. (2017) utilized data from the CPI component 'actual rents for housing' to estimate the average long-run real rental growth rate, there are limitations to this approach in terms of explicitness and the relatively short study period.

Recent academic research has explored the real rental growth rates over longer time periods, offering more comprehensive insights. Eichholtz et al. (2019) investigate real rental growth in housing spanning from 1500 to 2020 across seven cities, revealing a real rental growth rate of 0.18% for London. This rate is 0.44% lower than the estimate used by Giglio et al. (2014) and Bracke et al. (2017). Chambers et al. (2021) examine the period from 1901 to 1970 and found a real rental growth rate of -1.0% for residential real estate in the UK.

Figure 2.4 Implied net discount rates (London, Non-London, England and Wales)



Notes. The chart shows the term structure of net discount rates in London, non-London, England and Wales respectively. The net discount rate implied from the estimated leaseholds discount using repeat-sales model.

Considering the evidence from these studies, this research adopts a real rental growth rate of 0.18% for the long-run rental growth estimation. Incorporating this rate leads to an upward shift of 0.18% in the net discount rate, resulting in the estimation of the gross discount rate. The results indicate that households in England and Wales apply a gross discount rate lower than 1.3% using the repeat-sales model and 1.5% using the hedonic price model for housing cash flows extending beyond 100 years in the future. Moreover, households living in rich and poor areas apply gross discount rates lower than 1.2% and 1.5%, respectively, for housing cash flows exceeding 100 years. In terms of non-London and London areas, the estimated gross discount rates are 1.4% and 1.8%, respectively.

2.10 Threats to identification

Taking into account the potential effects of lease extension and leasehold enfranchisement on the relative leasehold discount and implied discount rates estimation is important for ensuring the accuracy and reliability of the analysis. Regarding lease extension, this analysis appropriately addresses the issue by considering the remaining lease term of the property, which reflects the corresponding transaction price regardless of whether a lease extension has occurred or not. By excluding observations with mismatched lease information due to delayed registration, I ensure that the analysis captures the appropriate relationship between remaining leases and transaction prices.

However, collective enfranchisement poses a challenge to the analysis as it signifies a transition from leasehold to freehold ownership. Properties that have undergone collective enfranchisement may have transaction prices that reflect the value of perpetual ownership rather than ownership for a limited number of years. To mitigate potential distortions caused by collective enfranchisement, I have manually identified properties with dual identities (both leasehold and freehold) and excluded them from the dataset. This approach helps ensure that the analysis focuses on properties with leasehold tenure and provides a more accurate estimation of relative leasehold discounts. By addressing the potential impacts of lease extension and collective enfranchisement on the analysis, I enhance the robustness and validity of the results, allowing for more accurate estimations of relative discounts and implied discount rates for leasehold properties.

2.11 Chapter summary and discussion

This research findings on the term structure of discount rates for housing cash flows and the differences in discount rates based on poverty level and location provide valuable insights into real estate economics and the understanding of price dynamics in the real estate market. The evidence presents the use of lower discount rates regarding households' recognition of future housing cash flows and their willingness to invest in the present for future returns, even for intergenerational period has implications for public policy, particularly in the areas like long-term infrastructure investment, ESG initiatives and climate change project. The discount rate found in this study echo the recommendation of 1.4% discount rate used in the public project valuation in Stern (2006), a landmark 2006 study commissioned by the UK government on the economics of climate change and the multigenerational impacts. A lower discount rate makes the far future look more important today and it will trigger a larger amount of investment on the long-term infrastructure, ESG and climate change project if the guided discount rate is lower. However, Nordhaus (1994) recommend relatively high discount rate of 4.3% with the aim of postponing necessary climate investments. Whether lower discount rate would lead to overinvestment on the climate change or long-term infrastructure project is controversary in both the academic and company view. As company has choice of investing in sustainable or unsustainable project. The lower discount rate increases the value of cash flows in the far future and hence encourage company's sustainable investing (Nishihara, 2023). Some public company would like to invest in the ESG project to attract individuals who support sustainable consumption to invest in their company. In the academic view, the Nordhaus-Stern debate shows there is a long-standing controversy about the appropriate discount rate for climate change mitigation and ESG initiatives as the project like this span long periods of time and the recommendation of lower or higher discount rate would lead to a great impact on the amount of investment on these projects (Schoenmaker & Schramade, 2024). Hence, there is no certain discount rate is solid over time, it should be used appropriately depends on the current status of investment preference and ESG preference. If the recent emphasize is on the economic development, then the investment for future generation should be postponed and if the climate change issues is becoming serious and can be seen a disaster for future generation, then the current investment for future should be emphasize. The guided discount rate should be reviewed in different stage by the policy designer based on the trade-off between economic objective and the social responsibility.

This chapter also further demonstrate the term structure of discount rate for real estate asset is downward sloping. However, this finding from real estate market also triggers the problems of whether policy designer should use the finding of discount rate in real estate market to discount investments in climate change abatement given that they have different risk level. The finding can only be used straightforward under the assumption that climate change abatement investments and real estate had similar risk level at all horizons. But how about the situation without the assumption. The implication of this downward sloping term structure from real estate market on the climate change abatement has been justified recently by Giglio et al. (2021). They use a tractable asset pricing model that incorporates features of climate change to show that the term structure of discount rates for climate-hedging investment should be upward sloping but bounded by the risk-free rate and the estimated housing discount rates should be the upper bound when the risk-free rates are unavailable.

In addition, the different slope finding from hedonic model and repeat sales model, households in rich and poor region, London and non-London area are statistically significant. This justifies the importance of the model chosen to estimate the price difference and to infer the implied discount rate as it shows the limitation, and the features of the model would lead to different result in the implied discount rate. Although there is no perfect model, the future studies can try to improve the estimating model as this is the foundation of the term structure of discount rate estimation. Also, the different finding under the same model for households in rich and poor area, households in London and non-London area indicate an important implication for the policy designer as they need to consider more when they design the policy and truly understand the objective and the potential downside of their policy. The different result shows in households in rich and poor area have different preference of investing money as they experience different level of life, households in rich area enjoy the health care, education, and have higher life satisfaction scores. Hence the policy designer should consider this different preference of investing and design more dedicated policies to mitigate affordable housing issues, wealth inequality and other public issues.

Moreover, this study contributes to the ongoing discussions on the valuation of lease extensions and enfranchisement, providing empirical evidence that can complement or challenge the subjective opinions of valuers in the leaseholds market. By shedding light on the relative discount between leaseholds of different terms and very long-term leaseholds, this research provides a basis for more informed and evidence-based valuations in leasehold transactions. Future research can further explore the impact of leasehold reforms, such as the Leasehold Reform (Ground Rent) Act 2022, on the valuation of leaseholds in the UK. This would help understand how these reforms shape the market dynamics and influence the perception of leasehold properties in relation to freehold properties. Overall, this study offers valuable insights into the discount rates applied by households, their preferences for future cash flows, and the implications for various aspects of the real estate market and related policy considerations.

Chapter 3

Buy-to-Let Market Responses to Transaction Tax Surcharge

3.1 Introduction

The housing needs of households can be fulfilled through either homeownership or renting. While homeownership is often considered the preferred choice, renting is a significant alternative, especially for lower-income households (Czerniak & Rubaszek, 2018). In the UK, the private rental market has historically been viewed as a less desirable option compared to homeownership. However, Kemp (2011) argues that the private rental market plays a crucial role in meeting the accommodation needs of households living in poverty and young people by offering affordable living spaces without the burden of a mortgage. It also provides a buffer for lower-income households against the periodic shocks in the real estate market, as evidenced by the impact of the 2008 financial subprime mortgage crisis (Arce & Lopez-Salido, 2011; Rubaszek & Rubio, 2019). While the private rental market serves an important purpose, governments have made significant efforts to implement rental regulations aimed at increasing homeownership rates. Homeownership is often associated with the "American Dream," or the aspiration to own a home in any country (Phillips & Vanderhoff, 2004; Matthews & Turnbull, 2007). Rising homeownership rates contribute to the development of safer communities, foster friendly neighborhoods, and provide households with a means to create and accumulate wealth (Rohe et al., 2002; Haurin et al., 2002). Homeownership is associated with higher satisfaction levels for households compared to being a tenant (Elsinga & Hoekstra, 2005; Diaz-Serrano, 2009). It also offers advantages such as increased investment in education or business, economic security during illness or job loss, and the potential for intergenerational wealth transfer (Herbert et al., 2013).

In recent years, the UK housing market has experienced regulatory changes driven by the political push for more home ownership. New supply of housing has been limited and far beyond what has been necessary. England is short of 2.5 million homes in total and needs 550,000 new home supply each year until 2031 to address the current home shortage issues and support the future population growth (Redmond, 2024) Given increasing new housing supply requires difficult and long negotiating process, politicians have tried to release existing rental stock to residential market. Over 4.4 million households live in rental accommodation in England, accounting for approximately one in five households in England as of 2020 (EHS, 2020). The most common form of rental accommodation is the so-called Buy-to-Let (BTL) which is often owner by mom-and-pop investors. BTL properties are a type of property purchased by investor who already has their main resident home and looking for an additional property with the intention to rent out as an investment. BTL investor can be a cash buyer or mortgage buyer, but it is subject to specific types of mortgage loans. One of the arguments used to release rental stock to residential market is that taxing more second homeowners would mitigate speculative investment on rental accommodations. Because if second home investor face more transaction tax when purchasing the property and needs to pay extra tax for renting out their property, then they would consider selling their exiting rental property and not investing in extra properties. This measure can release some existing rental stock to the residential market to mitigate the housing crisis.

Some academic studies explore the impact of this kind of transaction tax regulation movement on the housing market dynamics. Best and Kleven (2017) investigate housing market responses to transaction taxes changes finding that a temporary elimination of 1% transaction tax increased housing market activity by 20% in the short run and less than half of the stimulus effect was reversed after the tax was reintroduced. The Toronto housing market, where transaction volumes declined more than 15% in response to an increased transaction tax, as documented by Dachis et al. (2011) and Han et al. (2022). Time-on-market (TOM) represents the time difference between the property listing date and the actual transaction date, and it can significantly affect the prices. TOM has acquired attention in the literatures, especially its impact on housing prices (i.e., Genesove & Han, 2012; Han & Strange, 2016). Huang and Milcheva (2022b) use TOM as the representative of market liquidity level related to property transaction price and include it in the regression model as control. Notably, the recent tax reform does not appear to reveal a statistically significant impact on the TOM for property sales, a finding drawn by Huang and Milcheva (2022b). Their research into the SDLT holiday reveal a negligible influence on the TOM across the property market spectrum. Chi et al. (2020) examines the 2010 transaction tax surcharge policy on Taiwanese property market demonstrates that the average TOM for properties acquired for investment purposes does not significantly deviate from that of owner-occupied residences. Han et al. (2022) assesses the TOM fluctuations for single-family houses in Toronto in response to an increased land transfer tax. Apart from the direct analysis on the impact of transaction tax change on housing dynamics. Some Empirical studies have explored the effect of overall rental regulations on housing affordability. Using different models and data sources, these studies have found a positive association: higher levels of rental regulation exacerbate housing affordability issues. Early and Phelps (1999) found that rent control policies drive up prices and reduce the supply of affordable housing in the uncontrolled rental sector due to increased demand. This outcome contradicts the initial aim of reducing the rent burden for tenants.

Ambrose & Diop (2018) established a linear correlation between the rental regulation index and the percentage of renters burdened with over 30% of their income, highlighting the unintended consequence of exacerbating housing affordability issues through rental regulation. Landlord regulations may ultimately lead to a decrease in rental property supply, further impacting lower-income tenants (Ambrose & Diop, 2018). McCollum and Milcheva (2023) examined the impact of state-level renter protection regulations in the US on multifamily housing and found that higher levels of renter protection regulation result in lower cash flow volatility and better income growth prospects for institutional investors. While existing research has primarily focused on the effects of rent regulation on newly let homes, examining differences in rent, crime rates, and housing market dynamics between areas with and without rent control (Autor et al., 2014; Autor et al., 2019; Sims, 2007), or estimating the impact of housing transaction taxes on housing prices, transaction volumes, and timing (Besley et al., 2014; Best & Kleven, 2017; Montalvo et al., 2020), this study provides extra evidence of the effect of increasing housing transaction tax policy on rental housing.

While there has been a host of housing policies aimed to increase home ownership in the UK, this research focus on one specific policy, which is the introduction of a 3% additional transaction tax, or so-called Stamp Duty Land

Tax (SDLT), on properties that are not the main home residence, such as second homes, holiday homes and BTL properties. This research therefore uses the 3% tax surcharge as a natural experiment to assess the effects of the additional charges to taxation on supply and liquidity of rental housing, and transaction prices or rents movement. This research dedicates to say how the policy has affected rental housing supply and transaction prices as well as its effects on rent level, transaction volume and TOM. This can help to test to what extent the tax surcharge policy has achieved its intendent objective of creating a level playing field for individuals seeking to purchase their first home and for the government's housing commitment to mitigate housing crisis through restricting the invest purposed home purchase to release more available housing to the market and increasing the home ownership. This 3% tax surcharge was introduced during the Spending Review and Autumn Statement in November 2015. The implementation came into effect on 1 April 2016. The policy consisted in applying a 3% tax surcharge, which was levied on the existing transaction tax rates for individuals purchasing an additional residential property valued above £40,000. This policy was introduced as part of a broader set of measures aimed at addressing concerns related to the increasing cost of housing and the affordability challenges faced by first-time buyers. The tax surcharge primarily targeted second homes and BTL properties and aimed to discourage buying up residential properties for investment purposes and thereby freeing up rental accommodation stock for first-time buyers.

Given that the main challenge of this study is to be able to identify BTL properties, I merge two property-level datasets. For sales I use the state-of-the art PPD from the Land Registry (LR) which contains all housing sales in England and Wales since 1995. For rental listings, I use the major listing's portal Zoopla with data available from 2014. Zoopla offers both detailed rental and sales data. I fuzzy match the datasets using the property address. While it is not possible to directly identify BTL properties, it is able to see which of the properties that have sold have been subsequently rented. This research therefore proxy BTL properties as those that are listed for renting within 12 months of the sales transaction date. Inevitably, there is a segment of the rental housing that falls outside this timeframe, and this research accounts for those properties that are rented after more than 12 months as non-BTL rental properties. The properties that are not rented out at all after the sale date are called non-BTL residential properties. The non-BTL rental properties along with non-BTL residential properties constitute the non-BTL properties. This research hence considers the policy effect on any property that has been rented out after the purchase, even if it exceeds 12 months. The results remain robust to this specification.

Given the 3% tax surcharge implemented on 1 April 2016, which means only after this time the BTL properties will be affected by the policy, and nothing happen before this time. This scenario provides an appropriate situation for us to employ an econometric approach known as difference-in-differences (DID) and identify the fiscal policy effects on volumes, house prices, rents and time-on-market (TOM). Because DID is useful to estimate policy intervention effect on a scenario that if there exists two groups of observations and two periods, in the first period, both groups do no exposed to policy treatment, and in the second periods, only one groups get exposed to policy treatment but not for the other group (Schwerdt & Woessmann, 2020). Given the policy was implemented in 2016, this research conducts the analysis between 2014 and 2017. This research ends the analysis in 2017 to avoid overlapping with another policy change, which took effect in April 2017. It was the Bank of England's decision to tighten lending standards for BTL mortgages. In this analysis, the treatment group are the properties that have sold and have been rented out within 12 months. The control group are the sold properties that did not rent within 12 months. To make the properties as comparable as possible this research controls for a host of property characteristics (number of bedrooms, number of bathrooms, energy efficiency rating, property types, newbuilt dummy, tenure type and TOM) and local market conditions (through location-month fixed effects). Additionally, this research employs a dynamic DID method to examine policy effects over time, with the announcement date serving as the treatment time. The dynamic DID method is a typical method aligns with the DID method that replaces the simple post treatment indicator in DID setting with time to treatment date. This allows us to track treatment effect over time and test whether there is a differentiate pre-trend effects exists.

The research finds that when second homes are subject to a 3% tax surcharge, there is a significant decrease over 15% in the supply of BTL properties as measured by transaction volume. In line with the findings that the supply of rental accommodation decreases, the research also find that the policy leads to a decrease of 1.4% in transaction prices of BTL properties. However, the research also observes a dynamic trend in prices following the policy announcement. Immediately after the announcement but before the implementation, transaction prices for BTL properties experience an increase by 2%, as investors rush to purchase properties before the implementation of the tax surcharge. After the implementation date, BTL properties transaction prices drop by 5%. The effect becomes weaker with prices still 2% lower 4 quarters after the announcement date. This indicates the behaviour and balance between short-term speculative BTL investor and long-term BTL portfolio holder about how they react to the 3% tax surcharge policy. The estimated effects are not attributable to pre-treatment differences in transaction prices, changes in tax relief on rental income, or the identification strategy employed to identify BTL properties in this study. In addition to analyzing transaction prices, the research also is able to look at effects on the list rent of BTL properties and non-BTL rental properties. The tax surcharge led to a 6% increase in the list rent of BTL properties as compared to non-BTL rental properties. This indicates that BTL property owners, as the primary suppliers of rental housing, adjust their investment behavior to compensate for higher investment expense due to higher transaction taxes by asking for a higher rent. The observed rise in list rent for BTL properties is in line with the drop in supply of rental accommodation as shown above.

The analysis demonstrates that the TOM for renting a BTL property has escalated by 25%. This is in line with above findings of higher list rents, and shows that as list rents are higher, it takes longer to find a tenant. This is suboptimal for both, landlords and tenants. Landlords are faced with protracted periods of unoccupied properties, while tenants face higher rents and take longer to find a suitable property. This exacerbates the rent burden, undermines renter’s savings potential, and reduces housing affordability for those who do not own a home. Hence, the rental market is being squeezed by high demand and low supply. The resultant trend is an increasing number of individuals postponing homeownership, thereby perpetuating their status as renters.

The remainder of the chapter proceeds as follows: Section 3.2 reviews the literatures; Section 3.3 describes the data; Section 3.4 presents the methodology; Section 3.5 presents the results; Section 3.6 presents robustness estimations. Finally, Section 3.7 concludes the chapter.

3.2 Literature Review

The housing needs of households can be satisfied either in homeownership or renting. Homeownership is undoubtedly the priority choice of households, but renting is also a substantial alternative, especially for lower-income households (Rubaszek, 2019). For many years in the UK, the private rental market has been seen as an inferior alternative to homeownership and social housing. However, many studies have proven that the private rental market is a significant housing market segment. Kemp (2011) proposes that the private rental market plays a disproportionately important role in satisfying the accommodation needs of households living in poverty by offering affordable living space. The existence of a private rental market can also help lower-income households away from the shocks in the real estate market. The 2008 financial subprime mortgage crisis have been a catastrophic disaster for lower-income households, who encountered income shortage and struggled for mortgage payment. (Arce & Lopez-Salido, 2011; Rubaszek & Rubio, 2020). However, regulations on the private rental market with the aim of boosting homeownership rates have become a common trend recently in the UK.

The rental housing market is comprised of the social and private rental sectors (Haffner et al., 2017). The social rental stock in the UK is normally owned by housing associations or local authorities. Private rental housing is commonly owned by institutions or private landlords, which have no subsidies and frequently encounter regulations by housing authorities (Kettunen & Ruonavaara, 2020). The common sense between landlords and tenants in terms of the renting behavior is being written in the rental contract, giving tenants a right to live in a property with a certain amount of payment to the landlord. The landlord and tenant contracts regulate the right or obligations of landlords and tenants, such as the length of tenancy, rent, rent growth rate, etc. However, most of the time, it aims to protect the tenant's right and restrict the landlord’s behavior and income.

While the private rental market serves an important purpose, the UK governments have made significant efforts to increase homeownership rates. There are many reasons behind this decision. Rising homeownership rates contribute to the development of safer communities, foster friendly neighborhoods, and provide households with a means to create and accumulate wealth (Rohe et al., 2002; Haurin et al., 2002). Homeownership is associated with higher satisfaction levels for households compared to being a tenant (Elsinga & Hoekstra, 2005; Diaz-Serrano, 2009). It also offers advantages such as increased investment in education or business, economic security during illness or job loss, and the potential for intergenerational wealth transfer (Herbert et al., 2013). Disney et al. (2023) examine the causal impact of the 'Right to Buy' policy, a policy aim at boosting the UK homeownership in 1980 to 1990 on local crime rates. Their analysis shows that the reduction in crime rates was driven primarily by behavioural changes within the local community rather than the effect of 'gentrification' mentioned by Autor et al. (2019). However, the strong emphasis on boosting homeownership raises questions about whether this focus truly benefits lower-income households in terms of wealth accumulation and overall well-being and whether this boosting policy does not harm the tenants who could be the future first time buyers and the driver of homeownership. Lersch and Dewilde (2018) use the British Household Panel Survey find that landlord save more and financially wealthier than tenants. The disadvantage for tenants to accumulate wealth is very significant. In fact tenant is the future homebuyers, however the UK government keep restricting tenant’s right and focus only on the homeownership rate.

One of the main ways of the UK government boosting the homeownership is through regulating the rental market. The rental regulation implemented by government on rental housing mainly targets restricting landlords and protecting tenants, by setting rent price cap, rent increase rate, rental income tax, etc. Rent regulation has existed in many country’s housing policy systems even though there is a trend of liberalizing the private rental market (Kettunen & Ruonavaara, 2020). However, even the most well-intentioned regulation could have unexpected harm to the intended beneficiaries. Ambrose & Diop (2018) present a linear correlation between the rental regulation index and the percentage of renters burdened with over 30% of their income, showing the unintended outcomes of exacerbating the housing affordability issues by rental regulation. The increased cost caused by the regulation would be priced in the rent by the landlords, and the increased regulation is affecting the landlord’s willingness to rent. This would affect the rental housing supply, as the further analysis shows that the landlord regulations may eventually lower the supply of rental property and further hurt the vulnerable lower-income tenants (Ambrose & Diop, 2018). However, the rental regulation may have different impact on institutional investors, McCollum and Milcheva (2023) assess the effect of state-level renter protection regulation in US on multifamily housing and find that higher renter protection regulation leads to lower cash flow volatility and better income growth prospects for institutional investor. Regulation of the private rental market has many forms. Rent control is one of the primary forms of government regulation of the rental housing market. It is among the interests of a majority of empirical studies. The rent control also motivates landlords to consider alternative usage of their rental housing, either changing it to owner-occupied or changing it to non-residential use. This leads to losses in rental housing supply (Turner & Malpezzi, 2003). Spillover effects to an uncontrolled market have also been justified, leading to unintentional harm to the tenants. Levine (1999) found that rent growth control lowers the overall supply of rental housing and increases the median rent, although no spillover effects to the owner-occupied housing have been discovered. However, this study has an issue of not sufficient control for other housing supply and methodological problems. Recently, Kholodilin (2024) examines 112 empirical studies on the effects of rent control, and find that although the rent control policy has its intended and unintended effects on price, housing supply, and the distributional effect of mismatching housing between tenant and landlord. This study will also explore such unintended policy effects under tax surcharge scenario rather than the rent control scenario. Breidenbach et al. (2021) examine the 2015 German Government policy of rent control aiming at disburden low-income households, however, the result of the temporal dynamic effects show that the rent goes up by 5% for all properties and 9% for specific type of properties and it only last for a year. In addition, the benefits area locates mostly in the high-income households, which missing its original policy goal. Such thing happens all the time, my study on the BTL tax surcharge policy in the UK also would explore whether the policy missing its original goal. Mense et al. (2022) do a further analysis on the same German policy and exploit the temporal variation in rent control treatment dates in large-scale intervention in the German housing market using event study and find a positive spillover effect of rent control on free-market rent. This is a case similar to my study, but there is no varying treatment date nor the rent control, instead a treated group that would be affected by the tax surcharge policy intervention. This chapter will also estimate whether there is a spillover effect of rent between treated BTL properties and others, but this chapter does not just focus on rent, but also transaction price, volume and liquidity of untreated rental property and owner-occupied property over time. Hahn et al. (2022) examine the 2020 rent control in Berlin and their empirical tests show a notable rent gap along the Berlin’s administrative border. They also find the supply level of available rental properties drop significantly, which affect the matching between tenants and landlords. This is an unintended effect that I want to examine as part of this study to explore the effect of rental policy on the matching between supply and demand side.

While the literature has extensively studied rent control, the rental property associate tax regulations has received limited attention. The tax would normally be imposed into the rental income or the transaction of property, namely rental income tax or transaction taxes. This chapter will focus on the latter one, the transaction taxes on the rental property. Han et al. (2022) use the housing sales and leasing transaction dataset for Greater Toronto Area between 2006 and 2018 to examine the effect of new property transaction tax, which is applied in the City of Toronto but not other parts of the Greater Toronto Area. What they find is the divergent effects across the ownership and rental markets. First, the ratio of leases to sales rise by 23% and the ratio of prices to rents decline by 4%, suggesting the renting is becoming attractive. Second, the transaction volume falls 10% among the non-BTL buyers and rise 9% in the BTL investors. Third, the TOM of non-BTL market increase by 17%, which means the property take 5 days longer to sell. This heterogeneous treatment effect of the transaction tax on BTL and non-BTL markets indicate the need of focusing the flow between BTL and non-BTL markets. However, the tax surcharge policy I would examine is slightly different from the case in their study, the tax surcharge policy in the UK only apply to BTL market, and it is not applied to the overall property market, hence the non-BTL market would not be affected by the policy. This creates a suitable situation of separating the control group and treated group, exploring the effect of tax surcharge in the UK BTL market. Another impactful study focus on the housing market responses to the change of transaction taxes is presented by Best and Kleven (2017). Best and Kleven (2017) use all property transactions in the UK from 2004 to 2012 to investigate the quasi-experimental variation from SDLT notches and SDLT stimulus. They have two main findings, first the transaction taxes cause large distortions to property prices, transaction volume. Second, temporary transaction tax cuts have enormous stimulus effect, 1% tax cut lead to 20% increase of activity in the short run. The method they employ is DID approach as the SDLT holiday last 16 months and it is eliminating transaction taxes in a particular price range. This trigger the research on this chapter as I also focus the SDLT change, but in the tax surcharge not the tax holiday. In addition, the difference between my setting and their experiment setting is the treated group. The treated group in my study is the rental properties, specifically the BTL property, and not specific price range of housing. This makes my study unique as most of the literatures are examining the transaction tax either in the different price range or the zoning area. Based on the most recent review, this study is the first to explore the SDLT change to the rental property as the tax surcharge policy is only target at the second home, which creates an ideal setting to explore how the rental housing market responses to the change of transaction taxes.

3.3 Data

To investigate the impact of the 3% tax surcharge, this research utilizes two novel datasets, which are described in detail below. These datasets provide valuable insights into the effects of the policy on the real estate market and allow for a comprehensive analysis of the dynamics and implications of the higher transaction tax rates.

3.3.1 Residential Transaction Data

The residential property transaction data used in this study are sourced from the England and Wales Land Registry (LR) Price Paid Database (PPD), which contains comprehensive information on sales transactions dating back to 1995. In order to align the data with the available timeframe of the WhenFresh/Zoopla dataset (described below), I create a subsample of sales transactions from 2014 onwards. The analysis of the property market dynamics is deliberately confined to the period concluding in 2017, despite the availability of data extending through 2020. This temporal boundary is established due to government conducts an income tax relief for UK landlords commencing from April 2017. Subsequent to this time, landlords have been excluded from deducting their finance costs directly from rental income for tax purposes. Instead, they are restricted to obtaining tax relief solely at the basic rate of 20%, on whichever figure is lower: the finance costs, the profit accrued from rental income, or the total income itself. This change of landlord's tax relief can affect this analysis since it will affect the transaction price, market liquidity and transaction volume of rental housing.

The PPD provides detailed information for each transaction, including the transaction price, date of transfer, locational information (such as postcode, number, street name, city name, and district name), property type (such as flat, terraced house, semi-detached house, and detached house), tenure type (freehold or leasehold), and an indicator for whether the property is old or newly constructed.

3.3.2 Rental and Sales Dataset Matching

The WhenFresh/Zoopla dataset provides comprehensive information on all sales and rental transactions listed on the UK-leading internet listing platform Zoopla. The data this research have access to ranges from 2014 to 2021. The data is accessible through the Consumer Data Research Centre (CDRC).

TOM for the properties represent how quickly a property being transacted or being rented after listing on the market. In the regression analyses, controlling for TOM is important. This control allows for the detailed assessment of market liquidity and the identification of specific property characteristics that influence both the attractiveness of a property to potential buyers or renters and the duration it remains on the market. By incorporating TOM as a variable, this research aims to isolate and understand the factors that contribute to the transaction timeline, thereby providing a more granular understanding of market dynamics. To estimate the TOM for the observations, this research exploits the listing date information available in the Zoopla sales dataset[10]. This allows us to track the duration it takes for properties to be sold after being listed on Zoopla.

Furthermore, this research utilizes the Zoopla rental dataset to identify BTL observations within the LR PPD. The dataset represents approximately 70% of the privately rented market in the UK and includes detailed address information and property attributes (such as property type, number of bedrooms, bathrooms, receptions, and energy rating) for rental properties. Additionally, the dataset contains the listing date, asking rental price, and page views for each rental property. By comparing the transaction date in the LR

[10] The time between listing and transaction date for sales is the time-on-market in this research.

PPD with the date when the same property is listed for rent on Zoopla, this research can identify BTL properties[11]. This approach aligns with similar identification strategies employed by Bracke (2021), who estimates the price discount between BTL and non-BTL properties.

In Panel A of Table 3.1, I present the main data sources used in this study: the PPD sales data and the Zoopla rents/sales dataset. I match the Zoopla rents and sales dataset separately with the PPD sales dataset to obtain rental-related information and TOM data for the observations. The Zoopla dataset contains a total of 1,449,429 property transactions between 1st January 2014 and 31st December 2017, while the LR PPD encompasses 4,089,715 transactions for the same time period. The LR PPD is a comprehensive record maintained by the UK government and is considered the most accurate and complete source of information on property transactions in England and Wales because PPD includes information on all property sales in England and Wales that are being transacted and registered in the UK land registry. This means that Zoopla covers only approximately 38% of all transactions, as its access to property transaction data depends on cooperation with estate agents, property developers, and other third-party sources.

[11] In this analysis, if the relative time between sale completion and the rental listing created date for the same property is less than twelve months, I identify it as buy-to-let property.

Table 3.1 Data sources and matched dataset (From 2014 to 2017)

Panel A Original dataset			
	Zoopla Rents (No Duplicates)	Zoopla Sales	PPD
Observations	1,569,859	1,449,429	4,089,715

Panel B Matched dataset			
	Zoopla Sales (Full Dataset)	PPD-Zoopla sales (with TOM data)	PPD-Zoopla (No missing value)
Total Observations	1,449,429	1,339,814	570,631
BTL Observations	.	.	49,064
Non-BTL Observations	.	.	521,567
Non-BTL Rental	.	.	97,406
Non-BTL Residential	.	.	424,161

Notes. The tables show the main data sources and matched datasets, The final dataset contains matched data between above three sources. The final dataset thus contains sales, rental transactions and TOM information. LR PPD stays for Land Registry Price Paid Data. BTL stays for BTL properties. TOM stays for time on the market.

The Zoopla dataset provides additional property-related information that is not available in the PPD, such as the number of bedrooms, bathrooms, energy rating[12], and TOM. These additional details are important for this research, and hence, I will use the PPD-Zoopla merged dataset for this analysis. In addition to the sales listing data, Zoopla also offers a comprehensive dataset of rental transactions in the UK. This dataset includes property descriptions, list/asking rent, and property location among others. Zoopla sources the data from various partners, including estate agents and property developers.

[12] The Zoopla energy rating variable is the same as the Energy Performance Certificate (EPC), which is a rating of the energy efficiency of the property. A is the best rating, giving the highest mark for energy efficiency, G is the lowest rating, showing the lowest mark for energy efficiency. Zoopla explicitly attach the EPC level to the corresponding property, easing the effort of data merging process.

Moving on to Panel B of Table 3.1, I provide details of the matched PPD-Zoopla dataset. I first match the Zoopla sales data with the LR PPD data for the period of 2014 to 2017, resulting in the PPD-Zoopla sales dataset, which contains 1,339,814 observations (approximately 92% of the original Zoopla sales dataset). Using this dataset, this research is able to match the sales transaction date from the PPD with the sales listing date from Zoopla and hence calculate the TOM. The TOM measures how long it would take for a property to transact, i.e., which this research call liquidity.

Next, I match the Zoopla rental data with the PPD-Zoopla sales data. using fuzzy matching based on property address, using the postcode, street name, and street number. This approach helps minimize matching errors caused by typing variations and ensures accurate matching. Additionally, this research handle overlapping rental records by adopting a similar method as Bracke (2021), which involves keeping the first rental listing in case of overlapping data provided by multiple real estate agents. After matching the data and excluding missing observations, this research is left with 570,631 observations which form part of the final PPD-Zoopla dataset. The majority of those observations, 521,567, or 91.4%, are non-BTL properties, which contain a subsegment of non-BTL rental properties with 97,406, or 17%; 49,064, or 8.6%

of those observations, are identified as BTL properties. Around 19% of the households live in the private rented sector in England. In the dataset, this research has about 8.6% who appear to live in the BTL properties and 17% live in the non-BTL rental properties comprising this dataset. The reason for the 6% surplus can be explained by some of the rental accommodation having been rented out more than once, for example, the same rental properties being listed on the Zoopla several time because the previous renter moved out and the new tenancy contract signed for the same rental properties.

3.3.3 Matched PPD-Zoopla Data: Summary Statistics

The final dataset comprises of 570,631 property transactions that occurred between 2014 and 2017. Table 3.2 presents the summary statistics of the categorical variables for the entire sample and subsamples of BTL and non-BTL properties. Within the non-BTL properties, this research shows the non-BTL rental and non-BTL residential segments. This research assesses the variation in property characteristics and energy rating levels between them. I find that approximately 76% of the BTL property are new and about 84% of them have leaseholds tenure. For non-BTL properties, 80% of the property transactions involve old and 67% of them are freehold properties. BTL properties have high portion in flat type with about 90%, however, about 78% of the non BTL residential properties are house type. Rental properties have relatively higher portion in flat type. Semi-detached house has higher portion in non-BTL residential and not for renting out. In addition, most of the properties have energy rating level ranges lie in the C, D and E rating, but the property for renting out tend to have lower energy rating level as most of them in D or below level, at the same time, the energy rating level for residential property tend to have C energy level.

Table 3.2 Summary statistics (categorical variables)

	BTL	Non-BTL	Non-BTL Rental	Non-BTL Residential
Old	0.24	0.80	0.81	0.79
Freehold	0.16	0.67	0.35	0.88
Flat	0.90	0.13	0.68	0.22
Detached	0.04	0.22	0.08	0.24
Semi-detached	0.02	0.31	0.10	0.34
Terraced	0.03	0.33	0.13	0.20
Other	0.01	0.01	0.01	0.01
Observations	49,064	521,567	97,406	424,161
Energy Efficiency Rating				
A	0.01	0.01	0.01	0.01
B	0.03	0.03	0.05	0.03
C	0.26	0.38	0.28	0.49
D	0.46	0.34	0.44	0.23
E	0.18	0.19	0.17	0.19
F	0.03	0.04	0.04	0.04
G	0.01	0.01	0.01	0.01
Observations	49,064	521,567	97,406	424,161

Notes. The tables show summary statistics of categorical variables, including property characteristics (old/new indicator, tenure, and property type) and energy rating band (from A to G). For BTL, non-BTL properties, non-BTL rental and non-BTL residential.

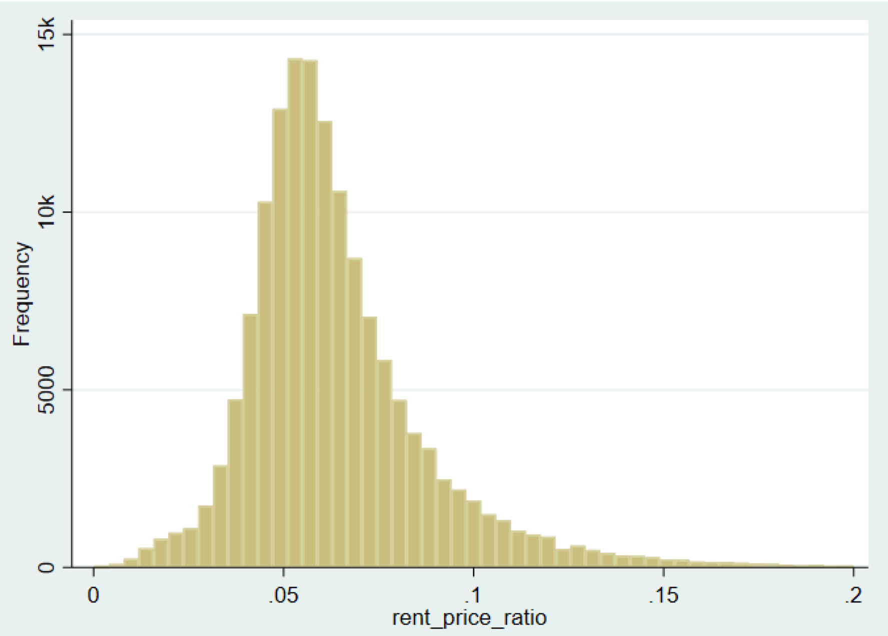
The availability of transaction data for both BTL and non-BTL rental properties allows us to test the effectiveness of the identification strategy on BTL properties. Additionally, this research has sufficient numbers of BTL and non-BTL transactions to conduct the main DID analysis, with a solid treatment group (BTL properties) and control group (non-BTL properties).

Table 3.3 presents the summary statistics for the main continuous variables in the analysis for the entire sample and sub-samples of BTL properties and non-BTL properties (including rental and residential properties). The median BTL property in England and Wales consists of two bedrooms, one bathroom, and when it was for sale, it has been on the market for an average of 4.56 months. The median weekly rent for BTL properties is £173, with a median price of £154,000. On the other hand, the median non-BTL rental property has a higher median price of £173,000. Rent-price ratio for BTL property has around 1% higher rate than rent-price ratio for non-BTL rental property. Figure 3.1 shows the distribution of rent-price ratio throughout the sample, most rental property has around 4% to 7% rate with 5.5% at the peak. BTL investors have very certain target of renting the property out before they select the targeted property, hence BTL investors tent to buy a lower quality and smaller properties in order to get higher income yields hence with lower price. While non-BTL rental property also being rent out, however, the non-BTL rental property buyers do not have certain target of renting the property out in the time of selecting properties, they rent out the property later because they change their investment strategy or move to a better home so that rent the old property out. Hence, the non-BTL rental property tends to have higher quality with higher prices compared to BTL housing.

Relative to the full sample, BTL properties tend to have a lower median price, ranging from approximately 73% to 80% of the value of non-BTL transactions. There are also other variations between BTL and non-BTL properties, as well as between rental and non-rental properties. For instance, non-rental properties generally have more bedrooms, longer TOM, and higher average prices compared to rental properties. BTL properties, on the other hand, tend to have a shorter TOM, lower weekly rents, and lower prices compared to non-BTL properties.

Rising BTL mortgage rates, less generous tax treatment and tightening regulations can result in these differences. BTL mortgages are specifically for landlords who want to let out their property, which are similar to normal mortgages but with higher fees and the interest rates. Lenders normally consider BTL mortgages risker than normal mortgages because they assume Landlords can make loss if their tenants don’t pay on time or don’t pay at all and the possibility that a property can be left empty for a certain period. Lenders also treat BTL mortgages differently as well with higher standard on Loan to value (LTV) and borrowers' income ability, hence with higher mortgage deposit, usually with 25% of the total value of the property. In addition to that, BTL mortgages are more expensive with bigger mortgage payments.

Figure 3.1 Distribution of rent-to-price ratio in the sample



Notes. The figure contains the distribution of rent/price ratio in the sample, representing the frequency of the yield.

Therefore, BTL investors tend to buy smaller properties with lower quality like lower energy rating level, which listed at lower prices to qualify the mortgage requirement and meet their investment need. BTL has become less tax-efficient investment for higher rate taxpayers as well because of the less generous tax relief on their mortgage interest.

Table 3.3 Summary statistics (continuous variables)

		Mean	Std. dev.	P1	P25	P50	P75	P99
All	Price (£'000)	308.6	123.5	40	135	210	325	1600
Obs: 570,631	Rent (weekly)	222.5	130.9	80	137	183	277	750
	Bedrooms	2.8	1.0	1	2	3	3	5
	Bathrooms	1.3	0.7	1	1	1	1	3
	Energy efficiency	5.9	1.1	3	5	6	7	8
	TOM (months)	5.3	2.6	1.1	3.3	4.7	6.9	11.7
	Rent/price ratio[13]	0.06	0.02	0.02	0.05	0.06	0.07	0.15
BTL	Price (£'000)	211.5	266.3	34	100	154	250	1020
Obs: 49,064	Rent (weekly)	211.2	121.2	81	133	173	254	692
	Bedrooms	2.5	0.9	1	2	2	3	5
	Bathrooms	1.2	0.6	1	1	1	1	3
	Energy efficiency	5.8	1.1	3	5	6	7	8
	TOM (months)	5.1	2.6	1.0	3.2	4.6	6.6	11.6
	Rent/price ratio	0.07	0.02	0.02	0.05	0.06	0.08	0.15
Non-BTL	Price (£'000)	312.7	126.0	40	138	210	330	1619
(all)	Rent (weekly)	227.8	134.9	80	138	185	277	760
Obs: 521,567	Bedrooms	2.8	1.0	1	2	2	3	6
	Bathrooms	1.3	0.7	1	1	1	1	3
	Energy efficiency	5.9	1.1	3	5	6	7	8
	TOM (months)	5.3	2.6	1.6	3.4	4.7	6.9	11.7
	Rent/price ratio	0.06	0.02	0.02	0.05	0.06	0.07	0.15
Non-BTL	Price (£'000)	258.1	482.8	33	114	173	285	1500
(rental)	Rent (weekly)	227.8	134.9	80	138	185	277	760
Obs: 97,406	Bedrooms	2.5	1.1	1	2	2	3	6
	Bathrooms	1.3	0.6	1	1	1	1	3
	Energy efficiency	5.9	1.1	3	5	6	7	8
	TOM (months)	5.2	2.6	1.1	3.3	4.7	6.8	11.7
	Rent/price ratio	0.06	0.02	0.02	0.05	0.06	0.07	0.15
Non-BTL	Price (£'000)	318.1	131.3	40	140	215	333	1630
(residential)	Bedrooms	2.9	0.9	1	2	3	3	5
Obs: 424,161	Bathrooms	1.3	0.8	1	1	1	1	3
	Energy efficiency	5.9	1.2	2	5	6	7	8

[13] Rent/price ratio represents the share of annual rent on the property transaction price, which shows to what extent the annual rent can repay the property transaction price. For example, rent/price ratio = 6% means one year rent accounts for 6% of the total property transaction price.

TOM (months)	5.3	2.6	1.2	3.4	4.8	7.00	11.70

Notes. The tables show summary statistics of continuous variables, including weekly rent, transaction price, number of bedrooms, number of bathrooms, energy efficiency and TOM. The table shows summary statistics of data with all observations and four subgroups: BTL, Non-BTL (all), non-BTL (rental) and non-BTL (Non-residential).

The regulatory environment for BTL has become tougher to protect tenants from landlords by raising energy efficiency requirement for example. Even though there still many shortfalls of BTL properties investment, the shortage of housing makes tenants queuing to bid price for one rental housing and push up the rent level. The expectation of higher rent, satisfying supply and demand level, making the BTL transactions become active but mostly among the lower quality and lower value properties.

3.4 Methodology

This research uses standard difference-in-differences (DID) research design where outcomes are observed for two groups of observations in two periods, before and after the treatment. In addition, a dynamic DID method to explore the treatment effect over time. DID method is often used in the quasi-experimental designs to estimate the casual effect of a specific policy intervention when one group is exposed to the policy intervention while the other group is not (Babu et al., 2017). DID method is particularly suitable to estimate the causal effect of housing policy changes. Examples include the effect of housing purchase subsidies on German housing price (Krolage, 2022), the urban renewal delineation effect on Taipei housing price (Lee et al., 2016), the effect of housing allowance on Swedish housing market (Öst, 2014) and the estimation of behavioral response to residential housing transfer taxes changes in Washington D.C. (Slemrod et al., 2017). DID requires panel data before and after the policy intervention. The treatment group is exposed to the treatment after the treatment but not being affected before the treatment. The control group is not being affected both before and after the treatment. The average difference in the control group is subtracted from the average difference in the treatment group to remove biases from comparisons over time and the differences between these two groups (Wooldridge, 2007)[14]. The logic of DID is by taking two differences between control group and treatment group in two period. The first difference shows the difference of two groups in the absence of treatment and under the assumption that this difference is constant over time if the treatment is absence. The second difference shows the difference of two groups if the treatment exists. The remaining difference between these two differences should reflect the causal effect of the policy intervention. In terms of this cases, the control group is non-BTL properties, and the treatment group is BTL properties. The assumption is that the two groups would have experienced the same movement in the absence of 3% tax

[14] The DID is defined as the difference in average outcome in the treatment group before and after treatment minus the difference in average outcome in the control group before and after treatment.

surcharge policy intervention. The difference between the assumed situation and the actual observed situation represents the 3% tax surcharge policy effect on the treatment group – BTL properties. This research examines the treatment effect on different aspects of BTL properties, including transaction price, transaction volume, TOM and listing rents.

However, estimation using DID approach for impact valuation needs three main assumptions (Lechner, 2010). First, the allocation of intervention was not determined by the outcome. In other words, if the intervention is not exogenous, the DID is not applicable, but this assumption can be fulfilled in this study as the intervention is purely design by the government and it is not endogenous effect. Second, the treatment group and control group have parallel trends in outcomes. The parallel trend assumption can also be called the “common trend” assumption (Lechner, 2010). In this study, I will use dynamic DID method to test the if the parallel trend exists. Third, no spillover effects between treatment and control groups (Duflo et al., 2007). Some concerns exist for DID assumption, typically the uncertainty over time for both groups. The way to reduce this type of uncertainty is to do more robustness check for different groups and conduct the dynamic DID examination. Despite the shortage of the DID setting, it remains an appropriate and popular approach in economics and quantitative research. The DID research design has several advantages. First, the results of the DID model can be interpreted directly. Not just the average effect, I can also verified the parallel trend assumption and check the treatment effect over time through dynamic DID model. Second, researchers can obtain casual inferences from the estimated results if the above assumptions stand. This is important for the purpose of this study, as this study plans to estimate the casual effect of the 3% tax surcharge on the BTL properties. Third, researcher can use either individual or group level data, the selection is flexible. Fourth, it can control for confounding factors that will lead to the difference in the outcome of two groups (Greene & Liu, 2020)

This section focuses on the regression specification and the main results of the DID analysis, which aims to estimate the effects of the tax surcharge on BTL transactions. Then I conduct similar DID analysis with a series of control groups in the subsequent mechanism analysis to ensure that the main coefficient is attributable to the tax surcharge and not influenced by other events. I also examine whether non-BTL rental properties are affected by the tax surcharge, as this would impact the identification strategy for the treatment group if other rental properties in the market experience similar effects as BTL properties. In this section, I begin by presenting the regression specification used to estimate the average treatment effect and then I present dynamic DID method employed to capture the temporal dynamics of the treatment effect. I also test for the presence of any differential pre-trends that could potentially confound the treatment effect estimation, thereby ensuring that the observed effects can be attributed primarily to the treatment of the 3% tax surcharge.

To measure the treatment effect of 3% tax surcharge on BTL transactions, this research estimates the following equation:

$$\ln(Y_{i,t}) = \alpha_i + \lambda_t + \omega_{g,t} + \alpha \cdot (Treated_i \times After_t) + \beta \cdot X_i + \delta \cdot Z_{r,t} + \epsilon_{it} \qquad (3.1)$$

where dependent variable $ln(Y_{i,t})$ is the logarithmic transformed number of the individual housing outcome of interests (transaction price, transaction volume, TOM and listing rent) i in time t. The variable of interest $Treated_i \times After_t$ is an interaction term between time of treatment and treatment group. $Treated_i$ is a dummy indicator showing whether the housing transaction is treated, $After_t$ is the dummy indicator showing whether the housing transaction happen after the policy intervention. The parameter of interest is (α), which represents the effect of 3% tax surcharge on the treated group. The model includes group fixed effects ($\omega_{g,t}$), district fixed effects (α_i) and year-month fixed effects (λ_t)[15]. Standard errors are clustered at both the

[15] UK full postcode contains two alphanumeric codes. The first named outward code, indicates the postcode area and postcode district. The second named inward code, which indicates postcode sector and delivery point. In this study, we use outward code as locational fixed effect.

year-month and district level, following the procedure in Petersen (2009). The vector X_i contains a variety of property-level and vector $Z_{r,t}$ contains the regional-level variables.

This research then proceeds with a dynamic DID method, which is a typical quasi-experimental method as a generalized extension of DID design or two-way fixed effects models. It allows for dynamic leads and lags to the event treatment, while controlling for location and time factors allowing for a visual representation of the dynamic effects.

To check for trends of treatment effect over time and test whether there are differential pre-trends, I replace the single $Treated_i \times After_t$ dummy indicator in equation (3.1) with the relative time-to-treatment indicators. The model is given as:

$$\ln(Y_{i,t}) = \alpha_i + \lambda_t + \omega_{g,t} + \sum_{q=-7}^{8} \beta_q \cdot SDLT_q + \epsilon_{i,t} \tag{3.2}$$

In the primary specification, postcode defines the locational variable. $SDLT_q$ are relative quarters to treatment indicators, which are set to 1 for treatment groups if time t is q periods from the treatment period. q ranges from -7 to 8, it means range from seven quarters before the treatment to eight quarters after the treatment, which is seven quarters before the announcement of 3% tax surcharge policy. The parameter of interest (β_q) represents the average change of price in treated groups relative to control groups between time q and the beginning of the study. The dynamic DID method assumes that treated and control groups would have maintained similar differences as in the reference period, hence, this model only allows to be used in the linear trend, when all unites face treatment at a certain time (Schmidheiny & Siegloch 2019; Borusyak & Jaravel 2018). This research estimates the data from 2014 to 2017 which leaves us with seven quarters preceding and eight quarters following the 3% tax surcharge policy announcement.

3.5 Results

3.5.1 Supply effects

The examination of transaction volume fluctuations is crucial in understanding the effect of 3% tax surcharge on the BTL properties as compared to non-BTL properties purchases. The results, as detailed in Table 3.4, reveal a pronounced reduction in BTL transaction volumes of 15 to 20 %. This decline illustrates the negative effect of increased transaction costs on the demand for BTL properties among prospective investors.

Table 3.4 Effects on transaction volumes

	(1 - District)	(2 - City)	(3 - County)	(4 - < Mar 2017)

Treat x Post	-0.189***	-0.205***	-0.173***	-0.148***
	(0.008)	(0.016)	(0.018)	(0.010)
N	42,390	13,388	478	33,378
Quarter	Yes	Yes	Yes	Yes
Location	District	City	County	District
Avg. bedrooms	Yes	Yes	Yes	Yes
Avg. bathrooms	Yes	Yes	Yes	Yes
Avg. energy efficiency	Yes	Yes	Yes	Yes
Avg. TOM	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Exclude	—	—	—	>Mar 2017

Notes. The table shows results from estimating equation (3.1) with a single posttreatment dummy, replacing the individual property with regional transaction volume, including district, city, and county. Treatment time is defined as the announcement date of the additional 3% transaction tax on BTL housing. Treated properties is defined as the BTL property. Control group is non-BTL properties. All specifications include year-month fixed effects, plus average metrics of energy rating, bedrooms, bathrooms, and TOM in the corresponding region. Standard errors are clustered by year-month level.

Table 3.4 presents the treatment effects of the 3% tax surcharge on BTL transaction volumes across various regional levels. Column (1) of Table 3.4 indicates a 19% decrease in transaction volumes at the district level post-treatment. In Column (2), I observe a drop about 21% in city level BTL transaction volume and in Column (3), 17% decrease in county level. In Column (4) I examine policy effect on district level BTL transaction volumes and excluding observations from March 2017 onwards. This temporal limitation is imposed to exclude the influence of concurrent policy changes affecting rental income tax relief. The findings indicate a 15% negative policy treatment effect, a relative mitigation of 4 percentage points from the 19% decrease reported in Column (1). Such difference in the treatment effect is instructive, as it shows the impact of the tax relief reform distinctly from the 3% tax surcharge effect. The fact that the treatment effect in column (4) of Table 3.4 is weaker than in the other specifications suggests that there were additional negative effects on transaction volumes resulting from the reduction in the tax relief for rental properties and stricter lending standards for BTL mortgages after March 2017.

The results are consistent with findings in other countries. Dachis et al. (2011) notice a 15% reduction in overall property transaction volumes following the introduction of a land transfer tax in the City of Toronto in 2008, affecting both BTL investors and owner-occupiers. Han et al. (2022) corroborates these findings, reporting a similar 17% decrease in transaction volume in the City of Toronto upon applying the same sample constraints as Dachis et al. (2011). In the UK, Best and Kleven (2017) observed an approximate 20% increase in the transaction volume of properties priced between £124,001 and £175,000 during the 2008 to 2009 UK SDLT holiday, which implemented a 1% cut in transaction tax. Even though using the similar UK property transaction data as in this research, the policy that Best and Kleven (2017) study is an opposite measure that UK government impose in transaction tax by cutting the transaction tax for certain value properties, whereas in this research is adding transaction tax for BTL properties. Although these differences in policy direction, this analysis aligns with Best and Kleven (2017) studies in illustrating the sensitivity of transaction volumes to changes in transaction tax rates. Specifically, the results prove the pattern that an increase in transaction taxes is likely to lower property transaction volumes, which is consistent with the broader literature on the subject.

3.5.2 Effects on prices

By estimating equation (3.1), this research can compare the effects of the 3% tax surcharge on transaction prices between what this research identifies as BTL properties and the rest of the properties, which this research considers them as non-BTL properties with two subsections: non-BTL rental and non-BTL residential properties. Table 3.5 presents the results of this estimation.

Table 3.5 Baseline results on the effect of the 3% tax surcharge announcement on transaction prices for BTL properties as compared to non-BTL properties

	(1)	(2)	(3)	(4)	(5)	(6)
Treat x Post	-0.014***	-0.016***	-0.015***	-0.010***	-0.018***	-0.006***
	(0.003)	(0.004)	(0.005)	(0.003)	(0.006)	(0.007)
N	570,631	570,631	570,631	433,157	413,518	157,113
Month	Yes	Yes	Yes	Yes	Yes	Yes
Property type	Yes	Yes	Yes	Yes	Yes	Yes
Tenure	Yes	Yes	Yes	Yes	Yes	Yes
Old or New	Yes	Yes	Yes	Yes	Yes	Yes
Location	District	City	County	District	District	District
Bedrooms	Yes	Yes	Yes	Yes	Yes	Yes
Bathrooms	Yes	Yes	Yes	Yes	Yes	Yes
Energy rating	Yes	Yes __	Yes __	Yes __	Yes __	Yes __
TOM	Yes	Yes __	Yes __	Yes __	Yes __	Yes __
Urban or Rural	All	All	All	All	Urban	Rural

Exclude	__	__	__	>Mar 2017	__	__

Notes. The tables show results from estimating equation (3.1) with a single posttreatment dummy for the period of 2014 to 2017. Treatment time is defined as the announcement date of the additional 3% transaction tax on BTL housing. Treated properties is defined as the BTL housing. Control properties are those properties with living purpose. All specifications include year-month fixed effects, plus energy rating, TOM, number of bedrooms, number of bathrooms and new or old indicators. Standard errors are clustered by district and year-month level. BTL stays for BTL properties. TOM stays for time on the market.

Column (1) of Table 3.5 provides the baseline estimation. Using the announcement date of the 3% tax surcharge policy as the treatment date, this research finds that the average transaction price for BTL properties significantly decrease by around 1.4% following the announcement. The baseline model includes a post-treatment dummy variable, incorporating district and time-fixed effects, and controlling for property characteristics, energy rating, and TOM. Column (2) replaces district fixed effects with city-level fixed effects, while column (3) employs county-level fixed effects. The result of column (2) and column (3) shows that the change of locational fixed effect from district level to city or county level does not lead to significant variations of the average treatment effect from the 3% tax surcharge policy. The average treatment effects on BTL properties is about negatively 1.4%, which is about half of the 3% tax surcharge. This result seems different from the finding of Dachis et al. (2011) and Han et al. (2022) that the decline level in the Toronto housing price is about equal to the tax implemented. This is because the target housing segment is different, their result shows the additional tax effect on the overall housing market, whereas the results show the effect of tax surcharge on the BTL properties segment, which have generally lower average housing price than the non-BTL properties as shown in Table 3.3[16]. The result indicates that even though this research has noticed a 15% reduction on BTL properties transaction volume in section 3.5.1, those investors who are still willing to invest in the BTL properties after the tax surcharge policy in fact are less price sensitive than others and they might be interested more in the future rent generated from the BTL properties. This is in line with the findings from interviews with UK market professionals that the main motivational factors behind BTL investments are rental income and the long-term saving alternative (Gibb & Nygaard, 2005). Additionally, column (4) excludes the period after March 2017 to mitigate potential additional policy effects associated with changes in tax relief. Column (5) restricts the sample to urban areas only while column (6) restricts the sample to rural areas.

To ensure the robustness of the analysis and address potential confounding factors, this research conduct additional robustness checks in the estimation. In column (4) of Table 3.5, I exclude transactions from March 2017 onward, which corresponds to the period when changes in tax relief for BTL owner and

[16] BTL properties average price is 211,500 and non-BTL properties average price is 312,700, which is around 48% higher.

higher lending standards for BTL mortgages were implemented. These are potential events that may directly affect the transaction price of BTL properties. By excluding this period in the estimation, I find that the estimated effects decrease slightly about 0.4% compared to the baseline model, reflecting the robustness of the baseline estimate on the average treatment effect. Then I use the 2011 rural and urban classification provided by the Office for National Statistics to identify the urban rural area in the dataset and compare differences between urban and rural area in column (5) and column (6). In the dataset, transactions in urban areas accounts for more than 72% of the total property transactions and only 28% in rural area, showing the concentration of BTL properties in urban area. The concentration of BTL properties in urban areas is due to the demands of rental properties, which normally locates in or near the highly densified areas because of the requirement of workplace and home distance from the rental housing targeted population. The results also in line with Michielsen (2018) who finds that most Dutch and UK BTL properties are located in the city or urban areas. This research finds that properties in urban areas are more strongly negatively affected by the policy than properties in rural areas. The effect BTL properties housing prices in urban area is 1.2% lower than BTL properties in rural area. This result shows that the transaction price of the urban BTL properties is more sensitive to the change of tax surcharge policy compared to the rural BTL properties. This is in line with the findings of Scanlon et al. (2016) showing that most of the investors invests in urban area due to high rental yields and financial certainty of return on investment. Once the certainty changed, the transaction price of BTL properties in urban area would decrease more compared to those in rural area.

3.5.3 Effects on listing rents

Despite its original aim of discouraging property investment behavior and promoting homeownership, the 3% tax surcharge can have significant implications for the rental market. The study compares the rents on BTL properties to rents for non-BTL rental properties, both before and after the announcement of the 3% tax surcharge. The findings reveal a substantial increase in listing rent for BTL properties compared to non-BTL rental properties, with an average rise of approximately 6% following the implementation of the policy.

Table 3.6 Effects of 3% tax surcharge on listing rents for BTL properties as compared to non-BTL rental properties

	(1)	(2)	(3)	(4)	(5)	(6)
Treat x Post	0.060***	0.058***	0.057***	0.058***	0.056***	0.050***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
N	146,470	146,470	146,470	135,690	118,386	135,501
Month	Yes	Yes	Yes	Yes	Yes	Yes
Property type	Yes	Yes	Yes	Yes	Yes	Yes
Tenure	Yes	Yes	Yes	Yes	Yes	Yes
Old or New	Yes	Yes	Yes	Yes	Yes	Yes
Location	District	City	County	District	District	District
Bedrooms	Yes	Yes	Yes	Yes	Yes	Yes

Bathrooms	Yes	Yes	Yes	Yes	Yes	Yes
Energy rating	__	__	__	Yes	__	__
TOM						Yes
Exclude	—	—	—	—	>Mar 2017	—

Notes. Table show results from estimating equation (3.1) with a single posttreatment dummy, $\ln(Y_{i,t}) = \alpha_i + \lambda_t + \omega_{g,t} + \alpha \cdot (Treated_i \times After_t) + \beta \cdot X_i + \delta \cdot Z_{r,t} + \epsilon_{it}$ .The dependent variable is lisint rent. Treatment is defined as the announcement date of the additional transaction tax. Treated properties is defined as the BTL properties. Control properties are non-BTL rental properties. All specifications include year-month fixed effects, plus energy rating, number of bedrooms, number of bathrooms and new or old indicators. Standard errors are clustered by district and year-month level.

Table 3.6 presents the results of estimating equation (3.1) with a single post-treatment dummy variable. Various columns test the robustness of the results using different samples and specifications. Column (1) controls for the sale location at the district level, column (2) at the city level, and column (3) at the county level. In column (4), I include a control for energy rating to assess the impact on the results. Column (5) excludes the period after March 2017 to avoid additional policy effects related to changes in tax relief. Column (6) incorporates the control of TOM in terms of rent. The results remain robust across different samples and specifications.

Column (1)-(3) in Table 3.6 show the policy effect on listing rent for BTL properties as compared to BTL rental properties under various locational fixed effect. The coefficients stay similar and validate the estimation result in the DID analysis. The treatment effect stays around positive 6%, meaning that the 3% tax surcharge led to 6% higher rent for BTL properties as compared to non-BTL rental properties. Even though the analysis includes the energy rating or TOM in the regression or excluding transaction after March 2017, the coefficient present consistently under different specifications. The trend of rising rent resulting from additional transaction tax is consistent with the finding from Chi et al. (2020) that a tax surcharge of 15% on the sale price of renting purpose properties within a holding period under one year and tax surcharge of 10% on sales with holding period between one and two years in Taiwan, in fact leading to a rising rent and lower price-rent ratio. Despite this, what they find is based on the behaviour of speculative investors, who buy or sell properties within a short period, this research can compensate the research in Chi et al. (2020) by providing the finding in rent level change of UK BTL properties market which investors may have the intention for mid to long term rental income and capital gain. From Section 3.5.1 I know that the transaction volume for BTL properties after the transaction tax surcharge in fact is going down, which is not the similar situation in the finding of Chi et al. (2020) even though the analysis both notice upward trend of rent after the imposition of transaction tax surcharge.

Combined the findings in Section 3.5.1 and Section 3.5.3, the observed increase in rent may be attributed to the sharp decline in transaction volumes for BTL properties due to the 3% tax surcharge, which subsequently affects the overall supply level of rental properties in the market, but the demand level of tenants to rent properties remain similar. In this case, BTL landlords obtain higher bargaining power, apply higher tenants searching criteria and compensate for their losses resulting from the increased transaction tax by raising rents, thereby transferring the burden to tenants. The non-BTL rental landlord will also push up their rent to follow the trend, hence, the overall rental properties market faces a rent upward situation. As the primary suppliers of rental housing in the market, the rising rents for BTL properties place an additional financial burden on tenants, and indirectly limit their ability to save for homeownership. This indirectly affect the original objective of the policy, which was to promote homeownership.

3.5.4 Effects on liquidity for sales and rents

In this study, the TOM is utilized as a measure of market liquidity, specifically focusing on the speed at which properties are either sold or rented out. For properties on the market for sale, TOM is operationally defined as the interval from the initial listing date to the date of sale completion. A shorter TOM for sales generally indicates a more active and competitive housing market, where properties are selling quickly. Conversely, a longer TOM can suggest less demand or issues with pricing, condition, or marketing and indicate lower matching rate between sellers and buyers. In the rental market, TOM is defined by the interval between the property's listing for rent and the execution of a lease agreement by a tenant. Analogous to the sales market, a shorter TOM for rentals indicates high demand and a competitive rental market. A longer TOM in this sector, however, may denote the presence of obstacles in securing tenants that align with landlords' criteria, thereby signaling a lower rate of landlord-tenant match success.

Table 3.7 Effects of 3% tax surcharge on TOM of BTL properties as compared to non-BTL properties

	TOM for asking price			TOM for asking rents		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat x Post	-0.003***	-0.005***	-0.006***	0.248***	0.250***	0.254***
	(0.004)	(0.004)	(0.005)	(0.010)	(0.010)	(0.014)
N	444,419	444,419	444,419	207,553	207,553	207,553
Month	Yes	Yes	Yes	Yes	Yes	Yes
Property type	Yes	Yes	Yes	Yes	Yes	Yes
Tenure	Yes	Yes	Yes	Yes	Yes	Yes
Old or New	Yes	Yes	Yes	Yes	Yes	Yes
Location	District	City	County	District	City	County
Bedrooms	Yes	Yes	Yes	Yes	Yes	Yes
Bathrooms	Yes	Yes	Yes	Yes	Yes	Yes
Energy rating	Yes	Yes __	Yes __	Yes	Yes __	Yes __
Exclude	>Mar 2017	>Mar 2017	>Mar 2017	>Mar 2017	>Mar 2017	>Mar 2017

Notes. The tables show results from estimating equation (3.1) with a single posttreatment dummy: $\ln(Y_{i,t}) = \alpha_i + \lambda_t + \omega_{g,t} + \alpha \cdot (Treated_i \times After_t) + \beta \cdot X_i + \delta \cdot Z_{r,t} + \epsilon_{it}$. The dependent variable is TOM. Treatment is defined as the announcement date of the additional transaction tax. Column (1) to (3) show the effect on liquidity of sales, column (4) to (6) show the effect on liquidity of rents. All specifications include year-month fixed effects, plus energy rating, number of bedrooms, number of bathrooms and new or old indicators. Standard errors are clustered by district and year-month level.

The results of the effect of 3% tax surcharge on the TOM of BTL sales and rents, with all analyses excluding post-March 2017 data to rule out confounding effects from changes in landlord tax relief. The initial three columns of Table 3.7 present the changes in TOM for BTL asking prices relative to non-BTL properties. The imposition of the tax surcharge is associated with a statistically significant yet very small decline in TOM for sales of approximately 0.3%, suggestive of a marginal enhancement in market liquidity post-policy implementation. This finding shows the tax surcharge does not substantially affect the searching and bargaining process of BTL sellers and BTL buyers, thereby inferring that BTL market participants have largely sustained their pre-existing strategies for property search, negotiation, and match-finding.

The finding is in line with the existing research on the UK housing market. For example, Bracke (2019), who use UK housing transaction data in the period of 2009 to 2014 to test BTL properties difference relative to other home purchase in general and find limited difference exists in TOM between BTL properties purchase and other purchases, even though there is price discount exist for BTL properties. Although not researching specifically on BTL properties market, Huang and Milcheva (2023) find economically small and no significant effect of the 2020 UK SDLT holiday on the TOM of overall property transactions, it only takes on average 4 days longer for properties sales in the case without SDLT[17]. These results are further proved by the research on the Taiwanese property market, where Chi et al. (2020) verify that the average TOM for properties sales acquired for investment purposes does not markedly differ from that for owner-occupied residences, even in the context of the 2010 Taiwanese transaction tax surcharge policy. Complementarily, this analysis enriches the literature by clarifying the TOM dynamics for BTL investment-type properties in response to increased transaction taxes, thereby augmenting the study of Han et al. (2022) on market liquidity dynamics for single-family houses in Toronto under increased land transfer tax.

The TOM for asking rents, as reported in Column (4) to (6), displays a significant increase after the transaction tax change, indicating a 25% rise. This research finding contributes to the research gap in understanding the TOM dynamics for rent level of properties with letting purposes under the transaction tax surcharge. The increased of TOM for BTL properties asking rent suggests a decrease in market liquidity for rental properties and demonstrates that the 3% tax surcharge has more effects on the TOM for rents of BTL properties compared to TOM of BTL properties sales, resulting in more

[17] 2020 UK stamp duty land tax holiday is a policy that raise the nil rate band of the stamp duty (transaction tax) from £125,000 to £500,000. In this way, home movers and first-time buyers can be exempted from the transaction tax if the value of the property up to £500,000. But BTL properties buyers still need to pay 3% tax surcharge.

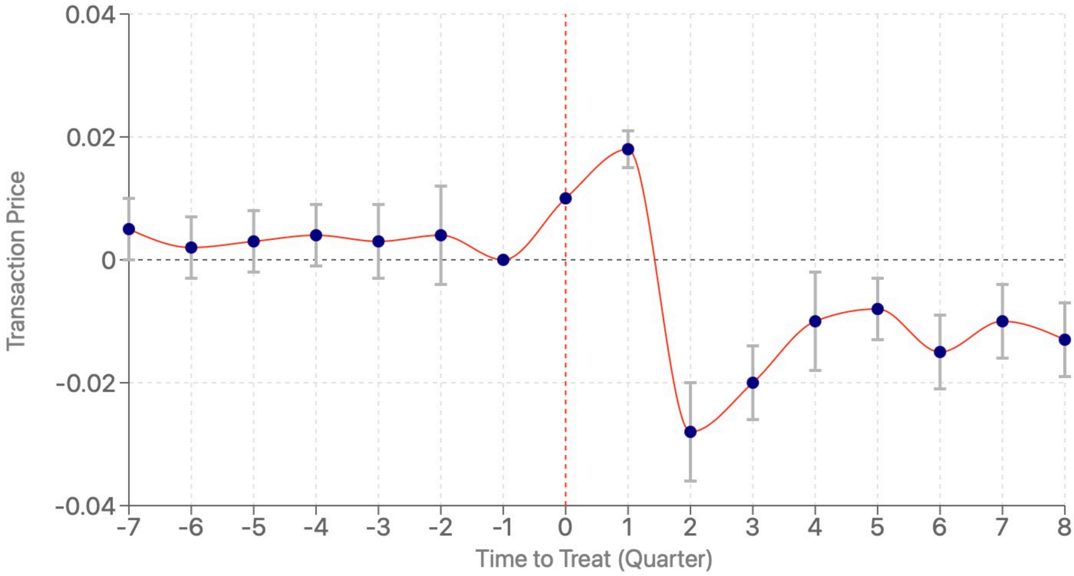
bargaining, searching, and matching time for both landlords and tenants. Landlords, in response to these changes, appear to lengthen negotiation times with potential tenants to enhance landlord’s bargaining power, raise standards and quality requirement of potential tenants in order to secure higher rents and good quality tenants, thereby shifting the burdens of landlords onto tenants. The finding is consistent to the result of study from Cajias and Freudenreich (2018b), they explore the determinants of liquidity in German rental market and find out that the longer the properties letting process led to higher asking rent.

3.5.5 Dynamic effects

Figure 3.2 presents the coefficients from equation (3.2), where the single indicator in equation (3.1) is replaced with lead and lag indicators for 7 quarters ahead and 8 quarters after the announcement of additional 3% tax surcharge. It shows the dynamic treatment effects over time and present parallel trend test. By analyzing these coefficients, I can assess whether there are differential trends in transaction prices between the treatment and control groups before the event occurs. This is important to address potential biases in the DID estimates and ensure the validity of the parallel trends assumption. From Figure 3.2, it can be observed that the coefficients on the time dummy variable are insignificantly different from zero before the announcement date, indicating that there were no significant differential pre-trends in transaction prices between the treatment and control groups. This supports the validity of the parallel trends assumption and underlines the validity of the DID estimates.

The horizontal line of Figure 3.2 represents the quarterly time to treatment. Zero represents the treatment time, which is the 3% tax surcharge announcement date. One quarter after the announcement date is the policy implement date. The reason why I use the announcement date as the treatment time in this research instead of the implementation date is because after the government announce the 3% tax surcharge would be implemented one quarter later, BTL property investors would react to the policy and adjust their investment strategy in order to avoid the 3% tax surcharge before the policy implementation date. If the analysis uses implement date as the treatment time, there would be a significant anticipant effect shown in the figure before the treatment time, which confront the principal of DID analysis that no significant differential pre-trends should be noticed in transaction prices between the treatment and control groups.

Figure 3.2 Dynamic treatment effects and parallel trend test on transaction prices for BTL properties following the 3% Tax surcharge.



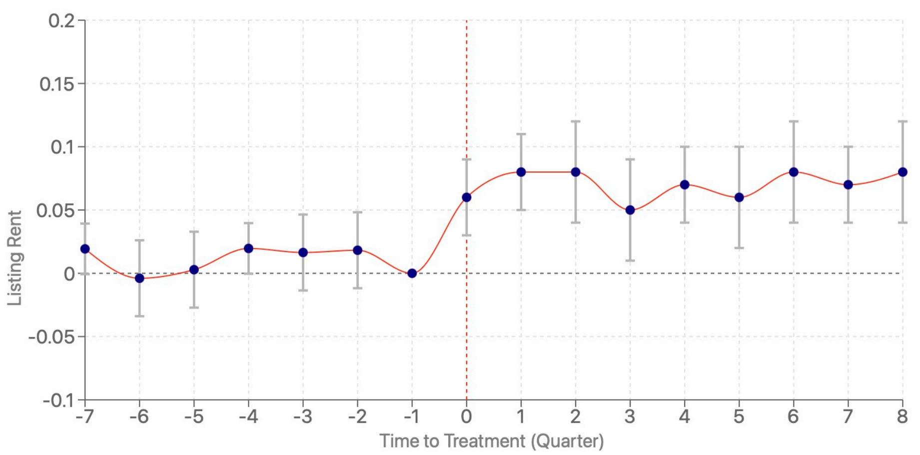
Notes. The figure shows dynamic treatment effects and 95% confidence intervals from estimating equation (3.2) on transaction price. Standard errors are clustered at both year-month and district level. Treatment time is defined as the announcement date of the additional 3% transaction tax on BTL housing. Treated properties is defined as the BTL properties. Control properties are non-BTL properties. The dotted vertical line represents the time of announcement.

However, it is worth noting that there is a slight deviation in the coefficient for the first quarter before the announcement date (treatment time). This could potentially be attributed to some investors reacting to leaked information or anticipating the policy change on BTL properties before the announcement of 3% tax surcharge. But it does not lead to a significant pre-trend pattern, hence the assumption of dynamic DID still valid.

In terms of the dynamic effects following the announcement of the 3% tax surcharge, Figure 3.2 shows an immediate increase in the average transaction price of BTL properties by 2%. This reflects the behavior of investors rushing to complete the transactions of BTL properties before the implementation date of the policy in order to avoid the additional transaction tax. Subsequently, there is a rapid decrease in the coefficient of 5%, which makes the coefficient for BTL properties transaction price reaches to negative 3% after one quarter from the policy implementation date, indicating a downward adjustment in BTL properties transaction prices. This transform of investment strategy on BTL properties starts immediately on the implement date of 3% tax surcharge, because the additional transaction tax implements immediately for every BTL properties transactions at the date of policy implement. The upward coefficient trends before the implement date and rapid downward after the implement date shows the speculative mindset of BTL properties investors facing the additional 3% tax surcharge on their transaction. As any investment market consist of two main types of investors. Short-term speculative investors and long-term portfolio holders. The investment mindset and strategy are different between them. Short-term speculative investors aim at short-term cash flow and whether they can gain the return back in a short time. Hence, they will be extremely sensitive to the 3% tax surcharge as it represents the cost of the investment is higher and it would need longer time to get the return back. Therefore, this group of investors would be pushing the price up before the policy implement date as they are rushing to finish the deal before that to avoid the extra tax. In contrast, the long-term portfolio holder is the most stable type of investor as they do not change their original investment strategy due to policy change. They do not focus on short-term gain. Hence this group of investors would stabilize the transaction price of BTL market. The transaction price would recover back a bit compared to the lowest point. The effects then gradually diminish after two quarters from the implement date and stabilize at around negative 1.5 to 2 %.

Figure 3.3 presents the dynamic treatment effects on the listing rent for BTL properties. The figure shows the listing rent for BTL properties increase around 6% compared to non-BTL rental properties since the 3% tax surcharge announcement. This can be explained by the introduction of 3% tax surcharge policy trigger the BTL landlords' behaviour of increasing rent due to the higher barrier of entrance for BTL investment that the policy raises the investment barrier. In addition, BTL landlord typically have higher interest rate to pay due to the specific BTL mortgage, this can explain why BTL landlords are more sensitive to the transaction tax change than the non-BTL rental landlords since they are originally carried higher interest rate burden than non-BTL rental landlords. From the Table 3.3 of the Section 3.3.3, the summary statistics of BTL and non-BTL rental properties, it shows that the average weekly rent of BTL properties is 7.8% lower than that of the non-BTL rental properties. BTL landlords should have the intention to mitigate the rent gap given the similar rental properties in the market have higher rent than BTL properties. Most of the treatment effect prior to the treatment are close to zero, implying the parallel trend pattern holds before the tax surcharge announcement.

Figure 3.3 Dynamic treatment effects and parallel trend test on listing rent for BTL properties following the 3% Tax surcharge

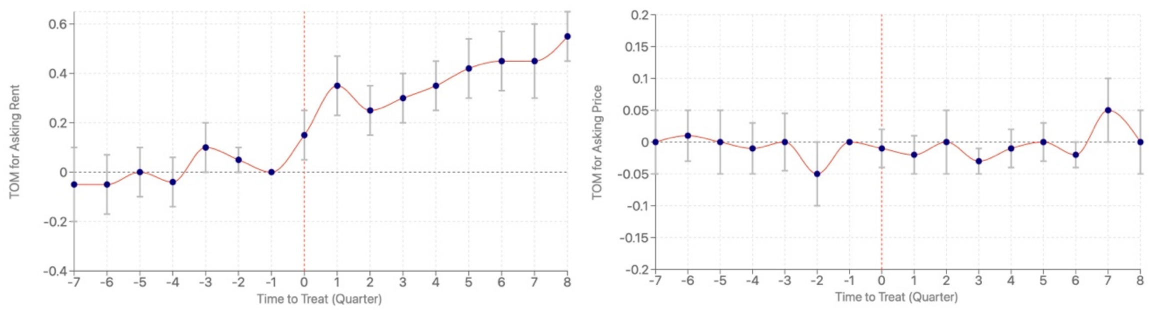


Notes. The figure shows dynamic treatment effects and 95% confidence intervals from estimating equation (3.2) on listing rent for BTL properties. Standard errors are clustered at both year-month and district level. Treatment time is defined as the announcement date of the additional 3% transaction tax on BTL housing. Treated properties is defined as the BTL properties. Control properties are non-BTL rental properties. The dotted vertical line represents the time of announcement.

Figure 3.4 presents the dynamic treatment effects on the liquidity for asking price and asking rent for BTL properties before and after the treatment date. Panel (A) of Figure 3.4 shows the TOM for BTL asking rent, it shows that the parallel trend pattern holds before the 3% tax surcharge treatment since the coefficients are close to zero. Just five quarter after the treatment date, the treatment effect on the TOM of BTL asking rent increase rapidly, reaching average level of around 25%. The results show that after six quarter from the treatment date, the effect increases to over 40%, this is because the rental tax reform policy implemented in April 2017. The analysis excludes this period from the average treatment effect estimation on section 3.5.4. The rapid growing effect on the TOM of BTL asking rent indicates the sharp decline in the tenant and landlord matching, as BTL landlords know the tax surcharge would limit the supply of the rental properties and they want high quality and higher payment ability tenant and long-term tenancy.

Figure 3.4 Dynamic treatment effects and parallel trend test on TOM for BTL properties asking price and asking rent following the 3% Tax surcharge.

(A) TOM for asking rent (B) TOM for asking price

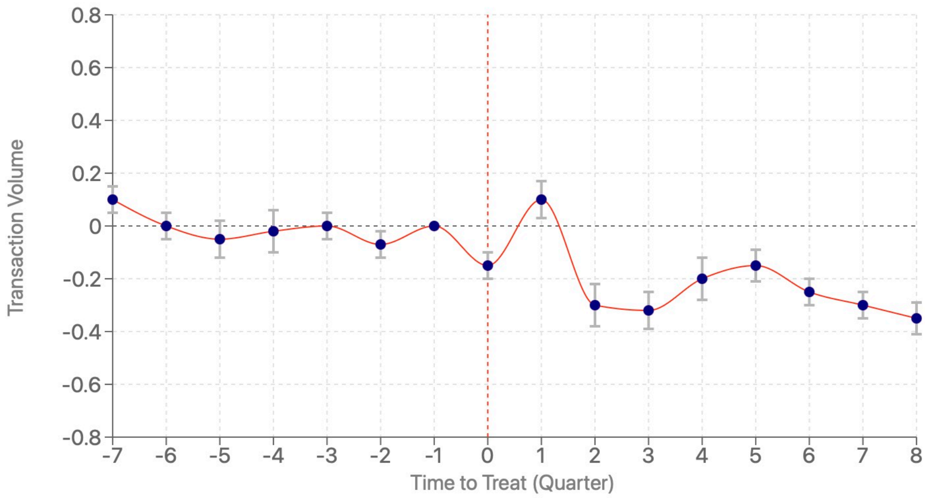


Notes. The figure shows dynamic treatment effects and 95% confidence intervals from estimating equation (3.2) on TOM for BTL properties asking rent and asking price. Standard errors are clustered at both year-month and district level. Treatment time is defined as the announcement date of the additional 3% transaction tax on BTL housing. Treated properties is defined as the BTL properties. Control properties are non-BTL rental properties. The dotted vertical line represents the time of announcement.

Panel (B) of the Figure 3.4 shows the dynamic effects on the TOM for BTL asking price, which shows the TOM for BTL sales. The result is consistent with what I have found in the average treatment effect in the section 3.5.4 that the tax surcharge has very few impacts on the TOM for BTL sales, this interesting finding indicate that the BTL buyers and sellers matching, and bargain does not been affect by the tax surcharge, even though the buyers face higher transaction tax. This may be due to the average price of the BTL properties has dropped as respond to the tax increased, the offset function results in the stable TOM of the BTL properties sales.

Figure 3.5 shows the dynamic treatment effects on the transaction volume for the BTL properties before and after the tax surcharge treatment. The result is consistent with the average treatment effect on the transaction volume in section 3.5.1 that the average treatment effect is around 20%. However, there are some interesting facts need to notice from Figure 3.5. The BTL transaction volume increases around 20% after the announcement of 3% tax surcharge, showing that BTL buyers and sellers quickly complete their transaction deal before the tax surcharge implementation. The tax surcharge leads to around 40% transaction volume drop after just one quarter from the tax surcharge implementation and then recover back to around 20%. This phenomenon indicates the same pattern as in the effect of BTL transaction price, showing the speculative mindset of BTL buyers and sellers facing the 3% tax surcharge on their transactions. The short-term speculative investors and the long-term portfolio holder would react differently to the policy implementation. Short-term speculative investors would be the quickest actioner push the transaction complete before the policy implement date. This led to the rapid increase of transaction volume before the implement date and drop rapidly after the date. However, due to the heterogeneity in the behaviour of long-term portfolio holders compared to the speculative investors. They tend to invest in the market with long-term mindset, so the change of policy would not impact their investment strategy, and because of these stable investors, the transaction volume gradually recover back to a certain level, although it still being affected by the speculative investor. From quarter six after the implementation, the transaction volume decline again due to the rental tax reform policy in April 2017, this analysis has excluded this period in Table 3.4 of Section 3.5.1.

Figure 3.5 Dynamic Treatment Effects and parallel trend test on transaction volume for BTL properties following the 3% Tax surcharge.



Notes. The figure shows dynamic treatment effects and 95% confidence intervals from estimating equation (3.2) on transaction volume of BTL properties. Standard errors are clustered at both year-month and district level. Treatment time is defined as the announcement date of the additional 3% transaction tax on BTL housing. Treated properties is defined as the BTL properties. Control properties are non-BTL properties. The dotted vertical line represents the time of announcement.

To summarize, the findings show the average treatment effect after the treatment date and dynamic effects of the 3% tax surcharge on the transaction price, volume, listing rent and TOM of sales and rent over time. Following the announcement of the 3% tax surcharge, prices for BTL properties decrease on average 1.4%, listing rent increases around 6%, transaction volume drop around 20%, TOM for asking rent increase around 25%, but the TOM for sales does not change much. The dynamic finding shows that the supply and demand level on BTL properties change significantly based on the timing of policy announcement and implement date. The speculative BTL investors behaviour raises the demand level of BTL properties after the announcement and before the implement date, which results in double shock of demand shortage and loss aversion mindset on BTL properties transaction price after the policy implement date.

3.6 Robustness

3.6.1 Non-BTL rental versus non-BTL residential properties on price

The identification of BTL properties might be imperfect in cases where the non-BTL properties owner chooses to rent out properties they purchased several years ago. Therefore, this analysis expands the rental categories by distinguishing properties rented out longer than one year since their purchase. Those are categorized as non-BTL rental properties, while those rented out within one year of purchase are classified as BTL properties. Properties that do not rented out at any time are categorized as non-BTL residential properties.

If non-BTL rental properties were significantly affected by the 3% tax surcharge compared to the non-BTL residential properties, it would have implications for the interpretation of the main results as it would mean that this analysis has not included non-BTL rental housing in the treated group for the baseline regression model in Table 3.5. To ensure the accuracy of the findings and avoid any misinterpretation, it is crucial to assess whether non-BTL rental housing is indeed impacted significantly by the additional transaction tax.

Table 3.8 Effects on transaction price of non-BTL rental properties vis-à-vis non-BTL residential properties.

	(1)	(2)	(3)	(4)
Treat x Post	0.003***	0.006***	0.002***	0.004***
	(0.002)	(0.003)	(0.003)	(0.002)
N	521,567	521,567	521,567	396,390
Month	Yes	Yes	Yes	Yes
Property type	Yes	Yes	Yes	Yes
Tenure	Yes	Yes	Yes	Yes
Old or New	Yes	Yes	Yes	Yes
Location	District	City	County	District
Bedrooms	Yes	Yes	Yes	Yes
Bathrooms	Yes	Yes	Yes	Yes
Energy rating	Yes	Yes	Yes	Yes
TOM	Yes	Yes	Yes	Yes
Exclude	__	__	__	>Mar 2017

Notes. This table presents the results obtained by estimating equation (3.1) using a single post-treatment dummy variable, with the treated group replaced by non-BTL rental properties rather than BTL properties.

The estimation period covers the years from 2014 to 2017. The treated time refers to the date of the announcement of the additional 3% transaction tax on BTL housing. The controlled group is the non-BTL residential properties with a living purpose. All specifications include year-month fixed effects, as well as controls such as energy rating, number of bedrooms, number of bathrooms, and indicators for whether the property is new or old. Standard errors are clustered by district and year-month levels.

To address this concern, this analysis draws upon the logic in the work of Bracke (2019), who conducted a similar robustness check to test whether there is problem of putting mortgage BTL and nonmortgage BTL transactions together to estimate the BTL discount compared to other purchase. Bracke (2019) shows that the BTL discounts are mostly unchanged after inserting a cash indicator in the regression to elaborate the inclusion of nonmortgage BTL in the overall BTL transaction sample do not change the result of BTL price discount estimation, even though nonmortgage investor has 7-9% reduction in TOM without the need from approval of bank. In this research, instead of inserting indicator in the regression, the analysis uses DID framework to test whether non-BTL rental properties have been affected differently from the policy compared to non-BTL residential properties. If there is significantly different effect between these two groups, meaning the main result of estimation is mistaken due to not including the non-BTL rental properties in the treatment group but in the control group. If no obvious difference noticed, the main result passes this check.

To examine the impact of 3% tax surcharge on non-BTL rental housing, the analysis presents the results of estimating equation (3.1) using a single post-treatment dummy variable, replacing the treated group of BTL housing with non-BTL rental housing. Table 3.8 displays these results across various specifications. In column (1), the analysis reports the estimation using a simple post-treatment dummy variable, incorporating district and time-fixed effects, and controlling for property characteristics, energy rating, and TOM. To test the robustness of the findings under different locational controls, column (2) replaces district fixed effects with city-level fixed effects, while column (3) employs county-level fixed effects. Furthermore, column (4) excludes the period after March 2017 to mitigate additional policy effects associated with changes in tax relief.

Across all estimations, the results reveal the effects on non-BTL rental properties compared to non-BTL residential properties under the influence of the 3% additional transaction tax. The magnitudes of the point estimates are small, indicating additional transaction tax effects of less than 1%. These negligible effects on non-BTL rental housing validate the appropriateness of the identification strategy for the treated group in the baseline regression model presented in Table 3.5. The similarity in prices between non-BTL rental housing and non-BTL residential properties allows non-BTL rental properties to be considered part of the control group in the baseline regression model. Therefore, the identification strategy for the treated group is valid, and the main results remain robust.

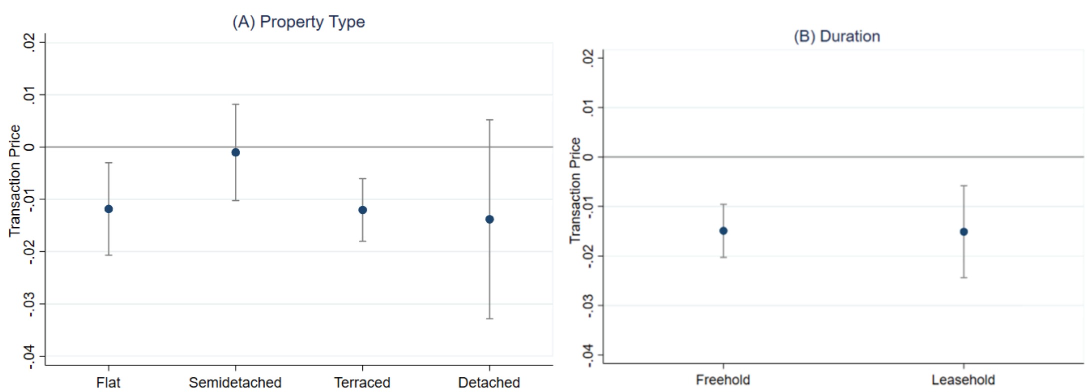
In addition, this estimation on the non-BTL rental versus non-BTL residential also indicate there is no spillover effect from the BTL market to the non-BTL market. As the 3% tax surcharge policy only apply to the second home purpose property, which normally is for renting purpose. If there will be spillover effect of this policy, it will only come from BTL to non-BTL rental, and hence the non-BTL rental property would be affected as there is a spillover effect. However, there is no significant difference between non-BTL rental and non-BTL residential property, this confirm that the non-BTL rental does not affected by the spillover effect, as if there is a spillover effect the difference would be significant among non-BTL rental and the unaffected non-BTL residential property. This estimation help the study to test and rule out the possible existence of spillover effect from BTL to non-BTL market.

3.6.2 Heterogeneity on property type and tenure

The regression results presented in Table 3.5 provide an average estimate of the DID models in terms of the effect of 3% tax surcharge on BTL properties transactions price. However, this average could cover a diverse distribution, hence, it is valuable to examine the estimates across different property types and tenures by running separate regression estimation to understand the policy effect on different property type and tenure. The results are presented in Figure 3.6. Panel A shows the effects by property type including flat, semi-detached, terraced, and detached. Panel B shows the effect by freehold and leasehold properties, respectively.

In the UK housing market, houses and flats represent the two predominant property categories, each exhibiting distinct characteristics across several dimensions, including pricing, tenure, amenities, and geographic distribution. Houses are typically associated with higher price points and are often held under freehold tenure, predominantly situated in suburban or rural settings. The freehold status affords owners indefinite property rights, circumventing the limitations inherent to leasehold arrangements, such as diminishing lease terms and potential complications with management entities. Moreover, houses tend to appreciate more rapidly in value compared to flats, reflecting their desirability and investment potential. Conversely, flats are frequently characterized by leasehold tenure and are commonly located in urban centers with cheaper price than similar sized houses. Leasehold tenure means the lease of the property will diminish over time and most mortgage companies do not lend on property with lease less than 80 years. In addition, the lenders see houses as lower risk compared to flats and require larger loan to value (LTV) for BTL investment in flat. Despite Bracke's (2019) observation that a significant proportion (47%) of BTL transactions are cash purchases—exceeding the overall mortgage usage rate (32%) in the Land Registry (LR) property transactions—there exists a substantial segment of BTL investors who are subject to the disparate lending criteria based on property type. This differential treatment has implications for the investment decisions of BTL investors, who must weigh their preferences for rental yield and capital gains against their risk tolerance. Consequently, the heterogeneous reactions of BTL investors to the imposition of the 3% tax surcharge may be indicative of there may have different reaction towards the 3% tax surcharges from BTL investors with preferences on certain property type or investment portfolio.

Figure 3.6 Treatment Effects of 3% tax surcharge on Transaction Prices by Property Type and Tenure



Notes. The figure shows DID coefficients and 95% confidence intervals from estimating equation (3.1) with different property types and tenures. Panel (A) shows the effects spread of different property types: Flat, Semidetached, Terraced and Detached. Panel (B) shows the effects for tenure: Freehold and Leasehold, respectively.

This analysis find that the tenure of the property does not lead to significant differences between freehold and leasehold BTL properties. Both tenures experienced negative effects on prices, with approximately a 1.4 % decrease. This suggests that the 3% tax surcharge had a similar impact on both freehold and leasehold properties, even though they are treated different from BTL mortgage lenders and having different right of ownership. This also show the 3% tax surcharge policy affect the BTL investors at the same level no matter leasehold or freehold tenure as this policy do not treat tenure differently. The tax surcharge will apply as long as the property is not serve as the first residency. In other word, this policy does not have impact on mitigating the gap between freehold and leasehold property. Nevertheless, when examining the effects by property type, the analysis observes that semi-detached and detached houses experience the insignificant effects. Flat and terraced house have around 1% average decrease on transaction price, facing the change of tax surcharge. Interestingly, Semidetached, detached, and terraced are within the house type. However, they show quite different reaction to the 3% tax surcharge, especially the semidetached is not being affected compared to other two. According to a report written by the Property Beacon (2023), the semi-detached properties are the most common type of housing stock in the UK and are the best in resale value, in addition, it tends to have space for extensions or loft conversions to add value to the house. It is more attractive to the property investor with potential value addition, hence, semidetached house does not affect significantly by the 3% tax surcharge in this data sample. The implication of this various policy effect within the house type is that policy design should design a more detail policy when consider the policy in housing market, as housing market consist of a range of different property type, tenure and location. When designing the policy, policy designer should think about the fundamental objective of the policy, whether it is for stimulating the economy, mitigating the wealth gap, increase housing ownership or lowing the rent burden, and most importantly the associated risk of unintended harm.

3.7 Chapter summary and discussion

In summary, this chapter contributes to provide valuable insights into the impact of the 3% tax surcharge on the BTL properties market. By examining the supply level, market liquidity, price and rent change of BTL properties compared to non-BTL properties before and after the policy announcement, this study contributes to the current gap in the academic research in the two main parts. First, the study highlights the 3% tax surcharge on the BTL properties in fact increasing the burden of the tenants as BTL investors transferring their additional transaction cost to tenant. This result is shown in the 6% rent increase of BTL properties to non-BTL rental properties and the TOM of asking rent for BTL has increased about 25%, which is about 22 days longer, the TOM indicates the tenants are becoming harder to get their interested room offer as landlords are increasing their standard. Second, the study uncovers evidence of speculative behavior among short-term speculative BTL investors and a subsequent rapid decline in prices after the policy implementation. The effect then offset by the long-term BTL portfolio holder investment strategy, however, it remains price discount compared to pre-treatment period. The result of this study indicates that housing policy like this would lead to speculative behaviour which further distort the housing market. Future policy implementation could consider leave no space for speculative investors by implementing policy overnight instead of giving one quarter space for them, but it needs to be a thoughtful policy which considers the collateral damage and unintended harm.

Some people may argue that the Help to Buy scheme and interest rates would also affect the estimation result in that period. Help to Buy was a government-backed scheme which aim to help first time buyers through providing equity loan to eligible buyers and it is only for newly built homes. In fact, this policy does not affect the BTL property market as it is only eligible for first time buyer. It is true that the Help to Buy scheme may affect the price of the non-BTL market. The Help to Buy scheme should apply to non-BTL residential properties only and it should result in different price if it has effect compared to non-BTL rental properties. But the robustness test in this study about the non-BTL rental versus non-BTL residential shows that the Help to Buy scheme does not have significant impact in the dataset employed in this study as there is nearly no difference between the price between non-BTL rental and non-BTL residential. In addition, the interest rate in the sample period is very stable at around 0.25%. Although BTL properties tend to carry higher mortgage interest rate, but this situation is already there before the 3% tax surcharge, hence the DID model could account for its impact as long as the interest rate before and after the policy implementation is stable, which is the case. Hence, both interest rate and Help to Buy scheme should not affect or distort the result of this estimation.

The findings of this study have important implications for housing policy. It raises concerns about the effectiveness of using transaction taxes to cool down housing prices, as it may lead to unintended consequences such as speculative investment behavior. In fact, the burden of increased taxes on rental housing transactions is transferred to tenants through higher rents, which negatively affects their ability to save for homeownership. The similar situation happened in the city of Toronto, as Han et al. (2022) propose evidence in the newly transaction tax lead to obstacle for the homeownership, it takes longer to sell property and harder for first -time buyer to own their first home. Currently, most of the countries in the world do not have suitable reference or experiences to help UK refine the housing policy, but I try to propose a possible way for the UK policy designer as below.

The chapter suggests that policymakers should carefully consider the impact of rental housing regulations and focus on addressing the underlying issues of housing affordability. Rather than solely prioritizing homeownership, recognizing the importance of rental housing in supporting potential first-time buyers and providing affordable living options is crucial. Regulating the rental housing market should be approached cautiously to avoid exacerbating the burden on tenants and to ensure a healthy and balanced housing market in the long term. To balance these competing interests, future policy design could be designed in a comprehensive way, not in a solo policy. For example, the 3% tax surcharge policy is pushing higher burden to the investor for purchasing second or more property and free some housing stock to the first-time buyer. But it will lead to the action of landlord to increase rent. Hence, the comprehensive policy should also set a rent control along with the 3% tax surcharge so that the policy not only free the housing stock from investors but also prevent landlord to increase the rent. This comprehensive policy could also protect tenants suffering from higher rent and give them more saving space to own their first property, which in turn meet the objective of higher homeownership.

This chapter is not without limitation, especially the parallel trends assumption. Roth (2022) review publications in three leading economics between 2014 and 2018 and found 70 papers use dynamic DID or “event-study plot” to visually test for pre-trends, which is the same method as in this chapter. This means the method of dynamic DID in parallel trend validation is well used in the academic paper. However, there are some papers criticize the use of this kind of method and trying to improve the estimation result, which is fare as pursuing more accurate estimation with less bias is the common goal for any academic research especially in the casual inference estimation. Gibson and Zimmerman (2021) indicate that although the results of dynamic DID model has given graphical examination and prove the parallel trends exist in the pre-treatment period, the key concern with this is that it only examines whether the parallel trends assumption is valid in the pre-treatment period and there is no guarantee that the parallel trends will hold in the treatment period as well. One of the approaches to examine whether the parallel trend is valid in the treatment period is to use sensitivity analysis. Gibson and Zimmerman (2021) extend the sensitivity metrics developed by Cinelli and Hazlett (2020) to validate the parallel trends assumption in DID analysis by quantifying how much stronger the unobserved time-varying confounders need to be, relative to an observed time-varying confounder, to materially change the conclusions of the study. Apart from this approach, Freyaldenhoven et al. (2019) propose an approach that exploits a vovariate assumed to be affected by the relevant confounding factors but not by the treatment itself. This covariate is then used to adjust for the counterfactual difference in trends, thus avoiding the need for non-zero pre-trends. Rambachan and Roth (2023) propose tools for robust inference in DID and event-study designs where the parallel trends assumption may be violated. Instead of requiring that parallel trends holds exactly, they impose restrictions on how different the post-treatment violations of parallel trends can be from the pre-treatment differences in trends. The casual parameter of interest is identified under these restrictions. Hence, there are papers continue improving the estimation model, and propose new estimation approaches in DID setting. Future research on the topic of this chapter can explore the different estimation result using these newly proposed approaches and validate the difference after controlling for unobserved confounders.

Chapter 4

Total Returns to Residential Rental Housings

4.1 Introduction

The interest in housing assets investment is expanding rapidly, with both private and institutional investors around the world putting enormous capital into the housing market, especially after the Great Recession. Since then, the housing markets all over the world have been booming and it attracts lots of investor interest. Given the important role of residential real estate in the economy and investment portfolios, it is significant to establish the annual total return to residential real estate in a way that avoids measurement problems as far as possible, using a data set that is large and representative enough for reliable inference. This chapter aims to measure total returns to residential real estate as accurately as possible in the aggregate level. In a recent paper, Jordà et al. (2019) aim to determine the total rate of return to housing and to compare it to the performance of stocks and bonds all over the world. They use secondary data to suggest that housing returns are surprisingly high given the risk. However, the housing returns data on their paper suffer from several measurement problems, which led to debate on whether the estimated high returns to housing are real or it is the result of mismeasurement (Chambers er al., 2021; Eisfeldt and Demers, 2018). The main objective of this paper is to shed light on this issue and present an accurate estimation on the total rate of return to housing.

However, existing academic literature has extensively researched the returns of bonds and equities, but lacks sufficient focus on housing, despite it being the largest asset class globally (Dimson et al., 2002). Residential rental housing assets represent a popular and representative type of housing investment (Mills et al., 2019). Unlike owner-occupied housing, rental housing yields two main components of returns: net rental income and capital gains. Many academic studies have focused solely on one of these components due to the challenge of obtaining data on both rent and property prices over time. Numerous academic studies refer the returns of residential rental housing investment purely on income yields as the rent-price ratio. For example, Campbell et al. (2009) employed the dynamic Gordon valuation model to examine how the rent-price ratio contributes to rent growth, real interest rates, and housing risk premia in U.S. metropolitan areas. Clark and Lomax (2020) used variations in the rent-price ratio to identify potential housing bubbles, noting that a low ratio indicates expensive property prices relative to rental rates in England. Similarly, Ambrose et al. (2013) estimated the rent-price ratio in Amsterdam over 355 years, dating back to 1650, to gauge housing market bubbles. Gallin (2008) applied the dividend discount model to assess whether the rent-price ratio can predict future movements in housing prices and rents at the city level in the U.S.

The prevailing literature primarily relies on the user cost formula popularized by Poterba (1984), which assumes no arbitrage exists, implying no discernible difference between being a tenant and owning property. This formula features the income yield on the left-hand side and the "user cost" on the right, representing the net cost of property ownership, encompassing the risk-free rate, risk premium, capital gain, depreciation, maintenance costs, and mortgage interest deductions (Himmelberg et al., 2005). However, this formula predominantly serves to estimate the cost differential between renting and owning property or to analyze cross-sectional variations in income yields within cities (Bracke, 2015; Hill and Syed, 2016). Instead of solely focusing on the relative disparities between renting and owning or the cross-sectional variations in income yields, the contribution lies in estimating the time-series total return at the regional level by amalgamating regional income yields and repeat-sales capital gains.

Capital gain has also received considerable attention in existing academic literature across various intriguing facets. Dusanskyl and Koç (2007) present a theoretical model of housing demand using periodically dynamic housing markets in Florida to estimate the effect of housing price increases on the demand for owner-occupied housing, demonstrating that housing can serve as an investment asset with capital gains. Bhatia and Mitchell (2016) analyze changes in household consumption decisions regarding capital gains on owner-occupied housing in Canada. Harding and Rosenthal (2017) explore the impact of housing capital gains on self-employment transitions. However, due to the scarcity of data on rent, prices, and ownership costs for the same property, most studies focus on the intersection of capital gains with household behavior, with fewer academic inquiries exploring capital gains, income yields, and their corresponding housing total returns.

Apart from solely research on income yield and capital gain, recent studies have made strides in estimating total returns by merging income yields and capital gains. Eisfeldt and Demers (2022) focused on the total returns of single-family rental homes at the city level across 30 U.S. cities from 1986 to 2014. However, they estimated rent prices using housing characteristics of owned properties through a hedonic regression model, then employed them to construct income yields instead of directly estimating actual income yields. Chambers et al. (2021) utilized the real estate investment portfolios of Oxford and Cambridge colleges to estimate the total returns of residential, agricultural, and commercial real estate in England from 1901 to 1983. They had property-level data on rent and costs over time, enabling accurate estimations of net income yields over time. Compared to this study, they had a longer period of property-level data and could also include the estimation of total returns on agricultural and commercial real estate. However, they used the housing price index presented by Knoll et al. (2017) to estimate their capital gains instead of deriving them from their own data, primarily due to the nature of fewer transactions as investment holdings by university colleges. Jordà et al. (2019) also employed the housing price and rent index estimated by Knoll et al. (2017) to estimate total returns for 14 countries. However, due to data limitations, combining rent and price data from different sources for total return estimates may introduce measurement errors in the time-series income yield estimate (Chambers et al., 2021; Eichholtz et al., 2021). In contrast, this study estimates actual income yields and capital gains by constructing my own repeat-sales housing price index and utilizing actual rent and price data compared to these existing literatures.

However, neglecting either of these components in housing return estimation can lead to measurement errors. To address this gap, the analysis constructs a dataset by matching rental listing information with corresponding price transaction records based on the exact property address. This allows us to gather data on rent, price, and costs for the same properties, enabling us to estimate income yields, capital gains, and total returns for residential rental housing across England from 2014 to 2021. The final dataset includes 265,052 residential rental properties in England. The analysis began the empirical analysis by constructing repeat-sales house price indices over the sample period, estimating these indices based on 125,186 housing price pairs for the same properties and adjusting for inflation. These indices capture annualized capital gains for different regions. The analysis finds that the average annualized capital gains rate for England is 2.2%, with significant cross-sectional variation among regions. For instance, the London region demonstrated a lower-than-average capital gain at 1.9%, while the East of England achieved the highest among all regions at 2.9%.

Next, the analysis estimate gross income yields by dividing aggregate annual rent by aggregate sales price in each region for each year. The results show a mean gross income yield of 4.9% in England, with significant regional variations. London had the lowest gross income yield at 4.2%, while the North East and North West had the highest at 6.0%. The substantial difference between regions underscores the importance of considering locational-level risks in residential rental housing investment. The analysis then investigates the costs of property ownership to determine net income yields by deducting the share of costs from gross income yields. These costs include vacancy rates, taxes, maintenance, improvements, and insurance. While obtaining cost data for individual properties is challenging, this analysis employ methods similar to previous studies to estimate cost-to-gross-income ratios. The average cost to gross income ratio in England was 38.8%, indicating a significant cost of ownership for modern residential rental housing. Combining the findings on capital gains, gross income yields, and cost-to-income ratios, this analysis estimates total returns for each region. The analysis finds total returns to residential rental housing in England to be 5.2%, with contributions from capital gains (2.2%) and net income yields (3.0%). Notably, net income yields contributed more than capital gains to housing total returns during the sample period.

London emerged as the region with the lowest total return at 4.5%, while the East of England achieved the highest total returns at nearly 6.0%. To further explore the dynamics within London, the analysis segments rental housing observations into quintile price tiers and estimated capital gains and net income yields for each tier. Interestingly, the analysis finds that capital gains were higher in higher-priced housing tiers, indicating greater capital inflow into expensive housing in London. In contrast, net income yields declined with increasing price tiers, suggesting that cheaper housing had higher net income yields, while expensive housing had lower yields. This indicates a disproportional increase in housing prices relative to rent in London. In conclusion, while housing in London may attract significant attention from investors seeking capital gains, the findings suggest that the East of England and North West regions offer better prospects for higher total returns on residential rental housing investments in England.

The remainder of the chapter is structured as follows: In Section 4.2, the analysis presents the data sources and descriptive statistics. Section 4.3 outlines the measurement of components of total return, including capital gains, gross income yields, and cost-to-income ratios. Section 4.4 presents total return estimates. Section 4.5 analyzes London with quintile price tiers, and Section 4.6 compares the results with existing academic research on total housing return estimation in the same country. Finally, Section 4.7 concludes.

4.2 Data and Descriptive Statistics

To estimate the total returns of residential rental housing, the analysis require data on real capital gain and net income yields (net of total costs). This analysis utilizes two primary data sources: HM Land Registry and WhenFresh/Zoopla data, to construct repeat-sales housing price indices and gross income yields. The repeat-sales index allows us to infer capital gains over time, while gross income yields, in conjunction with the total cost of property ownership, allow us to infer net income yields. Table 4.1 provides a concise summary of the data sources for key variables in the analysis. However, unlike Eichholtz et al. (2021) and Chambers et al. (2021), the analysis do not have data spanning over a century. The study period for key data covers a seven-year window, beginning in 2014 and extending until 2021.

Table 4.1 Data sources and key variables

Key variables	Source
Sale prices	HM Land Registry
Sale dates	HM Land Registry
Detailed addresses	HM Land Registry
Rent	WhenFresh/Zoopla data from CDRC[18]
Rent listing dates	WhenFresh/Zoopla data from CDRC
Rented out dates	WhenFresh/Zoopla data from CDRC
Regions	Office for National Statistics
Inflation rates	Office for National Statistics
Costs	Eisfeldt & Demers 2022; Eichholtz et al. 2021; Chambers et al. 2021

Notes. This table presents the key variables and their sources in this study for the period from 2014 to 2021. Sale related information are based on the registered record from Land Registry and Rent related information are based on the record from real estate agency WhenFresh/Zoopla.

The HM Land Registry provides sale prices, sales dates, and detailed addresses for nearly all housing transactions within the period, while the WhenFresh/Zoopla data from CDRC includes rent prices, listing dates, rented-out dates, and detailed addresses as well. To merge the sale and rent information for the same property, this research matches the two datasets

[18] Consumer Data Research Centre, an ESRC data investment project under monitored by University of Leeds.

based on their detailed addresses, using a conservative strategy where only those with identical room numbers, street names, and postcodes in both datasets are retained in the matched dataset. Initially, the matched dataset contains 844,384 housing observations. The analysis then retains only those properties that have transacted more than once to construct the repeat-sales price index, resulting in 265,052 housing observations in the matched dataset. After transforming it into repeat-sales housing pairs for the estimation of the repeat-sales index, the analysis has 125,186 housing pairs with observations including price and rent-related key variables in the matched dataset. For each housing observation, the analysis lists the registered sale price, sale date, detailed address, listing date for rental, rented-out date, and the rent price in the leasing contract. To obtain the real capital gain, the analysis deflates the capital gain estimated from the repeat-sales index using inflation rate data provided by the Office for National Statistics for each year over the sample period.

Instead of computing property-level income yields like Eichholtz et al. (2021) and Chambers et al. (2021) did, this analysis constructs time-series data of summed rent, summed price at regional level for nine England regions from 2014 to 2021. This has allowed us to estimate cross-sectional variation of gross income yields within the same country but in different regions as well as the time-series trend of gross income yields over the sample period. To add the regional indicator to the matched dataset, I use the districts and regions corresponding table provided by the Office for National Statistics. In this way, each housing observations have indicator to show which region the housing is located in. In this way, the analysis can obtain the summed sale price and summed actual rent for each region in each year. Table 4.2 presents the number of housing observations, mean and median sales price for each region in the sample time period, implying different average property value in different regions, within which London has the highest median sale price of £359,950 and North East region has the lowest median sale price of £70,750. The difference is high as £289,200.

Table 4.2 Descriptive statistics of regional prices

Regions	N	Mean (£)	Median (£)
East Midlands	15,356	149,592	132,500
East of England	27,729	228,611	195,000
London	45,466	460,380	359,950
North East	17,335	93,595	70,750
North West	39,931	128,958	105,000
South East	42,724	263,748	228,000
South West	22,395	207,775	180,000
West Midlands	28,793	154,301	135,000
Yorkshire and The Humber	25,323	131,361	112,500
England	265,052	226,486	170,000

Notes. This table shows the number of housing observations, mean and median sale price for each region in England.

To estimate the net income yields, the analysis needs the data of total cost of property ownership. Here I use the estimated vacancy rate and fixed cost fraction of other costs to estimate the total cost. To estimate the vacancy rate, I use the time difference of listing date for rental and rented out date as the vacant time for each residential rental housing. Then I divide the number of vacant housings by the total number of housings to get the vacancy rate in each region for each year. The rented-out date data only available for around 80,894 housing observations, I use them as representative for the vacancy rate estimation. The method of how the analysis decide the fixed cost fraction of other costs is explained in the Section 4.3. Indeed, the study would get better estimation result if the study can obtain the detailed cost data for each property. However, it is extremely rare for the property-level information on taxes and costs. Even Eichholtz et al. (2021) can only cover a subset of properties with taxes and costs. Hence, they combine their data with city-level data on taxes, costs, and vacancies, similar to Eisfeldt and Demers (2022). Although Chambers et al. (2021) obtain the cost data in property-level, however, the shortage of their data contains selection bias as their housing object is own by Oxbridge university, which is rarely transacted. Hence, for future study on this type of research, an available property-level cost data for normal type of housing can be an excellent improvement for the housing total return estimation. However, in this study, I use the experience from the most recent and typical studies as the reference for cost estimation. It is definitely some limitations on this strategy, but it remain stable as I compare different costs finding in those studies and they appear in a common number without significant difference.

4.3 Total Housings Returns Measurement

In this section, the analysis assesses the total returns of residential rental housing in England by combining capital gains, gross income yields, and the associated costs of property ownership, as shown in the following equation:

$$Return_{i,t} = \frac{HPI_{i,t}}{HPI_{i,t-1}} + \frac{R_{i,t}}{P_{i,t}}(1 - c_{i,t}) \tag{4.1}$$

where $HPI_{i,t}$ represents the House Price Index of region i at time t, constructed using the repeat-sales method (Bailey et al., 1963). $P_{i,t}$ and $R_{i,t}$ denote the summed rental sales price and rent, respectively, for rental housing in region i at time t. The total return equation comprises three components. Capital gain, estimated as the change in HPI between time $t-1$ and t. Gross income yield, calculated by dividing the summed rent by the summed sales price of each region for each year.[19] $c_{i,t}$ denote the cost ratio of property

[19] The rent I observe is the rent at the time of lease agreement signed by landlord and tenant. t also assumes the rent stays same for the rest of the years in the sample period.

ownership on the gross income yield, including maintenance expenses, vacancy rates, insurance, and other associated costs. Non-vacant costs are derived from existing studies, while vacancy costs are estimated based on available samples with data on listing dates and rented out dates.

The total return estimation can be improved if the study uses individual property as the studied object, for example, the total return to holding property between time $t-1$ and t, net of the costs associated with property ownership. And it could further improve by analyzing total return in different property type, like agricultural and commercial real estate. However, because the infrequent trading and temporal variation in property quality, the capital gains may be difficult to estimate without bias if estimate the return in individual property level. Chambers et al. (2021) propose a way to use the property-level income growth rate between time $t-1$ and t as share of the price change in the same period. It is great method to estimate total return of housing in individual level and it could improve the robustness and reliability of the estimation, however, it requires the transaction data for the same property for a very long time, which is not available publicly and even Chambers et al. (2021) can only use rarely transacted Oxbridge university property data to estimate. Hence, if future studies can manage to do this individual level total return estimation, the result could be enhanced a lot.

4.3.1 Capital gain

The primary challenge in estimating housing capital gain through changes in the housing price index lies in adequately controlling for quality changes in housing over time. While the hedonic model (Rosen, 1974) is a common method for estimating housing price indices, it falls short in accurately accounting for changes in housing quality due to the lack of comprehensive housing quality data in the study. To address this limitation, the analysis employs the repeat-sales model (Bailey et al., 1963), which allows us to control for quality changes by analyzing the price changes of the same properties over time. In addition, the sample period covers 2014 to 2021, which has smaller window of quality change as modern housings are likely to maintain its quality in less than ten years period. The nature of the sample period helps the estimation control better in quality change than existing academic literatures. The repeat-sales model enables us to estimate a standard housing price index while mitigating the impact of quality variations. Repeat-sales model is the value change of a property n between two periods s and t (s < t), the standard repeat-sales framework can be written as follow:

$$\ln P_n^t - \ln P_n^s = \sum_{t=0}^{T} \delta^t D_n^t + e_n^t \tag{4.2}$$

where P_n^t and P_n^sdenotes the price of property n in time t and s. D_n^t is a dummy variable with value -1 in the first sales of time s, 1 in the second sales of time t, and 0 for the rest time. e_n^t is an error term.[20]

After conducting regression on equation (4.2), the repeat sales housing price index over time can be estimated through the exponential value of the corresponding regression coefficient δ^t as follow:

$$P_s^t = \exp(\delta^t) \tag{4.3}$$

The standard repeat-sales model only necessitates the use of dummy variables to distinguish between first sales, second sales, and subsequent transactions when the analysis have matched address property transactions over time within the sample period (OECE et al., 2013).

Based on equation (4.2), the analysis can estimate the coefficient for each year on each region and infer the house price index for each year through the exponential value of the corresponding coefficient in equation (4.3). The analysis estimates the standard repeat-sales index for nine different regions in England and for England as a whole for the period from 2014 to 2021.

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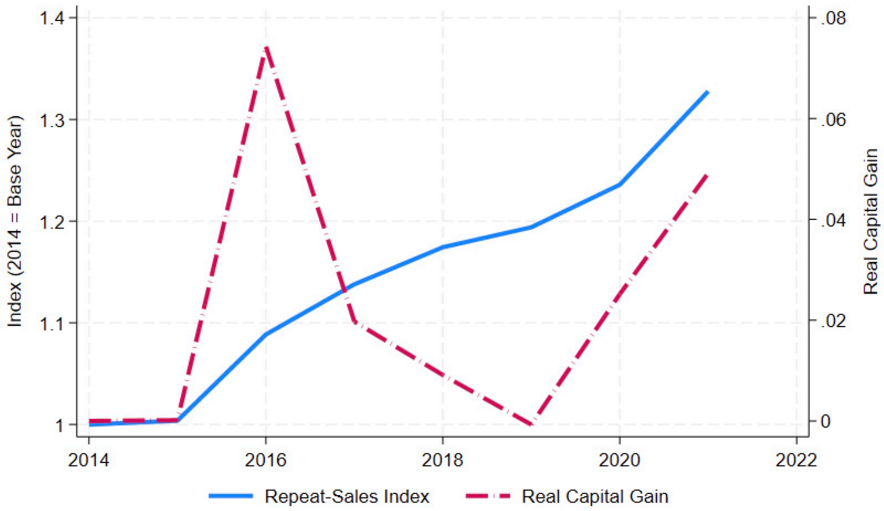
[20] Under the classical assumptions, the errors have zero mean and constant variance. The equation can be estimated through OLS regression.

Figure 4.1 House price index and real capital gain



Notes. This figure graphs repeat-sales house price index and real capital gain (inflation-adjusted) over the sample period for overall samples.

Subsequently, the analysis computes the percentage change of the index for each year to construct a time-series of capital gains for different regions and England. Figure 4.1 illustrates the repeat-sales index of England overall for the sample period, with the year 2014 serving as the base year. Using this index, the analysis derives the annualized mean capital gain by estimating the geometric mean of the index percentage changes over the sample period. To reduce the affection from extreme outlier, which may have extreme quality change, the analysis excludes price pair with log price difference more than absolute value of 1.95 as Eichholtz et al. (2021) did. This removes 7340 price pairs and leave us with 125,186 price pairs for the capital gain estimation. To adjust for inflation, the analysis utilizes the time-series CPI indexes published by the Office for National Statistics represents the inflation level for each year in the sample period. Figure 4.1 presents the real annualized capital gain for all samples in England after adjusting for inflation rates.

The temporal pattern shown in Figure 4.1 is particularly revealing. The sharp spike in real capital gains around 2016, followed by a decline and then recovery in 2020, suggests that political and economic events significantly influenced market dynamics. The initial surge might reflect pre-Brexit buying activity, while the subsequent decline shows the impact of Brexit-related uncertainty on property values. The recovery in 2020, despite the pandemic, likely reflects the impact of government support measures and changing housing preferences during lockdowns.

Table 4.3 Capital Gains

	N	Geometric Mean	Real Geometric Mean
East Midlands	7,255	3.9%	2.5%
East of England	13,131	4.4%	2.9%
London	21,762	3.3%	1.9%
North East	7,946	2.4%	1.0%
North West	18,681	3.6%	2.2%
South East	20,280	3.7%	2.3%
South West	10,619	3.8%	2.4%
West Midlands	13,625	3.9%	2.5%
Yorkshire and The Humber	11,887	3.5%	2.1%
England	125,186	3.6%	2.2%

Notes. This table reports the annualized capital gains for different regions in England and complete samples in geometric and real geometric (inflation-adjusted) terms.

Table 4.3 illustrates the cross-sectional variation of capital gains in different regions and their corresponding deflated real capital gains. The North East region exhibits the lowest real capital gain at 1.0%, compared to other regions, while London demonstrates a relatively low real capital gain of 1.9%, excluding the North East region. Conversely, the East of England boasts the highest real capital gain among all regions, standing at 2.9%. Across all samples in England, the annualized real capital gain, derived from the repeat-sales index and adjusted for annual inflation rates, amounts to 2.2%.

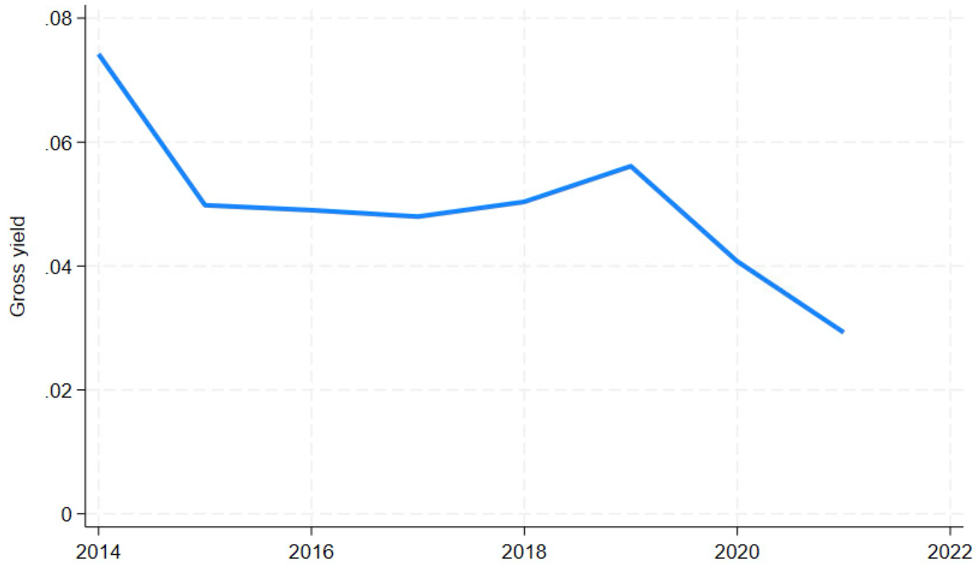
The East of England's strong performance can be attributed to several structural factors. Its proximity to London creates spillover benefits from the capital's economic strength while offering more affordable housing options. The region has also benefited from significant infrastructure investment and the growth of technology clusters around Cambridge, creating high-skilled employment opportunities that drive housing demand. London's relatively modest real capital gains (1.9%) deserve particular attention given its traditional position as a property market leader. This performance likely reflects a combination of factors: the already high base price levels making further appreciation more challenging, Brexit's impact on international investment flows, and changing work patterns during the pandemic period. The capital's property market appears to have reached a point of price resistance, where affordability constraints limit further appreciation potential. The North East's lower performance (1.0%) highlights persistent regional economic disparities. Despite lower base prices that might suggest more room for appreciation, the region's economic structure, with greater reliance on traditional industries and lower average incomes, has constrained price growth. This underscores how capital gains in housing markets are fundamentally tied to regional economic vitality and employment opportunities. These patterns have important implications for both policy and investment. For policymakers, the persistent regional variations in capital gains highlight the need for targeted economic development strategies to address regional inequalities. For investors, understanding these regional differences is crucial for portfolio allocation decisions, suggesting opportunities for diversification across regions with different economic drivers and risk-return profiles.

4.3.2 Gross income yields

To calculate gross income yields for each region, the analysis divides the total rent in each region by the total sales price of properties in the corresponding region for each year. To mitigate the influence of extreme outliers, the analysis excludes observations with gross yields deviating more than 300% higher or 75% lower than the median yield in the sample, as well as instances of extremely high rent levels (exceeding >800% of the median house rent), following the approach outlined in Eichholtz et al. (2021). This filtering process leaves us with a total of 260,052 housing observations to estimate the trend of mean gross income yield overall, with approximately 20,000 to 40,000 housing observations available for each region to analyze regional variations. Figure 4.2 depicts the time-series gross income yield of the overall samples in England for the period 2014-2021. The mean yields remained stable around 5% from 2015 to 2019 but experienced a decline following the official commencement of Brexit and extreme quantitative easing policy in 2020. The temporal pattern shown in Figure 4.2 is particularly revealing. The stability of yields around 5% from 2015-2019, followed by a decline post-2019, suggests that the market was in relative equilibrium before being disrupted by major economic events. The sharp decline after 2020 coinciding with Brexit and quantitative easing indicates how monetary policy and economic uncertainty can impact the relationship between rents and property values.

Pooling all observations in the Figure 4.2 for gross income yield estimation, Table 4.4 illustrates that housing in overall England for the sample period has a geometric mean gross income yield of 4.9%. Remarkably, this result closely aligns with the estimated historical result of a 4.7% mean gross income yield for the institutional real estate portfolios of Oxbridge colleges over the period 1901-1983 as reported by Chamber et al. (2021).

Figure 4.2 Gross income yield



Notes. This figure graphs gross income yields to rental housing for England over the sample period (2014-2021) for overall samples (all regions).

Table 4.4 Gross income yields

	Geometric Mean
East Midlands	5.3%
East of England	4.7%
London	4.2%
North East	5.9%
North West	6.0%
South East	4.8%
South West	4.7%
West Midlands	5.6%
Yorkshire and The Humber	5.7%
England	4.9%

Notes. This table reports the estimated gross income yields for different regions in England and complete samples in geometric term.

However, cross-sectional variation in gross income yields exists across different regions. From 2014 to 2021, the lowest gross income yield is observed in the London region (with a mean of 4.2%), while the highest yields are found in the North East and North West regions (with means of 5.9%). On average, there is a difference of approximately 1.7% in gross income yields between the London region and the North East/West regions. This finding underscores the significance of considering regional-level risks in housing investments within the same country. The result imply that the London region remains low in both capital gain and gross income yield among all regions in the England, despite the fact that London is the superstar city and accounts for a majority share of England economy.

Table 4.3 and 4.4 show that London is underperformance in both capital gains (1.9% vs England's 2.2%) and gross income yields (4.2% vs England's 4.9%) during 2014-2021 period. The combination of low yields and low capital gains suggests London may have reached a critical affordability threshold. With property prices already at extreme levels relative to incomes, there's limited room for either rent increases or price appreciation. The average London house price had become so high, which makes tenants could not afford higher rents and buyers are also hard to bear higher purchase prices. In addition, the sample period, particularly post-2020, experiences a significant shift in work patterns with increased remote working. This disproportionately affected London, as it reduce a large amount of people willing to pay for premium rent and price for living in London, instead they choose to live in near regions. This structural change might have contributed to both lower capital appreciation and reduced rental demand. The performance of regions near London (the East of England and South East) is very interesting, the strong capital gains in these regions likely reflect a spillover effect from London, with households and businesses relocating while maintaining economic ties to the capital. These regions benefit from London's economic strength while offering more affordable housing options. While property prices in these regions are higher than northern England, they remain more affordable relative to local incomes compared to London. This creates more room for sustainable price appreciation and rental growth, explaining the higher yields compared to London. The high yields in northern regions (North West: 6.0%, North East: 5.9%) reflect strong rental demand from younger populations and students relative to property values. The East of England's strong capital gains suggest sustained demand from London outmigration, while London's weaker performance indicates changing preferences and remote working impacts.

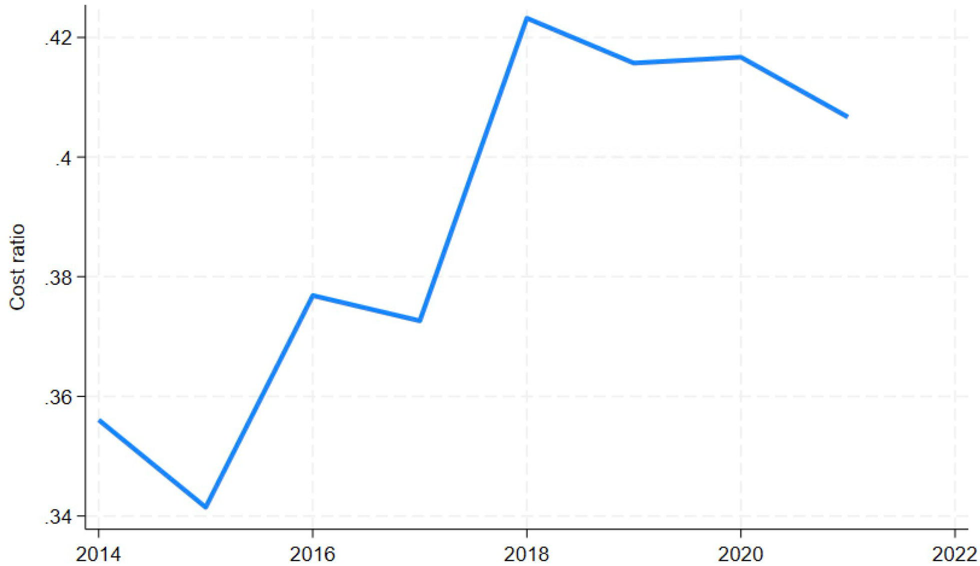
These patterns have significant implications for investment strategies and policy. For investors, the yield differentials suggest opportunities for portfolio diversification, with different regions offering varying combinations of current income and capital growth opportunity. For policymakers, these patterns highlight how regional economic development and housing market outcomes are linked, suggesting the need for coordinated approaches to regional development and housing policy.

4.3.3 Costs

The analysis now delves into the assessment of costs associated with property ownership, focusing primarily on tax, vacancy rates, and other expenses such as maintenance, improvements, agency fees, and insurance. Unlike the United States where different states impose varying property tax rates, there is no property tax in the United Kingdom for landlords (Hoyt et al., 2010). Instead, landlords or tenants in the UK are subject to Council Tax, a local tax levied to fund services such as police, environmental maintenance, and waste collection. However, this tax is applicable only to individuals residing in the property and is not specifically targeted at landlords. Given that all the observations pertain to rental housing, tenants bear the responsibility for Council Tax payments, thereby not directly impacting landlord income. Furthermore, the analysis do not account for mortgage interest deductions, as this tax relief was fully abolished in the United Kingdom in 2000, which will not affect the estimation on the sample period from 2014 to 2021.

To measure vacancy rates, the analysis initially calculates the time difference between the listing date and the rented date of rental housing observations to determine their vacancy status in specific years.

Figure 4.3 Cost ratios



Notes. This figure graphs annual cost-to-income ratios over the sample period (2014-2021) for overall samples (all regions in England).

This time difference represents the vacant time after the landlords has the willing to rent their property and list the property information on the leasing agency. Subsequently, the analysis divides the number of vacant housing observations by the total number of housing observations for each year in the sample period. Due to some missing rented dates in the matched dataset, the analysis includes only observations with available rented dates in the vacancy rate estimation, resulting in a dataset of 80,484 housing observations for the estimation. The geometric mean of the vacancy rate across England is computed to be 8.8%, notably higher than the historical research findings of 3.1% in Paris and 2.0% in Amsterdam from 1900 to 1979 (Eichholtz et al., 2021), indicating a significant increase in vacancy rates in the modern rental housing market in England.

Figure 4.3 displays the time-series of total cost-to-income ratios over the sample period for England as a whole. The ratio initially increases from around 34% to over 42%, gradually declining thereafter but remaining around 40%. Table 4.5 presents the mean total cost-to-income ratio for all housing observations as 38.8%, consistent with modern findings from a total return study of recent single-family rental housing in the United States spanning from 1986 to 2014 (Eisfeldt & Demers, 2022). Table 4.5 also illustrates the cross-sectional variation in the total cost-to-income ratio across different regions of England.

Table 4.5 Cost to income ratios

	Geometric Mean
East Midlands	37.9%
East of England	38.1%
London	38.7%
North East	41.3%
North West	39.7%
South East	37.4%
South West	39.4%
West Midlands	38.4%
Yorkshire and The Humber	38.6%
England	38.8%

Notes. This table reports the geometric mean of the annual cost-to-income ratios for different regions in England and complete samples.

The North East region exhibits the highest cost-to-income ratio at 41.3%, which is 3.9% higher than the lowest ratio observed in the South East region. Since the fixed cost ratio for other expenses is consistent across all regions, the disparity arises from variations in vacancy rates, highlighting regional-level differences in the rental housing market.

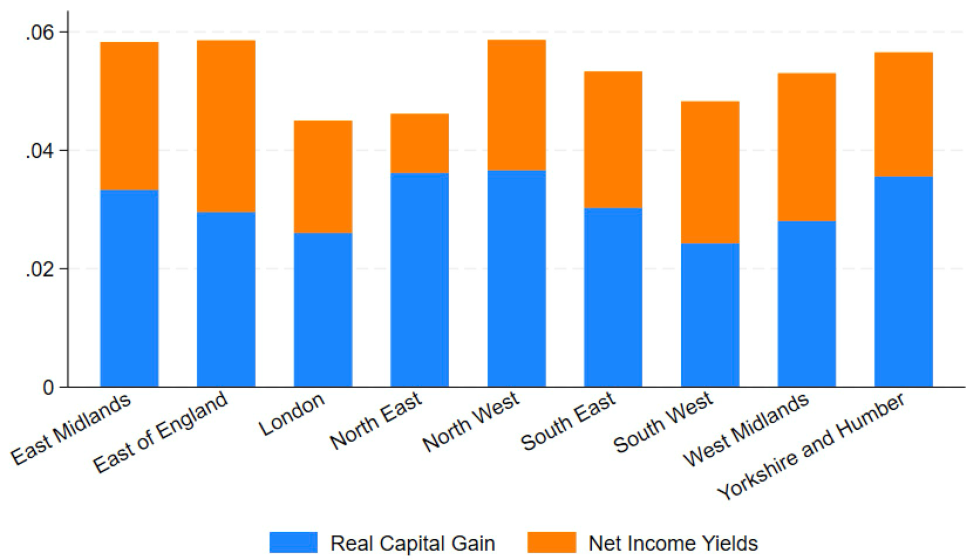
One limitation of the sample is the absence of information on costs other than the estimated vacancy rate, although the analysis does not need property tax information on this study. Consequently, the analysis must rely on data from existing literature and other sources to incorporate the additional costs. This approach has been adopted in related studies of total return estimation, both historical and recent (Eisfeldt and Demers, 2022; Eichholtz et al., 2021). Eisfeldt and Demers (2022) employ a combined total of 2.13% of property value and 6.63% of rental value as the ratio of total other costs to income, equivalent to approximately 35% of rental income based on their estimated gross income yield for single-family rentals in the United State from 1986 to 2014. Similarly, Eichholtz et al. (2021) survey existing literature and apply a fixed fraction of 30% on costs other than vacancy rate and tax, consistent with the approach in this research. Some studies provide comprehensive information on costs, including tax and other expenses. Chambers et al. (2021) discover an actual cost-to-income ratio of 32% for residential real estate in the investment portfolio of Oxbridge colleges, encompassing tax and other costs but excluding vacancy rate costs. Therefore, based on robust findings from other studies, the analysis opts to apply a fixed fraction of 30% for other costs relative to income, in addition to the vacancy rate, to determine the total cost-to-income ratio in this study.

Hence, the cost structure in this study primarily consists of two components: the observed vacancy rates based on 80,484 housing observations and a fixed 30% ratio for other costs relative to rental income. Someone may argue while the study applies uniform cost assumptions across regions, actual management costs likely vary significantly. Professional management costs in London might be higher due to higher service costs and more complex regulatory requirements. However, it does not mean the robustness of the estimated returns would be significantly affected. First, costs are calculated as a proportion of rental income, their impact on total returns is proportional across regions, preserving the relative performance patterns between regions. Second, the vacancy rates, which do vary by region and are based on actual data (80,484 housing observations), drive the main regional variations in cost ratios I observe as they are primarily driven by differences in actual vacancy rates rather than the fixed 30% assumption for other costs. This suggests that the key regional differences in returns are robust to the cost assumptions, as they reflect real market dynamics captured in the vacancy rate data. The vacancy rate data can capture some features of regional difference. Third, the study's findings align well with other empirical research and the basic cost structure appears stable across different markets and time periods. This consistency suggests that even if the fixed 30% assumption isn't perfectly accurate, it's likely within a reasonable range that wouldn't fundamentally alter the study's conclusions about regional return patterns.

4.4 Total Return Estimates

In this section, the analysis presents estimates of total returns at the regional level, comprising the sum of capital gains and net income yields (gross income yields minus total costs). The contribution of net income yields and capital gain to the housing investment total return are varies between different regions. The analysis then discusses the results in comparison to existing literature within the same research domain.

Figure 4.4 Regional capital gains, net income yields, and total returns



Notes. This figure graphs geometric mean of real capital gain, net income yields and total returns over the sample period (2014-2021) for different regions in England.

Table 4.6 Capital gains, income yields, and total returns

Regions	Capital Gains	Gross Yields	Net Yields	Total Returns
East Midlands	2.5%	5.3%	3.3%	5.8%
East of England	2.9%	4.7%	3.0%	5.9%
London	1.9%	4.2%	2.6%	4.5%
North East	1.0%	5.9%	3.6%	4.6%
North West	2.2%	6.0%	3.7%	5.9%
South East	2.3%	4.8%	3.0%	5.3%
South West	2.4%	4.7%	2.4%	4.8%
West Midlands	2.5%	5.6%	2.8%	5.3%
Yorkshire and The Humber	2.1%	5.7%	3.6%	5.7%
England	2.2%	4.9%	3.0%	5.2%

Notes. This table reports geometric mean of the annual capital gains, gross income yields, net income yields, and total returns by time-series and cross-section regions in England from 2014 to 2021.

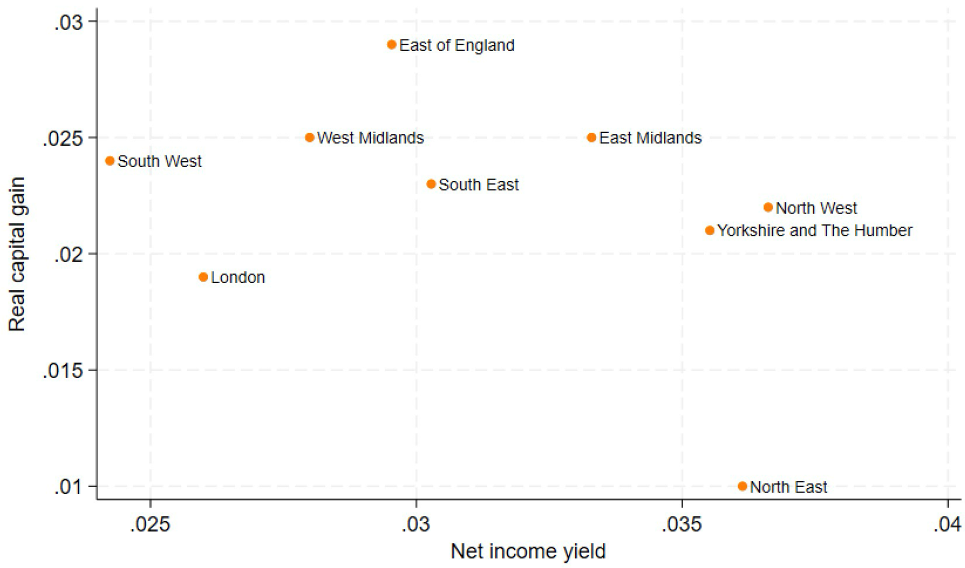
Figure 4.4 illustrates the average annualized real capital gains and net income yields for different regions from 2014 to 2021, with the underlying data presented in the Table 4.6. Surprisingly, the lowest total return on rental housing among all regions is observed in the 'superstar' region of London with a geometric mean of 4.5%. The South East and West Midlands regions exhibit similar geometric returns, averaging around 5.3%, positioning them in the middle among all regions. Conversely, the highest total returns are observed in four other regions: the East of England, North West, East Midlands and the Yorkshire and Humber. London’s underperformance can be attributed to several economic and demographic factors. One of the primary reasons is the city’s high house prices, which have led to affordability constraints that limit further price appreciation. Beyond the housing price levels, the geographical disparity in housing returns, particularly London’s lower performance, can be explained by several economic and demographic factors. One major economic factor is employment growth. In the March 2020 budget, the UK government committed to moving 22,000 civil service jobs out of London by the end of the decade (Nickson et al., 2021). They will do this by moving central government jobs to other cities and towns. Therefore, London has experienced slowing employment growth relative to other UK regions, which reduces the growing demand for housing, particularly for the first-time buyers (Minford et al., 2021). The combination of slow growing wage and an increasing cost of living has made it more difficult for buyers to enter the market, hence slowing capital gains. Migration patterns and demographic composition further compound these effects. Szumilo (2019) demonstrates how the concentration of young, mobile professionals in London creates distinct rental market pressures. The study found that high population turnover in such areas correlates with lower risk-adjusted returns for property investors.

Notably, In the middle and east part of England, regions located adjacent to each other tend to demonstrate similar returns, such as the East Midlands, East of England as well as the Yorkshire and Humber. However, in the north of England, neighboring regions North East/West exhibit a 1.3% difference in total returns, while London and the East of England also show a 1.4% disparity in total returns. Some previous literature has suggested a pattern of declining total returns as housing prices increase (Eisfeldt & Demers, 2022; Bracke, 2015). However, this finding fails to explain the variation in returns among regions with similar housing price levels. Moreover, the distance between regions does not account for the regional variation in housing returns, underscoring the importance of conducting cross-sectional estimates of total housing returns in different regions within the country, as I have done in this research.

Table 4.6 provides a detailed summary of capital gains, gross income yields, net income yields, and total returns for each region in England. The mean total return for England stands at 5.2%. Notably, London, the North East, and the South West fall below the average total returns for England, while the remaining regions surpass this average. Additionally, it is apparent that the average real capital gains contribute 0.8% less to the total returns compared to net income yields. Moreover, property ownership costs result in approximately a 1.9% deduction from gross yields. Of note, the West Midlands exhibits the highest cost share of gross income yield at 2.8%.

Figure 4.5 displays a scatter plot illustrating the time-series geometric mean of real capital gains versus net income yields from 2014 to 2021 at the regional level. Interestingly, there appears to be no discernible relationship between real capital gains and net income yields across different regions. Most regions show real capital gains ranging from 2% to 2.5%, with the exception of the East of England, which is above this range, and the Northeast, which is notably below, at only 1%. This Figure reveals no consistent pattern or relationship between capital gains and net income yields in the English regions. To further explore the relationship between capital gains, net income yields, the analysis delves into the data with price tiers using London as an example in the Section. The aim is to uncover any potential housing price effects on changes in capital gains and net income yields, and subsequently, on total returns.

Figure 4.5 Regional capital gains versus net income yields



Notes. This figure graphs geometric mean of real capital gain versus net income yields over the sample period (2014-2021) for different regions in England.

Next, the analysis explores the cross-sectional variation in total returns across different house price tiers in the London region, representing the most expensive and frequently transacted housing market in England. The analysis categorizes house prices into quintiles from 1 to 5, with the lowest to highest price tiers in London. Utilizing a similar methodology as described in previous sections, the analysis employs equations (4.2) and (4.3) to estimate the annualized capital gains for each price tier, as well as the annualized net income ratio using aggregate annual rent, total price, and cost ratio for each tier.

4.5 London Quintile Price Level Estimations

To measure the impact of house price levels on residential rental housing investment returns within a region, the analysis initially discusses the relative cross-sectional variation in net income yields across price tiers within London. On average, the net income yield is 2.6% for London as a whole. Comparing the net income yields of each price tier to the London average reveals discernible patterns. Panel B of Figure 4.6 illustrates the relative net income yields to the London average by house price quintile from 2014 to 2021. Within London, net income yields decline with increasing price tier. The first to third price tiers exhibit yields above the London average, notably with the lowest price tier surpassing the average by 1.5%. Conversely, the fourth and fifth price tiers demonstrate yields below the average, with the highest-priced tier falling more than 1.5% below the average.

Figure 4.6 Price quintile level relative difference to London averages

(A) Capital gain

(B) Net income yield

Notes. This figure graphs the relative geometric mean of real capital gain and net income yields in quintile price tiers to the London average level over the sample period (2014-2021).

This trend aligns with existing academic findings indicating that housing in more expensive locations typically yields lower income returns, consistent with observations in U.S. single-family rental returns estimations (Bracke, 2015; Eisfeldt and Demers, 2022).

In contrast, the analysis observes that real capital gains in quintile price tiers do not exhibit a similar declining pattern as net income yields with price tiers. Instead, capital gains tend to increase with price tier within London. Panel A of Figure 4.6 illustrates the relative real capital gains to the London average of 1.9%. The data indicates that lower-priced quintiles experience lower capital gains, while higher-priced quintiles yield higher capital gains over the sample period from 2014 to 2021. The first price tier properties appear to hover near negative 1% compared to the London average, while fifth price tier properties show a 1% increase over the average. Notably, this pattern of capital gains with price tiers in London is a novel discovery. This finding suggests a more uniform distribution of total returns across different price tiers in London.

The pattern of declining yields but increasing capital gains with price has important implications for market efficiency and investment strategies. The market appears to be pricing in expected future appreciation in expensive segments, with investors accepting lower current yields in anticipation of capital gains. This creates a self-reinforcing cycle where luxury property prices continue rising despite weak rental fundamentals. These findings also suggest potential market segmentation, where different investor types target different price tiers. Lower-priced properties, with their higher yields but lower capital gains, likely attract income-focused investors such as small landlords and pension funds. In contrast, premium properties appeal more to wealth preservation investors who prioritize capital appreciation over current income. The uniform distribution of total returns across price tiers, despite the opposing patterns in yields and capital gains, suggests the market may have reached an equilibrium where risk-adjusted returns are similar across segments. However, this equilibrium might be fragile and dependent on continued strong demand for premium properties.

The findings regarding capital gains and net income yield exhibit a similar pattern to observations in the estimation of single-family rental returns in the largest 30 cities in the U.S. (Eisfeldt and Demers, 2022). The observed increase in capital gains with price tiers implies excessive demand for expensive housing in London compared to lower-end housing, likely driven by factors such as location, education, neighborhood quality, safety, and amenities. Furthermore, the decline in net income yields with price tiers suggests that rental levels do not proportionally increase with housing prices, resulting in lower net income yields for expensive housing. This analysis has important implications for both policy and investment. From a policy perspective, the declining yields in expensive segments might indicate inefficient capital allocation, potentially justifying interventions to encourage more investment in lower-priced, higher-yielding properties that could better serve housing needs. For investors, these patterns suggest the need for clear strategy alignment by choosing between higher current income in lower tiers versus potential appreciation in premium segments. This indicates that investors targeting expensive housing in London anticipate higher house price appreciation, which appears more likely to materialize.

4.6 Comparison with Prior Research

After estimating total returns for nine different regions within England and overall England for the period from 2014 to 2021, I decide to compare the total return estimates with those presented in Jordà et al. (2019) and Chambers et al. (2021). This research aims to discuss the possible factors that may result in differences between the results in this study and existing estimates within the same country.

Table 4.7 Comparison of total returns in the same country

	Results in this study	Jordà et al. 2019	Chambers et al. 2021
Period	2014-2021	1896-2015	1901-1983
Country	England	United Kingdom	England
Capital gains	2.2%	1.6%	-0.7%
Net income yields	3.0%	3.9%	3.0%
Total returns	5.2%	5.4%	2.3%

Notes. This table shows the comparison between the geometric mean estimates of capital gains, net income yields and total returns with the existing estimate of previous papers in the same country.

In Table 4.7, the analysis presents an estimated housing return of 5.2% in modern England, which closely aligns with the historical estimates of 5.4% over centuries reported in Jordà et al. (2019). However, the contribution of capital gains and net income yields to the total returns in the estimates differs from those of Jordà et al. (2019). Specifically, the capital gains contribution in this estimate in this study is 0.6% higher, while the contribution of net income yields is 0.9% lower, despite the similarity in the total housing returns. As an influential paper written by Jordà et al. (2019), they constructs the total return indexes from a great number of existing house price and rent indexes, based on construction methods that vary over time and across countries. It's important to note that Jordà et al. (2019) employs aggregate data on rent and prices, similar to this study, but their estimates on capital gains are based on the U.K. house price index of Knoll et al. (2017). Given the ambition of their paper to assess housing investment returns and risks for a large cross-section of countries between 1870 and today, their data collection is enormous. However, their analysis may suffer from measurement eerror in all dimensions of the total return, including the capital appreciation, the gross rental yield, the taxes and costs. To be specific, although their indexes aim to connect with nations as a whole, they mostly use data on the major cities of a nation for the early parts of their indexes and then switch to national data at different available time slot for each index. All this fact may lead to unconvincing and unreliable result. Most of the existing literature uses implied rental income yields from other studies that do measure actual yields rely on small samples from a limited set of investors (Bracke, 2015; Chambers, 2021). In contrast, this analysis constructs the repeat-sales housing price index based on the own observations at aggregate level, thereby potentially reducing measurement errors in the estimate compared to those in Jordà et al. (2019). The key motivation or the contribution of this study is to investigate the extent to which such return measured by Jordà et al. (2019) is affected by measurement errors.

Differing from Jordà et al. (2019), Chambers et al. (2021) utilize property-level annual rent and costs over time, along with matched prices at the time of transaction from real estate investor archives. This approach allows for more accurate measurement of housing returns. Their estimates indicate a housing return over a long time period of 2.3%, which is 3.1% less profitable than that reported in Jordà et al. (2019). It's worth noting that they report a decline of 0.7% in capital gains. This substantial difference may be attributed to the granular property-level estimation and the less frequent nature of transacted properties in the colleges' real estate investment portfolio. Relative to this paper, their study do act as an complementary study as they also cover the agricultural and commercial real estate and specifically investigates the role of costs in driving asset-level returns. However, due to the nature of Oxbridge colleges infrequently transacted property, they cannot directly measure aggregate capital gains and total returns. Similar to Jordà et al. (2019), Chambers et al. (2021) use changes in the U.K. house price index of Knoll et al. (2017), and then adjust it to the yields of their estimation, in this way they derive the total return statistic for the entire period.

This analysis is not comparing housing returns to other countries to minimize measurement errors, the analysis focuses solely on comparing housing returns within the UK. The results demonstrate that despite the shorter period of observation, the analysis can still provide similar estimates compared to those conducted over centuries in previous studies. This makes it easier to conduct research on housing returns using decades of data rather than centuries, which are extremely challenging to obtain. Moreover, comparing the results to those of Jordà et al. (2019) and Chambers et al. (2021) highlights that while property-level data can provide granular estimates, the frequency of transactions can lead to substantial differences in housing return estimates. The key contribution of this study is that I construct a dataset includes rents and prices for a large group set of properties, the aggregated price and aggregated rent are all estimated by the individual properties with match price and rent. This is achieved by matching two dataset through detailed address, which has not be done and explored by any other research studies yet.

4.7 Chapter summary and discussion

In this chapter, I leverage data from HM Land Registry and WhenFresh/Zoopla to create a unique dataset focusing on residential rental housing in England. This dataset encompasses information on rental income and sales prices for each rental housing observation spanning from 2014 to 2021. The aim is to construct a repeat-sales house price index, enabling us to estimate annualized capital gains. Additionally, I aggregate annual rent and sales prices for nine regions in England to analyze gross income yields over time and explore cross-sectional variations in the geographic dispersion of residential rental housing yields. By deducting the share of property ownership costs from gross income yields, I manage to find the net total returns of residential rental housing over approximately a decade in modern England.

The key contribution of this study is that I observe the rents and prices for the same residential property to establish new capital gain and rental income yield indexes. Then, use the indexes to describe the net total returns of housing and compares the result to returns estimated in recent work (Jordà et al., 2019; Chambers et al., 2021). These indexes are based on previously unexplored and unused data that I use specific method to match price dataset and rent dataset through detailed address for this study. In addition, the repeat sales measures approach allows the study control for changes in asset quality.

The key empirical findings are as follows. First, the annualized capital gains and net income yields for rental housing in England are approximately 2.2% and 3.0%, respectively. Second, the average share of property ownership costs as a proportion of gross income yields is around 38.8%, surpassing historical findings reported by Chamber et al. (2021). Third, the estimated net total return for rental housing in England stands at 5.2%, with the London region achieving the lowest net total return level at 4.5%. Fourth, capital gains are more pronounced in higher-priced housing tiers, while cheaper housing exhibits higher net income yields, particularly in the superstar London region. This finding aligns with city-level U.S. single-family rental housing returns estimations but contrasts with the zip-code level results reported by Eisfeldt and Demers (2022). This research underscores the significant contribution of both capital gains and net income yields to the total return of rental housing. This differs from prior studies which suggest that net income yields contribute the majority of housing returns, with capital gains being minimal (Chambers et al., 2021; Eichholtz et al., 2021). In conclusion, the estimation results highlight the importance of understanding residential rental housing dynamics. Furthermore, the total investment returns of rental housing are attractive, making them a compelling addition to investment portfolios.

Although this study does not directly estimate returns from alternative assets, like bond and equity. However, I can use the rate of return of housing in the UK compared to the equity and bond return estimation in (Jordà et al., 2019). Jordà et al. (2019) provide country-level evidence and find that housing has been as good a long-run investment as equities. But look into the UK specifically, their full sample show that equity in the UK has about 6.8% total return over time. This is higher than the 5.2% finding of UK housing return in this study. However, in their finding, although the aggregate total returns on equities exceed those on housing, equities do not outperform housing in simple risk-adjusted terms. In fact, housing provides a higher return per unit of risk with Sharpe ratios on average more than double those for equities. This stability likely stems from the dual nature of housing returns, combining capital appreciation with rental income. The rental component, shown in the data as gross yields of 4.9% for England, provides a relatively stable income stream that helps reduce return volatility. In addition, return on bond is quite low at about 2.3% in the UK compared to 5.2% of UK housing. However, bond is always be considered as the safe asset, this safe return has important implication for government and investors. Apart from risk, liquidity also need to be discussed, housing involves significant transaction costs and longer execution times compared to equities and bonds, which can be traded almost instantly. These characteristics have important implications for portfolio strategy. The different risk-return profile of housing compared to equities and bonds makes it valuable for portfolio diversification, as the lower correlation with traditional assets helps reduce portfolio volatility. The higher transaction costs and lower liquidity of housing investments suggest they are more suitable for longer-term investment horizons where the impact of transaction costs can be mitigated over time. Hence, the investors need to consider their objective of investment and balance the risk and liquidity on their investment portfolio. Although housing seems to have high return given its risk, but bond is the safe asset that need to be considered in the portfolio as hedger of overall risk.

The period from 2014 to 2021 encompasses two major economic shocks. The Brexit referendum in 2016 and subsequent uncertainty during negotiations created significant economic policy uncertainty. The COVID-19 pandemic from 2020 lead to unprecedented market conditions. These unique conditions likely influenced the return of housing estimated in this study because this study do not use very long-term data on the estimation. The initial Brexit uncertainty likely suppressed price growth in the early part of the sample and impact the capital growth component, while the pandemic created unusual price dynamics, particularly benefiting regions outside London. This might explain why the London has such low capital gains compared to other regions. In more “normal” economic periods, the regional pattern might be different. Both Brexit and COVID-19 introduced significant market uncertainty. The spread in gross yields between regions might narrow in more normal conditions as temporary pandemic migration normalize. The unusually high yields in some northern regions might moderate as market dynamics stabilize. In more stable periods, we might expect lower volatility in returns and more predictable patterns in both capital appreciation and rental yields. Hence, future studies can try to use long-term dataset to estimate a more accurate total return of housing if the long-term dataset available because in this way, the impact from unexpected economic and policy shock can be mitigated through time.

In short, the study's findings on regional variations in both returns and costs suggest different optimal entry strategies for different investor types. Institutional investors might focus on building scale in specific regions to optimize operational efficiency, while individual investors might need to be more selective in their market choice based on their investment objectives and operational capabilities. Regarding risk management, the study's findings on return components (capital gains versus yields) across regions help inform risk management strategies. The lower but potentially more stable returns in some regions might appeal to risk-averse investors, while areas with higher returns but greater volatility might suit investors with higher risk tolerance. In addition, the temporal patterns shown in the study, including variations in returns and cost ratios over the 2014-2021 period, suggest the need for long-term investment horizons to smooth out market cycles.

Chapter 5 General Conclusion

This thesis examines three fundamental economic mechanisms in the UK housing market: valuation processes through discount rates, policy transmission in the BTL sector, and return generation in residential rental housing. Through comprehensive empirical analysis, the research demonstrates how these mechanisms are interconnected and collectively impact the housing market. The research begins by investigating how market participants value future housing benefits. The valuation patterns are important to understand the policy effectiveness, in this research is the analysis of the BTL tax surcharge. Finally, the valuation and policy transmission mechanisms ultimately influence the patterns of housing returns.

For examining the term structure of discount rates, this study makes several significant contributions to the understanding of real estate economics and the term structure of discount rate from the evidence of UK housing. First, it demonstrates a downward-sloping pattern reaching 1.3% over 125 years, significantly lower than previous estimates. The term structure of discount rates exhibits a downward-sloping pattern over a 125 years period, contributing to the broader literature on asset pricing and long-term valuation. The findings align with and support previous theoretical frameworks while offering new insights specific to real estate markets. Specifically, the implied discount rate for very long-time horizons is around 1.3%, which is 0.6% lower than the estimates reported by Giglio et al. (2015) and Bracke et al. (2018). The empirical evidence supporting lower discount rates for long-term investments provides valuable guidance for public infrastructure projects and environmental initiatives. Second, the research advances the understanding of socioeconomic disparities in housing markets by documenting significant differences in discount rates between wealthy and economically disadvantaged areas, as well as between London and non-London regions. This is the first empirical evidence to show differing evaluation preferences among households based on location and wealth. This finding has significant implications for policy design and implementation. The observation of different discount rates across socioeconomic groups and regions suggests that policy makers should consider these variations when designing housing market interventions and long-term infrastructure investments. Third, the study provides empirical evidence that complements the ongoing discourse on discount rates for public projects, particularly in relation to climate change initiatives and long-term infrastructure investments. The alignment with Stern

(2006) recommendations of a 1.4% discount rate offers valuable validation from the real estate market perspective. Fourth, the research makes a substantial contribution to the literature on leasehold valuation by providing empirical evidence that can inform professional valuations and policy decisions. This is particularly relevant in the context of recent leasehold reforms and ongoing debates about lease extension valuations. In terms of methodological consideration, This study adopted a repeat-sales approach alongside the traditional hedonic model. The repeat-sales method was chosen for its ability to control for unobserved property characteristics. This approach assumes property quality remains constant between sales and may suffer from selection bias as only properties sold multiple times are included. However, while these established methodologies provide valuable insights, the method chosen in this research is not without limitation and challenges. A key methodological challenge lies in controlling for unobserved property characteristics and temporal market changes. The repeat sales model may not fully capture maintenance levels, property improvements, or evolving neighborhood dynamics that influence property values. These unobserved factors could systematically bias the estimated discount rates, particularly when comparing properties across different socioeconomic areas or time periods. This study mitigates these limitations by comparing results with the hedonic model and conducting robustness checks across different subsamples. To address the limitation, future research could pursue several promising directions. The development of hybrid models combining hedonic and repeat sales approaches while incorporating machine learning techniques could improve property matching and control for unobserved characteristics. Or adopt the instrumental variables approaches to effectively address potential endogeneity issues, particularly regarding location choice and property improvements. However, future studies should note that while these methods might avoid some limitations of the repeat-sales approach, they would introduce their own challenges regarding data availability and potential response bias. Despite this, the methodological framework of this study for estimating discount rates through leasehold price differentials could be particularly relevant for markets with similar property ownership structures. For instance, Hong Kong and Singapore maintain substantial leasehold property markets, making the methodology directly applicable. For countries considering leasehold reform or similar property ownership structure, the research provides valuable insights into the housing market valuations. However, adaptation would be necessary based on different nature of housing markets. Countries with different regulatory environments, tax systems, and property rights structures may exhibit varying relationships between discount rates and market outcomes. For example, In the United States, the fixed-rate mortgages and tax deductibility of mortgage interest might influence how households discount future housing cash flows differently from the UK market. In the German market, strong rental protections and regulated rent increases might lead to different discount rate patterns, the methodology could be adapted to examine how rental contract terms affect property valuations.

For analyzing the BTL tax surcharge effects, this study provides significant empirical evidence regarding the impact of transaction taxes surcharge on the BTL property market, making substantial contributions to both academic literature and policy discourse. The research employs a DID methodology to analyze market responses, examining supply levels, market liquidity, and price dynamics before and after policy implementation. The results reveal two key findings. First, a significant transfer of tax burden to tenants through increased rent and extended time-on-market periods. The supply of BTL properties, as measured by transaction volume, has decreased by over 15%, and transaction prices have dropped by an average of 1.4%. Additionally, the research demonstrates that the TOM for renting a BTL property has increased by 25%, which aligns with findings of a 6% increase in BTL listing rents. Hence, the tax surcharge has extended the time needed for matching BTL landlords with tenants, as landlords leverage the policy to raise listing rents and seek higher-quality tenants. This exacerbates the rent burden and undermines tenants' ability to save, who are the potential first-time buyers and must continue renting while saving for deposits. The research findings have substantial implications for housing policy design and implementation. The evidence of cost transfer to tenants suggests that transaction taxes may not effectively achieve intended market cooling effects without creating unintended consequences for rental market participants. Second, the dynamic DID results suggest a speculative mindset among BTL investors, who rushed to complete transactions before the policy implementation and significantly reduced their activity afterward. The observation of speculative behavior in response to the announced policy implementation period suggests that immediate policy implementation might be more effective than phased approaches, but it still needs careful consideration. The study relies on the DID methodology, while appropriate for the research objectives, presents several important limitations requiring careful consideration. The fundamental parallel trends assumption for DID validity, remains a primary methodological concern. Although the research employs dynamic DID and event-study plots to validate pre-trends, recent academic discourse suggests these approaches may insufficiently guarantee the maintenance of parallel trends in the post-treatment period. Gibson and Zimmerman (2021) indicate that pre-treatment parallel trends validation alone may not adequately ensure the assumption's validity throughout the study period. Roth (2022) points that the analysis on the result of a pretest can distort estimation and inference, potentially exacerbating the bias of point estimates and under-coverage of confidence intervals. For future studies, several alternative methodological frameworks could enhance the study's analytical robustness. The implementation of sensitivity metrics, as proposed by Gibson and Zimmerman (2021), could quantify the potential impact of unobserved time-varying confounders on the results. This approach would provide greater confidence in the robustness of findings to potential violations of parallel trends assumptions. In addition, the covariate exploitation method suggested by Freyaldenhoven et al. (2019) offers another approach. This methodology utilizes covariates affected by confounding factors but not by the treatment itself to adjust for counterfactual trend differences. These methods might have provided additional validation but would require different assumptions about market behavior. Despite this, the research findings regarding the transfer of tax burden to tenants have significant implications for other housing markets considering similar policy interventions. The observed speculative behavior following policy announcement suggests the importance of implementation timing. Cities like New York and San Francisco, which have considered various measures to regulate investor activity in their housing markets, could benefit from understanding the UK experience. In the United States, where rental markets are generally less regulated, the transmission of tax impacts to tenants might be more direct. However, the state level variations in landlord-tenant law could create different patterns of policy effects across regions.

For the total rate of return estimation on residential rental properties, this study makes significant contributions to understanding residential rental housing returns through the creation of a dataset combining HM Land Registry and WhenFresh/Zoopla data. The research matches rental and price data through detailed address information, enabling the research examines two main components of returns: capital gains and net rental income. The result shows that the total rate of return for residential rental housing in England is 5.2%, comprising 2.2% capital gains and 3.0% net income yield. London, as a "superstar city," has the lowest total rate of return at 4.5% and a capital gain of 1.9%, one of the lowest in England, while the East of England boasts the highest at around 6.0% and the highest capital gain at around 2.9%. The research further investigates why London has such low returns and finds that capital predominantly flows into expensive housing in London, leaving little room for capital gains. Expensive housing also generates lower net income yields due to the significant gap between prices and corresponding rents. The research findings have substantial implications for both policy makers and investors. The observed regional variations in returns and costs suggest the need for regionally tailored policy approaches to housing market regulation.

Moreover, the finding of relative importance of capital gains and income yields challenge previous research conclusions. The finding of regional variations in returns and costs provide valuable guidance for portfolio diversification and risk management strategies. The research constructs repeat-sales house price indices for different regions in England to capture annualized capital gains. Regarding net income yield, the research first estimates gross income yields by dividing aggregate rent by sales prices for each region annually, then deducts the average cost-to-income ratio. The methodology combined repeat-sales indices with aggregate rental yields, balancing data availability constraints with the need for robust regional estimates. Although the methodology employed in this study is innovative, it presents several limitations. The first challenge lies in the matching process between price and rental datasets. This process may introduce selection bias if successfully matched properties systematically differ from unmatched ones. Second, the repeat-sales approach, while controlling for quality changes, may also introduce bias by excluding properties that trade less frequently. Third, the study period (2014-2021) includes significant events, including Brexit and COVID-19, which may limit the generalizability of findings to more stable economic periods. To address these limitations, future studies can consider the property-level panel analysis or hedonic decomposition of returns or use spatial econometric techniques account for neighborhood effects and local market conditions. In addition, use longer-term datasets to provide more reliable estimates of housing returns across different market cycles. This would help distinguish between cyclical and structural patterns in returns and costs. While these methods might provide more granular insights, data limitations and complexity would present significant challenges. Despite this, the approach employed in this study to combine property transaction and rental data through detailed address matching offers valuable methodological insights for international housing market research. This methodology could be particularly relevant for markets with similarly structured property databases. For instance, the approach could be adapted for U.S. markets using Multiple Listing Service (MLS) data combined with local property tax records, though modifications would be necessary to account for different data structures and availability. In addition, the observed patterns in capital gains and rental yields provide valuable insights for international comparison. In the United States, the methodology could be particularly valuable for analyzing returns across different U.S. housing markets, where significant regional variation exists in both property values and rental yields. Finally, the finding that capital gains are more pronounced in higher-priced housing tiers while cheaper housing exhibits higher net income yields might have parallels in the housing markets of other countries.

This thesis provides a comprehensive analysis of how fundamental economic mechanisms shape housing market. By demonstrating the interconnections between valuation patterns, policy responses, and return generation, the research contributes to both theoretical understanding and practical application in housing economics. The research demonstrates that housing market is being affect by the complex interaction of multiple mechanisms, requiring sophisticated approaches to both analysis and policy intervention.

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