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Is buy-to-let still worthwhile?
Estimating the impact of residential landlord tax reform on prices and demand of buy-to-let properties

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Is buy-to-let still worthwhile? Estimating the impact of residential landlord tax reform on prices and demand of buy-to-let properties

Heng Ying Li*

29th January 2024

Abstract

This study examines the changes in buy-to-let property prices and their transaction shares before and after the implementation of Section 24 of the Finance (No. 2) Act 2015, a residential landlord tax reform. A novel data set of 7,318,913 property transactions spanning from October 2013 to December 2021 is constructed from 53.27GB of raw data. The data is organised into two sub-samples: one with all transactions and one with only new properties. Difference-in-differences and Logit are used to investigate price change and buy-to-let likelihood. In general, the results show that, after the reform, buy-to-let prices did not fall compared to non-buy-to-let prices but rather climbed slightly. Due to additional limitations, the results should primarily be considered descriptive. Only the new-build property sub-sample passes the common trend test, and the models used cannot adequately account for other concurrent events like COVID-19 and the increase in stamp duty.

Keywords: house price, policy
JEL Codes: C55, R31, R38

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1 Introduction

Unaffordable housing has been a major contributor to inequality in the UK since the 1960s, with a growing disparity in the GINI coefficient after housing costs (Francis-Devine and Orme, 2023). In his budget statement in summer 2015, then-Chancellor George Osborne pledged to "create a more level playing field between those buying a home to let and those buying a home to live in" by introducing a "fairer tax system" (HM Treasury, 2015)[1]. This protocol limits landlords' income tax relief on residential property finance costs (e.g. mortgage interest) to the basic tax rate (20%); which means that high-earning private landlords must now pay more tax. Section 24 of the Finance (No. 2) Act 2015 formalised this legislation (The National Archives, 2015), presenting the most significant change for landlords in recent history. Independent organisations such as National Residential Landlords Association, 2023 and National Property Buyers, 2023 speculate that the government implemented Section 24 to reduce the demand for buy-to-let properties in an effort to control the private rental market and assist first-time home buyers. However, the policy paper by HM Revenue & Customs, 2017 expects this effect to be minimal due to the small share of the market affected. In addition, the government claims that this restriction affects less than 20% of landlords and that it prevents higher-income taxpayers from receiving greater tax relief than lower-income taxpayers (UK Government and Parliament, 2023).

The change in demand for buy-to-let properties can be explored through two separate channels: price and quantity. According to the government's assertion, neither should change after this reform. To investigate the aforementioned claims further, this study looks at how the prices of buy-to-let properties change over time compared to non-buy-to-let properties and how many transactions are buy-to-let in the years before and after the reform. While this reform affects the entire United Kingdom, this question is explored in the context of England and Wales, where property-level transaction data is publicly accessible.

[1]Tax policies are implemented in fiscal years; all years discussed in this paper are fiscal years unless noted otherwise. In the United Kingdom, the fiscal year runs from April 6th to April 5th of the following year.

A novel data set of 7,318,913 observations is constructed using 53.27GB of raw data from five data sources: Price Paid Data (PPD), domestic and overseas companies owning properties in the UK (CCOD and OCOD), Energy Performance Certificates on residential properties (EPC), and Postcode to Output Area Hierarchy with Classifications data (derived from census 2011 and 2021). The sample spans from October 2013 to December 2021, before and after the intervention. A combination of Unix/Linux Bash scripts and Stata are used because the file sizes exceed the physical memory of most standard machines. After careful optimisation, the full analysis starting from the raw data still takes over 6 hours. PPD property-level transaction data provides basic property information such as address and property type, which is supplemented with individual property and regional characteristics via matching with EPC and Output Area data. The PPD category is used to identify transactions impacted by Section 24. Category B includes buy-to-let mortgages, corporate purchases, and repossessions. CCOD and OCOD data sets can identify corporate acquisitions; however, inseparable repossessions are a concern. Two approaches are used to address this issue: either repossessions are disregarded owing to their limited proportion or a sub-sample of only newly built properties is used. Price change is investigated using the Difference-in-Differences method, and the likelihood of a transaction being buy-to-let is investigated using Logit. All analyses are carried out on both sub-samples, using time-fixed effects and controls.

The analyses take 2016, one period before intervention, as a reference and estimate all likelihoods at mean values. The prices of all buy-to-let properties are higher in 2017 to 2019 by 0.9%, 1.4%, and 0.8%, and lower in 2020 and 2021 by 2.6% and 3.7%, respectively; the likelihood of a transaction being a buy-to-let increases by 0.17 % points in 2017, 0.18 % points in 2018, and 0.62 % points in 2019, with a decrease of 0.16 % points in 2020 and no change in 2021. For new-builds, the prices are higher in 2017 to 2020 by 7.2%, 6.0%, 4.7%, 12.6%, and lower in 2021 by 12.2%, respectively; the likelihood is lower by 0.62 % points in 2017, 0.62 % points in 2018, 0.89 % points in 2019, 1.4 % points in 2020, and higher by 1.1

% points in 2021. In general, the data shows that, after the reform, buy-to-let prices did not fall in relation to non-buy-to-let prices but rather climbed slightly. The findings are mixed, and only the new-build property sub-sample passes the common trend test. The sample of all properties is tainted by repossessions and the prices of new properties may exhibit a distinct pattern. It is also possible that the demand for buy-to-let and non-buy-to-let does not follow the same long-term trend. Other events, such as additional stamp duty increases and COVID-19, occur during the same time period as this study, and they cannot be fully captured by a simple DiD and a Logit. These limitations diminish causal interpretations, rendering the study mainly descriptive.

The subsequent portions of this work encompass an examination of the policy context, a comprehensive review of existing literature, the development of a novel data set, the main analyses, and closing remarks.

2 Policy Background

Prior to April 2017, private landlords could reduce their taxable rental income by deducting the finance costs associated with financing the property. Finance costs include mortgage interest, overdraft interest, interest on loans to purchase furnishings, fees, and any other incidental costs incurred when obtaining or repaying mortgages and loans, as well as discounts, premiums, and disguised interest (HM Revenue & Customs, 2016a). While furnishings and other incidentals affect all landlords, private landlords' mortgage interest only affects those with mortgages. Two out of every three landlords plan to use a mortgage to fund their next buy-to-let property, and about 60% of landlords own some or all of their properties using a buy-to-let mortgage, according to a survey by Foundation Home Loans, 2022.

The rules became more complex beginning in April 2017. The ultimate objective is for landlords to no longer be able to deduct finance costs from their taxable income; instead, they will be able to claim a tax credit on finance costs at the basic rate (currently 20%).

This is done in four stages to further complicate matters, beginning with 75% of finance costs being deducted from taxable rental income and 25% of finance costs being claimed as a tax credit at the basic rate, progressing by 25% each year, and reaching the ultimate goal in four years. The particulars are provided in Table 1.

Table 1: Description of Section 24 progress by years

Tax year	% of finance costs deductible from rental income	% of basic rate tax reduction (can be claimed as tax credit)
2017 to 2018	75%	25%
2018 to 2019	50%	50%
2019 to 2020	25%	75%
2020 to 2021	0%	100%

From HM Revenue & Customs, 2016a.

If the landlord's total income (rental income plus other sources, such as day employment) places them in a higher tax bracket, they may wind up paying more taxes on the finance cost portion of their rental income. In comparison to prior years, they incur a net loss equal to the difference between their tax bracket and the basic rate multiplied by the finance cost. The UK basic rate begins with total taxable income greater than £12,571, and the higher tax band begins with any additional income greater than £50,270 (HM Revenue & Customs, 2023).

Private landlords could incorporate and pay a 19%-25% corporation tax instead of the 40% higher band income tax (HM Revenue & Customs, 2022), but corporations face higher interest rates and few mortgage lenders will offer buy-to-let loans to corporations without restrictions (Mugleston, 2023). Borrowers must disclose whether they plan to rent when applying for a mortgage. Most residential mortgages prohibit renting without lender approval (Aspen Woolf, 2022).

In the 2015 Spending Review and Autumn Statement, George Osborne raised stamp duty by 3% for buy-to-let and second homes (HM Revenue & Customs, 2016b, March). The £45,000 base line effectively impacts 99.9% of second-home property transactions (calculated using Price Paid Data in subsequent sections). This baseline rose to £250,000 in 2022.

3 Literature review

In most English-speaking developed countries, home ownership has been declining since the early 2000s in favour of private renting (Ronald and Kadi, 2018); as a result, more properties are now in the hands of landlords. A 2016 survey by the Council of Mortgage Lenders (Scanlon and Whitehead, 2016) finds that over 60% of landlords own only a single rented property; 7% owned five or more, but these larger landlords accounted for nearly 40% of the rented dwellings. These findings support George Osborne's claim that an increase in taxes is needed because wealth is concentrated at the top.

The buy-to-let market is geographically concentrated in the south of England, according to Houston and Sissons, 2012. Paccoud, 2017 extensively examines small-area socioeconomic and tenure data from the 2001 and 2011 UK Census and reveals that buy-to-let has become a significant tenure trend in gentrifying districts. Tenure changes related to gentrification lead to notable asset appreciation opportunities, which in turn drive up property values. These geographic findings suggest that extreme values can be anticipated in affluent areas, particularly London, where luxury properties are rented, as shown in the following data analysis. Since 2015, the number of gross buy-to-let mortgage advances has decreased, but gentrification may not lower the average buy-to-let property prices; and gross advances includes re-mortgage. As of 2023 Q1, buy-to-let represents 9.8% of UK gross mortgage advances (Bank of England, 2023b).

It is worth noting that if a tenant resides in a buy-to-let property, the property is typically not sold at full market value. If the occupants are protected, market value will decrease even more (Leyshon and French, 2009); thus, buy-to-let properties should be cheaper on average.

However, buy-to-let investments appear to be profitable. Jones and Mostafa, 2021 use a financial model to simulate the average buy-to-let purchases in eleven regions from 1996 to 2015. The paper provides convincing proof that from 1996 to 2015, investors earned an average internal rate of return (IRR) of 12%, compared to 5.8% from the stock market. There has been no similar literature documenting 2015 onwards, but if these trends continue, buy-to-let transactions should rise every year without intervention.

3.1 Empirical analysis

The Difference-in-Differences (DiD) method is frequently used to evaluate laws, policies, and large-scale programmes, comparing the program-involved intervention group and the non-involved control group over time. Examples include the classic Card and Krueger, 1994 study on the impact of policy on minimum wages and the more recent Rodnyansky and Darmouni, 2017 and Fatouh et al., 2021 studies on monetary policies. There is no additional literature on this specific policy, and the literature on DiD and property prices in general is limited. One example of a study on a comparable policy is Ferentinos et al., 2023, which uses DiD to investigate the effect of a minimum energy efficiency standard on transaction prices.

The parallel trend assumption requires the control and treatment groups to continue the same trend without policy intervention, thus making DiD valid. Conventional validation approaches use visual inspections or linear pre-intervention trends. Given the importance of this assumption for DiD validity, visual conclusions should be statistically validated. Testing the preceding trends is one of the most common choices for regression analyses (Freyaldenhoven et al., 2019; Roth, 2022).

Predicting binary dependent variables with logistic regression models helps determine buy-to-let transaction likelihood. In this case, a transaction is either buy-to-let or not. The effectiveness of a policy intervention could be measured in terms of the likelihood of achieving the desired outcome (King et al., 2011; Spertus et al., 2016).

3.2 Literature on data

The creation of the data set would represent a significant challenge for this endeavour. Most readily available data sets are aggregated, such as Ministry of Housing, Communities & Local Government, 2013 and Valuation Office Agency, 2014, which is sub-optimal given that individual-level data is preferable in the context of DiD. A previously created data set from Chi et al., 2019 contains property-level transaction data from Price Paid Data (PPD) merged with Energy Performance Certificates (EPC) with property-specific characteristics. This study cannot use Chi et al., 2019 because it lacks buy-to-let property transactions. However, address matching and other data cleaning and merging methods in Chi et al., 2019 are useful.

4 Data

To address the research question of this study, an original data set of residential property transactions in England and Wales is compiled from five different sources. Tables 11, 12, and 13 contain full descriptions on the variables used from data sources PPD, EPC, and CCOD with OCOD and they are in Appendix A. All raw data sets are being continuously recorded; the version used in this work is retrieved in August 2023, including observations through June 2023.

4.1 Data collection

4.1.1 Property transactions (PPD)

The property-level transaction data is derived from Price Paid Data (PPD) obtained from HM Land Registry, 2023b, August; It lists all residential property transactions in England and Wales since 1995. The purchase price, date, address, and basic property information like type, tenure, and new construction are listed. In property types, there are detached, semi-detached, terraced, flats or maisonettes, and other property types. Properties in the

"Other" category do not belong to any of the above categories. This category includes, but is not limited to, land with no built structure and multiple properties or parcels of land in a single transaction. Tenure has two categories: freehold and leasehold. PPD is divided into two categories: A for the Standard Price Paid entry for a single residential property sold for full market value, and B for the Additional Price Paid entry, which includes transfers under a power of sale or repossession, buy-to-let (where identifiable by a mortgage), transfers to non-private individuals, and sales where the property type is classified as "Other".

The buy-to-let (with a mortgage) portion of Category B transactions would be of interest to this study because they are in the treatment group and are consequently subject to Section 24. Category B transactions are not considered to be transactions at full market value, and they were identified from 14th October 2013 onwards. Empirical research requires Category B transaction data. Therefore, all transactions before 14th October 2013 are removed. Transactions without postcodes or prices are also excluded because these variables are important in the analysis.

4.1.2 Property and regional characteristics (EPC and Census)

The public register of Energy Performance Certificates (EPC) on residential buildings in England and Wales issued by the Department of Levelling Up, Housing, and Communities (DLUHC) is used to determine additional property characteristics (DLUHC, 2023). This register covers information on all residential properties that have been constructed, sold, or let since 2008. Important factors that would have a significant effect on transaction price are obtained from EPC and matched to the transactions in PPD: total floor area, energy efficiency of the building, main fuel type used for heating, and the construction age band. An accredited energy assessor visits the property to gather the necessary data before issuing EPCs. EPCs are valid on a property for 10 years; whenever properties are built, sold, or rented, the owners need to ensure that their properties have valid EPCs. Even though the EPC includes the property's rental status, it is not a reliable source for identifying buy-to-let transactions. An EPC is valid for ten years if the property's energy efficiency has not changed; however, the property's rental status may have changed during that time, as rental status is highly dynamic.

The classification used in the 2011 Census clusters communities into eight different types: (1) Rural Residents; (2) Cosmopolitans; (3) Ethnicity Central; (4) Multicultural Metropolitans; (5) Urbanites; (6) Suburbanites; (7) Constrained City Dwellers; (8) Hard-Pressed Living (Gale et al., 2016). The aforementioned categories are delineated at the level of the output area (OA), with each output area containing an approximately equivalent population size: around 125 households and a population of 300. The Postcode to Output Area Hierarchy with Classifications data set, which is derived from the 2011 and 2021 Census and obtained from the Open Geography Portal (ONS, 2022), is used to supplement the transaction data with information characterising the area surrounding each property. Output areas are mapped onto postcodes using this data set and then matched to PPD data using the postcodes.

4.2 Identification of buy-to-let (with a mortgage) transactions

Due to privacy concerns, it is not possible to directly identify the subcategory a transaction belongs to in PPD Category B (HM Land Registry, 2013). Because transaction data on price and address is considered property data and thus publicly available, whether the transaction is repossession or buy-to-let is considered personal information and is not available on the public register. By leaving out "Other" property type transactions, corporate purchases, and repossessions from category B, one can figure out which transactions are buy-to-let with a mortgage and therefore subject to Section 24 intervention. Transfers to non-private individuals are not considered personal information and can be identified using data on UK domestic and overseas companies that own property in England and Wales (CCOD and OCOD) from HM Land Registry, 2023a. These data sets have been recorded since 1995; they cover information on all properties that have been owned by UK and overseas companies, including both residential and non-residential properties. Repossessions can be identified at an aggregated level, but they are unidentifiable at the transaction level (Ministry of Justice, 2021).

There are three proposed ways to get around this problem. One approach involves disregarding the repossessions inside Category B, as their representation within the Category B entries is rather minimal (Ministry of Justice, 2021). This raises issues, such as the presence of biassed estimation in the context of buy-to-let properties.

The second method is to identify repossessions based on price data, as they are frequently sold via auction and banks would want to recoup the money quickly by selling the property at below market value (JMW Solicitors, 2023, May; John Charcol, 2022, September).

The final method is to use a sub-sample of only newly constructed properties, which can be identified using PPD, then match with CCOD and OCOD to get rid of non-private individual transactions. New properties sold to private individuals directly from the developer cannot be repossession properties. Using only new build property sub-sample has disadvantages, such as not being representative of the entire population, but new builds may be interesting and significant subjects for study in their own right. The term "new build" refers to the property's structure, not the building; it is possible to have a newly built property within an existing building. It is sufficient to use this identifier on new build properties to eliminate repossessions. All three methods are investigated in the following analysis.

4.3 Processing, matching, and merging the data sets

The data sets are large; the total size of the raw data files is 53.27GB. Stata reads the entire data set into RAM at once, and the computer becomes unresponsive when the data set in memory exceeds the physical memory of the machine. It is therefore extremely difficult to process them with conventional methods on standard machines. The data is processed by combining Unix/Linux Bash scripts with Stata. Due to the way the files are organised (especially the EPC files, which are chopped into 377 small files) and the fact that Stata is not I/O optimised, completing everything would take more than 12 hours of clock time on Stata alone. Bash is primarily utilised for I/O, while Stata is employed for econometric analysis. After optimisation, the total execution time on a 2021 Apple M1 Pro with 32GB of DDRL5 RAM is approximately six hours of clock time[2].

4.3.1 Matching PPD with EPC

The PPD data, which is the population of England and Wales residential property transaction data since 1995, is 4.7GB and contains 28,418,165 observations. Table 11 contains a detailed description of the variables in PPD that are used. The sample contains 9,577,098 observations after deleting observations with no postcode or price and excluding observations prior to 14th October 2013 (when category B began to be recorded). Analysis-useful transaction data would require additional processing.

Residential EPC data is the largest data set at 46GB, with 377 separate files for each local authority, and it contains 24,894,036 observations. The files are first stitched together into one large file to see if there are any disagreement in file formats between individual files, then a new file with only the desired columns is created at 36GB. Because the entire file still exceeds the physical memory of the machine, it is partitioned into two equal parts and read into Stata sequentially. In Stata, the descriptive factor variables such as energy efficiency, construction age, and fuel types are converted into numerical values using a specific coding scheme, further reducing the file to a more manageable size for analysis before being merged together as the desired EPC data set.

Address information is used to link EPC to PPD. Both files have a relatively clean and consistent address format, with the first and second lines of the address separated into two columns. However, matching them without manipulation is still difficult due to the fact that the order of the words and numbers may vary, and punctuation may be included or

[2]Stata SE is used for this analysis, but the computation time can be reduced even further with Stata MP with multi-core processing function.

omitted. For example, the address “Flat 1 Example House 2 Sample Road XX1 1YY” could be written in variations such as “Flat 1, Example House, Sample Road 2, XX1 1YY” or “Flat 1, Example House, 2 Sample Road, XX1 1YY”.

For successful matching, methods similar to Chi et al., 2019 are used to establish a common format for addresses between the data sets. Certain rules and standards are adhered to: the postcode is kept intact, only numerical values in each line of the address are kept, and if the whole address contains no numerical value, the property name in the first line is used to identify the property. The method is summarised below:

1a. The numerical values of each line of address are extracted.

1b. If no numerical value is present in all lines of address, take the property name in the first line, put it all in uppercase, and remove special characters such as commas, dashes, and brackets.

2a. Concatenate numerical values from the first and second lines of the address.

2b. Use the house name from 1b if no numerical value is present.

3. Concatenate step 2 with the postcode to create a unique address for each property in the transactions.

This method ensures consistency between EPC and PPD. EPCs are valid for ten years and must be renewed if the property has been renovated and the EPC measurements have changed. To make sure that each transaction is matched with the correct EPC at the moment of the transaction, the EPC data and PPD are organised into yearly files, with only the most current EPC data from that year being linked to the associated transaction.

Described in Table 2, 93.4% of PPD transactions are associated with an EPC. 50% of the non-matches are properties with no numbers and only house names; this is unavoidable because property owners can freely change house names but not property numbers. 38% of the non-matches are type “Other” properties that could be residential land with no built structures. There are a few Scottish transactions in PPD that are discovered while matching it to EPC; they account for 0.7% of the non-matches. The remaining 11.3% of unmatched properties are most likely due to address errors or because the owners may have chosen to opt out of the open EPC register.

Table 2: PPD matching to EPC

	Observations	Percentage
Matched	8944209	93.4
Non-matching		
Non-matching type O	242662	38 (of non-matching)
Non-matching alphabetic	317786	50 (of non-matching)
Non-matching Scotland	2433	0.7 (of non-matching)
Non-matching total	632889	6.6 (of all obs.)
Total observations	9577098	100

It is worth noting that EPCs provide characteristics of the property but can come with some typographical and measurement errors (DLUHC, 2023; Hardy and Glew, 2019). As EPC is an amalgam of information from different sources, inconsistency in how missing values or suspected typos are handled is an important factor. Many zero floor areas are recorded, as well as a few abnormally low floor areas, which could be due to typographic mistakes, such as a missed decimal place. The Housing and Planning Act, 2016 requires that an adult bedroom in a house in multiple occupation (HMO) must be at least 6.4 square metres in size (The National Archives, 2016). Any observations that fall below this minimum are removed from this study since they are likely to be errors or unfit for habitation.

The Postcode to Output Area Hierarchy with Classifications data set matches the geodemographic characteristics of each transaction by postcode. All transactions are properly matched because postcode data is precise.

4.3.2 Identification of buy-to-let (with a mortgage) transactions

The company owned properties CCOD and OCOD data sets are totaling 1.43GB with 4,151,841 observations; after dropping observations without a postcode or price of transaction, there remain 882,388 observations;

CCOD and OCOD record properties with consecutive numbers belonging to the same company on one line; this makes it impossible to machine match the property addresses to PPD as there are entries such as Flat 1-10 X Road. This lack of consistency in addresses poses a major challenge in accurately linking the property addresses to PPD. To match PPD with CCOD and OCOD, the transaction price and the property postcode are used as identifiers. Multiple properties with the same postcode and price are matched multiple times, with many to one matching. It is unlikely that two transactions with different parties purchasing them would have the same postcode and price. Only 5% of the entries in the entire CCOD and OCOD data sets are duplicated.

For the sample of this analysis, 672,742 transactions are identified as non-private individual transfers, 76,598 transactions are matched to Category A entries, and 596,144 are matched to Category B entries. Due to the inclusion of both residential and non-residential buildings in the company data sets, the accuracy of this identification approach cannot be guaranteed. For specific years, aggregate data on buy-to-let approvals and the proportion of new purchases are available from UK Finance, 2020, February and the Buy to Let Mortgage Index published by Mortgages for Business, 2022. A sanity check is performed in Table 3, and the total number of actual buy-to-let transactions agrees well with the estimates obtained by removing company matched data from Category B entries, with less than 10% variation. This check considers repossessions and company purchases to be mutually exclusive, which may be incorrect and cannot be validated. As a result, the precision of this estimate is compromised.

By comparing the prices of comparable houses in the same area, it may be feasible to detect repossession transactions. The UK postcode contains two decipherable parts. The first half together with the first digit in the second portion identify communities with around 3000 addresses called sectors (ONS, 2022). There are 8,271 unique sectors in the sample.

For each transaction, the price per square metre is determined using the total floor area

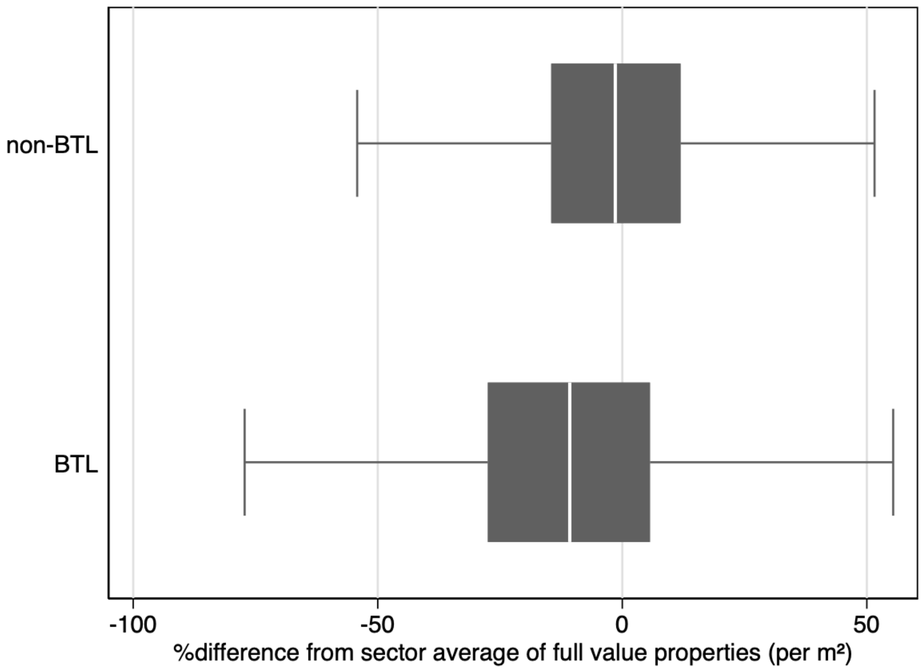
Table 3: Sanity check on matched company entries

Year (1)	Cat B (2)	Mortgage repossession (3)	% (4)	Total BTL mortgage (5)	Purchase % (6)	actual BTL (7)	Company matched (8)	Estimated BTL (9)	%Δ (10)
2013	29230*	28900		160000			8046		
2014	69456	20850	30	185000			20263		
2015	106591	10220	9.6	235000			37064		
2016	123122	7700	6.3	240000			49430		
2017	152793	7330	4.8	205000			66666		
2018	158903	6750	4.2	200000			76565		
2019	158594	7920	5.0	200000	35.6	69900**	80663	70011	-1.7
2020	148774	2660	1.8	180000	33	59400	82508	63606	7.1
2021	164299	2240	1.4	185000	41.2	76220	87934	74125	-2.7
2022	114359	3920	3.4	215000			80325		
2023	9422						6680		
Total	1235543						596144		

Not all values are available.
* data only available from 14th Oct 2013.
** actual number of BTL with mortgage from UK Finance, 2020, February
(3) from Ministry of Justice, 2021
(4) is the % of (3) in (2)
(4) and (5) from Mortgages for Business, 2022
(5) is the total BTL mortgage including re-mortgage. (6) is the % of (5) that is purchase only.
(7) is estimation of actual BTL with mortgage purchases in that year, calculated from (5) and (6) except ** is the percise number of BTL with mortgage given by UK Finance, 2020, February
(9) is estimated by (8)=(2)-(3)-(7)
(10) is the % difference of (9) form (7)

from the EPC and the transaction price from PPD. For each sector in the sample, the average sector price per square metre on full-value transactions (Category A) is calculated and tabulated by property type each year. This average sector price per square metre is then used to compare with all transactions' prices per square metre (both Categories A and B). It has been discovered that the price difference dispersion is too large to identify repossessions as it overlaps with buy-to-let with tenants in situ, and this dispersion is also substantial in Category A transactions within $+/-50\%$ of the mean price, see Figure 1. Even after controlling for location, property type, and year, prices can vary greatly depending on a variety of factors. Property conditions such as decor quality and building materials have a significant impact on price but are not captured in the available data.

Figure 1: The spread of price per square metre compared to neighbourhood (sector) average

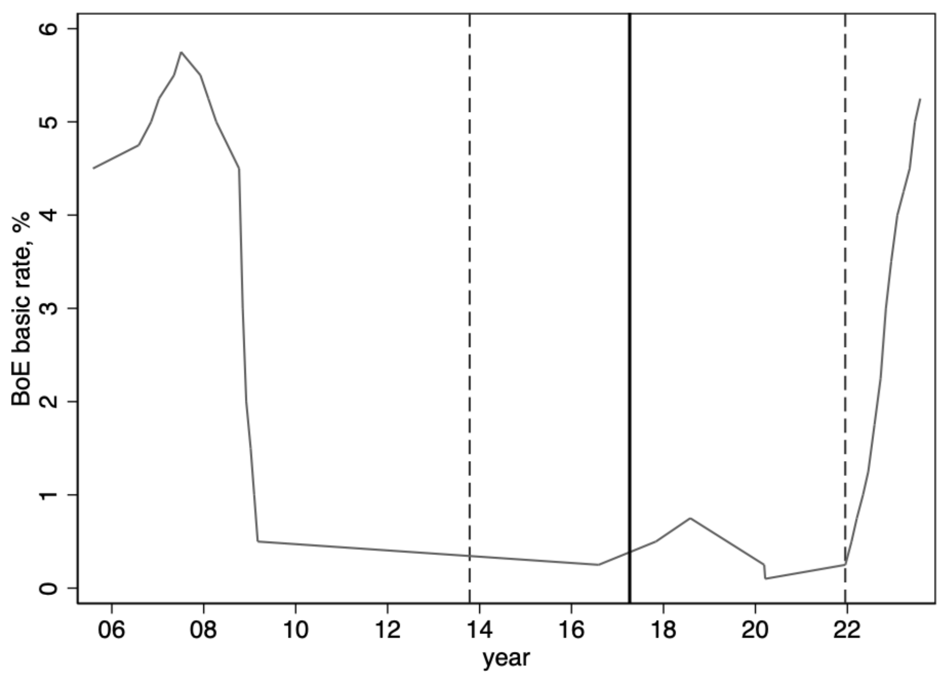


It is also found that certain transactions, such as the transfer of the freehold on a leasehold property, have outrageously low transaction values of only £1 or a few thousand pounds; these transactions are not categorised as "Other" in property types. There is no easy way to identify those transactions; therefore the transaction prices in the England and Wales local authority with the lowest average housing price is used as a guide. This is Ferryhill in 2021 (ONS, 2021). Anything below 1% of Ferryhill Category A transactions is considered a non-property transaction and thus excluded; this threshold is £15,000. On the other end of the scale, expensive homes worth millions of pounds are included in the sample because they are similarly impacted by Section 24 as less expensive homes are.

4.4 Final sample

Dropping company purchases, EPC non-matches, and further dropping observations with property type "Other", leaves 9.57 million transaction observations. In addition, it is deemed appropriate to truncate the data after 15th December 2021, shortly before the Bank of England's interest rate began to skyrocket due to inflation (Bank of England, 2023a), and after Section 24 intervention was completed in 2020. As mortgage rates are affected by the Bank's basic rates, this would distort the behaviour of prospective landlords and result in bias. Subject to matches with EPC and company data sets, the final sample consists of PPD entries from 14th October 2013, to 15th December 2021, with 7,318,913 observations. Figure 2 illustrates the time frame along with interest rates and Table 4 describes the development of the final sample.

Figure 2: Bank of England basic rates and sample frame



Dashed lines indicate the sample frame: 14th Oct 2013 to 15th Dec 2021.
Solid line indicates when the policy begins: 6th Apr 2017.
basic rates from Bank of England, 2023a

Table 5 and Figure 3 describe the price distribution and show that buy-to-let properties have a lower average price in terms of both mean and median, as well as a broader spread with a higher standard deviation, when compared to non-buy-to-let properties. The price ranges across all sub-samples are comparable, ranging from the low threshold of £15,000 to more than £40 million.

Table 4: Development of observations in the final sample

	Obs. dropped	Obs. remaining
Total PPD		28418165
no postcode and/or price in PPD	-46140	28372025
remove before 14th Oct 2013	-18794927	9577098
remove company transaction matched	-614162	8962936
remove no EPC matched	-632889	8330047
remove remaining type Other	-36298	8293749
truncate price and/or floor area	-3783	8289966
remove after 15th Dec 2021	-971053	7318913
Final sample		7318913

Table 5: Price distribution of the samples

	All			New only		
	Total	non-BTL	BTL	Total	no-BTL	BTL
Mean	291163	294565	222615	333909	334925	303864
Median	226000	230000	156995	276750	279950	207785
SD	317612	313627	382931	363452	350184	641259
Min	15000	15000	15000	15000	15000	15000
Max	56000000	56000000	44300000	56000000	56000000	44300000
No. obs.	7318913	6972913	346004	808720	782272	26451

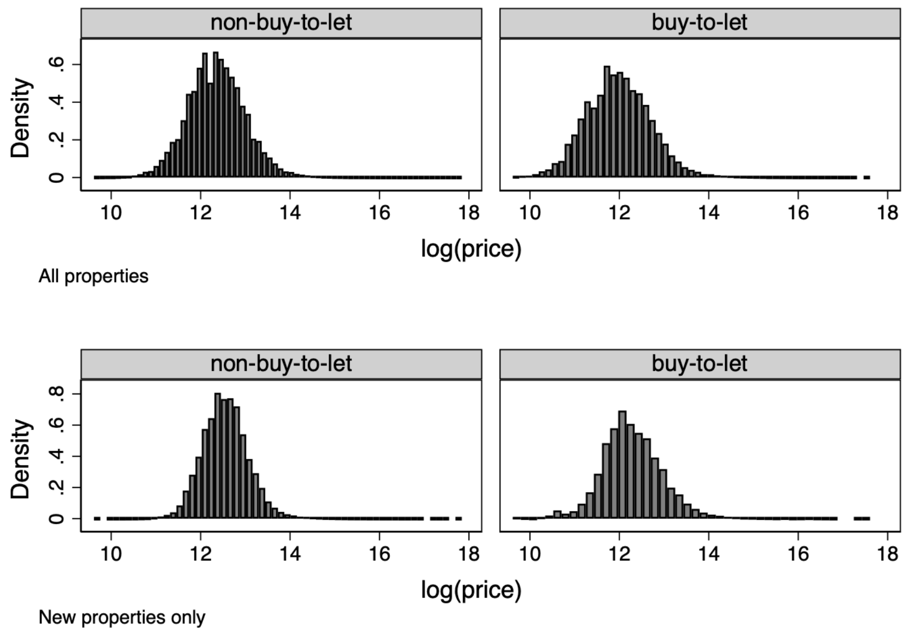
Table 6 shows a detailed breakdown of the final sample based on its characteristics. The sample is subdivided into all properties and new properties only, because the sub-sample of new properties only would be used for analysis as it excludes the repossession problem. It can be shown that new properties have broadly comparable characteristics to the overall sample but differ in type of construction, location, and primary fuel type used. The majority of newly built buy-to-let properties are located in South East of England especially Greater London. They are mainly flats (72%) and using electricity as their main fuel (55%), while terrace houses are the most popular form of buy-to-let overall.

Figure 4 shows a year-by-year comparison of the proportion of buy-to-let with mortgage transactions identified in both sub-samples. It can be seen that the proportion of buy-to-let transactions does not vary greatly over the years for all property transactions; however, in

Table 6: Description of data

Sample	All Total	non-BTL	BTL	New only Total	non-BTL	BTL
Number of observations	7318913	6972913	346004	808720	782272	26451
% share		95.04	4.96		96.62	3.38
Total floor area (m^2)						
mean	95.90	96.47	84.33	97.48	98.25	74.93
% share from now onwards	%	%	%	%	%	%
Property type						
Detached	25.28	25.93	12.20	35.91	36.88	7.26
Flat/Maisonette	28.10	17.50	27.03	26.93	25.41	71.86
Semi-detached	28.67	28.41	21.84	22.17	22.59	9.78
Terrace	17.95	28.16	38.93	15.00	15.13	11.09
Construction Age						
no data	15.62	15.77	12.71	90.11	90.31	84.34
before1900	8.97	8.95	9.25	0.29	0.28	0.64
1900-1949	24.58	24.29	30.29	0.37	0.36	0.77
1950-1982	28.29	28.46	24.72	0.39	0.38	0.74
1983-2002	14.64	14.74	12.75	0.31	0.29	0.83
2003 onwards	7.90	7.79	10.28	8.53	8.39	12.68
Tenure						
Freehold	76.98	77.46	67.45	68.17	69.57	26.62
Leasehold	23.02	22.54	32.55	31.83	30.43	73.38
Demographics						
Rural Residents	12.33	12.63	6.48	19.92	20.28	9.49
Cosmopolitans	5.62	5.49	8.11	6.90	6.57	16.67
Ethnicity Central	4.12	4.01	6.29	7.50	7.26	14.55
Multicultural Metropolitans	10.48	10.17	16.74	8.49	8.37	12.31
Urbanites	24.50	24.62	22.16	20.63	20.60	21.66
Suburbanites	23.11	23.58	13.57	19.29	19.59	10.59
Constrained City Dwellers	4.68	4.55	7.43	4.31	4.20	7.80
Hard-Pressed Living	15.15	14.95	19.21	12.94	13.14	6.93
Regions						
East of England	9.55	9.66	7.23	9.66	9.73	7.74
West Midlands	10.15	10.12	10.87	10.45	10.49	9.19
South West	11.52	11.67	8.40	11.70	11.76	9.93
North West	14.40	14.28	16.75	12.51	12.52	12.24
South East	15.09	15.25	12.03	15.51	15.54	14.70
Greater London	13.58	13.47	15.66	14.47	14.09	25.57
Wales	5.19	5.20	4.99	4.03	4.04	3.77
East Midlands	11.43	11.40	12.02	11.64	11.73	8.99
North East	9.10	8.95	12.05	10.03	10.10	7.88
Main fuel type						
Gas	84.91	85.05	82.00	79.04	80.37	39.61
Electricity	8.97	8.76	13.27	16.66	15.76	55.44
Other	6.13	6.19	4.73	4.30	3.87	4.96
EPC rating						
average (D) or higher	83.07	83.04	83.77	99.41	99.44	98.54
below average (D)	16.93	16.96	16.23	0.59	0.56	1.46

Figure 3: Price distribution

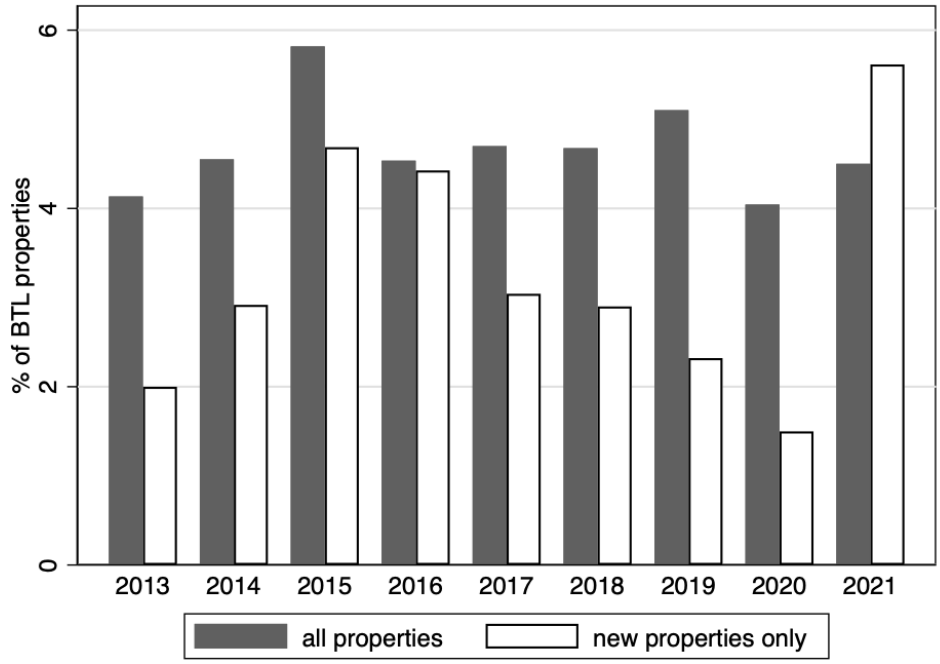


the sub-sample of new properties only, the fraction of buy-to-let properties has been slowly falling over the years but growing in 2021 near the end of the sample.

5 Main analyses

The main topics in this section are the effect of the tax relief for residential landlords policy intervention for the period of 2017 to 2020 (Section 24) on transaction prices and the likelihood that the transaction will be a buy-to-let transaction. A Difference-in-Differences design is used to investigate the treatment effects of the reform. Understanding whether the proportion of buy-to-let transactions has changed requires the use of a logistic model. Two different kinds of samples are drawn from the data section: one that includes all properties and one that only includes new properties. The sample that consists of only newly constructed properties is not tainted by repossessions; hence its results can be used as both a stand-alone study and a robust check for the sample of all properties. Discussing the characteristics of

Figure 4: The share of BTL in both samples



the estimation and evaluating the validity of the parallel trend assumption that underlies this research's methodology will aid in assessing the significance of the findings.

5.1 Empirical strategies

5.1.1 DiD

The buy-to-let status of the transaction is used to determine whether this status impacts the transaction price compared to a non-buy-to-let property. A Difference-in-Differences approach is used to estimate this effect. In order to quantify the effect of the Section 24 intervention, this approach compares the transaction prices of properties in the treatment group, which are properties identified as buy-to-let transactions, to the transaction prices of properties in the control group, i.e. the properties not affected by the reform.

The estimated Difference-in-Differences regression model takes this form:

$$log(price)_{it} = \beta_1 BTL_i \times Post_t + \beta_2 BTL_i + \beta' X_{it} + \sigma_t + \epsilon_{it} \tag{1}$$

Because the intervention was rolled out in four stages and in order to capture yearly effects, all years are used for $Post_t$, where $t = -3, -2, -1, 0, 1, 2, 3, 4, 5$ from 2013 to 2021. The year 2016 is used as the reference year at $t = 0$, which is one period prior to the treatment commencing in 2017. The coefficient β_1 on the interaction term $BTL_i \times Post_t$ captures the effect of the buy-to-let status on the transaction prices. The main focus of the analysis is on this coefficient for the post-intervention periods from 2017 onwards ($t > 0$).

BTL_i indicates the buy-to-let status of the transaction. X_{it} is a vector of property-level characteristics that are retrieved from PPD and matched with EPC. These characteristics are employed to control the distinction between various qualities. For instance, having a large floor space and being a detached house both increase the value of a property, even with all other attributes controlled. The vector X_{it} also includes variables to control for regional and demographic variations in order to recognise that house price trends vary across the country. Time-fixed effects σ_t are included as housing prices are naturally trending. OLS is used to estimate the model given in Eq. 1 on the two separate samples.

5.1.2 Logit

Does Section 24 have an impact on the decision to invest in buy-to-let at all? To answer this question, it is not sophisticated to examine the number of buy-to-let transactions each year; it is more suitable to examine whether the intervention has affected the probability of buy-to-let transactions among all transactions.

$$Pr(BTL = 1|Post_t, X_{it}) = F(\beta_1 Post_t + \beta' X_{it}) \tag{2}$$

The logistic function $F(\cdot)$ limits the dependent variable to values between 0 and 1. The meaning of the variables is comparable to Eq. 1; instead of regressing on price, the likelihood that the transaction is a buy-to-let is considered. Again, individual and regional effects are taken into account in vector X_{it}.

5.2 Results and discussion

Full regression results Tables 14 and 15 are reported in Appendix B.

5.2.1 DiD

The regression results of the DiD specification in Eq. 1 on the whole sample are shown in Table 7. The interaction coefficients of interest are all significant except in 2019 without controls and 2017 with controls. Using the specification in Eq. 1, which accounts for individual and geographical characteristics, the result shows that overall, prices of buy-to-let properties are 18.6% lower than non-buy-to let in the reference year. However, after the implementation of Section 24, compared to non-buy-to-let properties in the reference year 2016 ($t = 0$), the prices of buy-to-let properties are higher in 2017 to 2019 by 0.9%, 1.4% and 0.8%, and lower in 2020 and 2021 by 2.6% and 3.7%, respectively.

The same DiD regression is re-estimated on new properties only in Table 8. Again, the coefficients of interest are all positive and significant with and without controls under the specification in Eq. 1. The results are similar to the sample with all transactions. It indicates that overall, the prices of newly built buy-to-let properties are 18.1% lower compared to newly built non-buy-to-let counterparts in reference year 2016. After the introduction of Section 24, compared to newly built non-buy-to-let properties in the reference year 2016 ($t = 0$), the prices of newly built buy-to-let properties are higher in 2017 to 2020 by 7.2%, 6.0% 4.7%, 12.6%, and lower in 2021 by 12.2%, respectively.

The results for both samples are broadly consistent. Except for 2017, the price increase in the first post-intervention years is minor but significant. It is evident that even though buy-to-lets have lower prices overall with a negative β_2, the signs on β_1 suggest that the prices of buy-to-let transactions have become higher after the policy intervention until the policy intervention is finished or a year after in 2020 or 2021, even with time-fixed effects accounted for. One reason could be that buy-to-let properties after 2019 are significantly less expensive than non-buy-to-let properties, and this influence dominates the overall buy-to-let

Table 7: DiD regression on all properties

	log(price)	log(price)
BTL	-0.3493***	-0.1857***
	(0.0038)	(0.0022)
Year		
2013	-0.1823***	-0.1417***
	(0.0007)	(0.0012)
2014	-0.1216***	-0.0913***
	(0.0005)	(0.001)
2015	-0.0585***	-0.0348***
	(0.0005)	(0.0009)
2017	0.0376***	0.0335***
	(0.001)	(0.0005)
2018	0.0542***	0.0551***
	(0.001)	(0.0005)
2019	0.0836***	0.0704***
	(0.001)	(0.0005)
2020	0.1931***	0.129***
	(0.001)	(0.0005)
2021	0.197***	0.1865***
	(0.001)	(0.0005)
BTL× year		
1 2013	-0.0904***	-0.0329***
	(0.0069)	(0.0041)
1 2014	-0.0715***	-0.0227***
	(0.0054)	(0.0031)
1 2015	0.0102**	0.0121***
	(0.0049)	(0.0029)
1 2017	0.0212***	0.0087
	(0.0054)	(0.003)
1 2018	0.031***	0.0139***
	(0.0053)	(0.003)
1 2019	0.002	0.0078**
	(0.0052)	(0.003)
1 2020	-0.0916***	-0.0264***
	(0.0055)	(0.0032)
1 2021	-0.0847***	-0.0373***
	(0.0055)	(0.0032)
Year FE	yes	yes
Controls	no	yes
R^2	0.038	0.7054

No. of observations: 7318913
Robust Standard errors in parentheses

Table 8: DiD regression on new properties only

	log(price)	log(price)
BTL	-0.3021***	-0.1813***
	(0.0099)	(0.0064)
Year		
2014	-0.2371***	-0.1977***
	(0.0018)	(0.0018)
2015	-0.1717***	-0.138***
	(0.0014)	(0.0014)
2016	-0.0883***	-0.0755***
	(0.0013)	(0.0024)
2017	0.042***	0.0422***
	(0.0024)	(0.0013)
2018	0.0677***	0.0672***
	(0.0023)	(0.0013)
2019	0.0927***	0.0884***
	(0.0023)	(0.0014)
2020	0.1301***	0.1186***
	(0.0023)	(0.0013)
2021	0.1254***	0.2087***
	(0.0025)	(0.0023)
BTL× year		
1 2013	0.1927***	0.0764***
	(0.0277)	(0.0179)
1 2014	0.0564***	-0.0001
	(0.0174)	(0.0111)
1 2015	0.039***	0.0003
	(0.0141)	(0.0093)
1 2017	0.1369***	0.0718***
	(0.0165)	(0.0094)
1 2018	0.0977***	0.0597***
	(0.0155)	(0.0097)
1 2019	0.1174***	0.047***
	(0.0168)	(0.0108)
1 2020	0.2101***	0.1261***
	(0.0253)	(0.0133)
1 2021	-0.1917***	-0.1218***
	(0.0147)	(0.0097)
Year FE	yes	yes
Controls	no	yes
R^2	0.0492	0.7357

No. of observations: 808720
Robust Standard errors in parentheses

effect. This pattern is contrary to what one would expect if the reform reduced the relative demand for buy-to-let properties. It is possible that the Difference-in-Differences analysis is capturing a composite effect, which includes both the real policy effect and the effect of property features that affect prices but aren't part of the model. This raises concerns about the DiD regression's validity due to omitted variable bias and the violation of common trend assumption.

However, it is also conceivable that the demand for buy-to-let and non-buy-to-let properties follows entirely distinct long-term trends over time, and what is being interpreted as the effect of the reform is the combined effect of the long-term trend and the policy. In addition, it should be noted that significant changes in stamp duty taxes occurred in 2016, and the COVID-19 pandemic occurred in 2020-21; all of these could affect buy-to-let properties and non-buy-to-let properties differently, but in this model they are only captured as the coefficients of 2016, 2020 and 2021. These are the apparent limits of the causal interpretation of DiD, and given the data supplied, there is little that can be improved. Yet, it may impact the conclusion; thus the analysis should be maintained as mostly descriptive.

5.2.2 Validity of the parallel trend assumption

The estimated intervention effect calculated using the DiD specification is only valid under the assumption of a parallel trend. In other words, in the absence of policy intervention, the results in both the treatment and control groups must follow the same temporal trend. This assumption cannot be evaluated directly, because a counterfactual that contains prices for both the treatment and control groups that are unaffected by the policy is not available for verification.

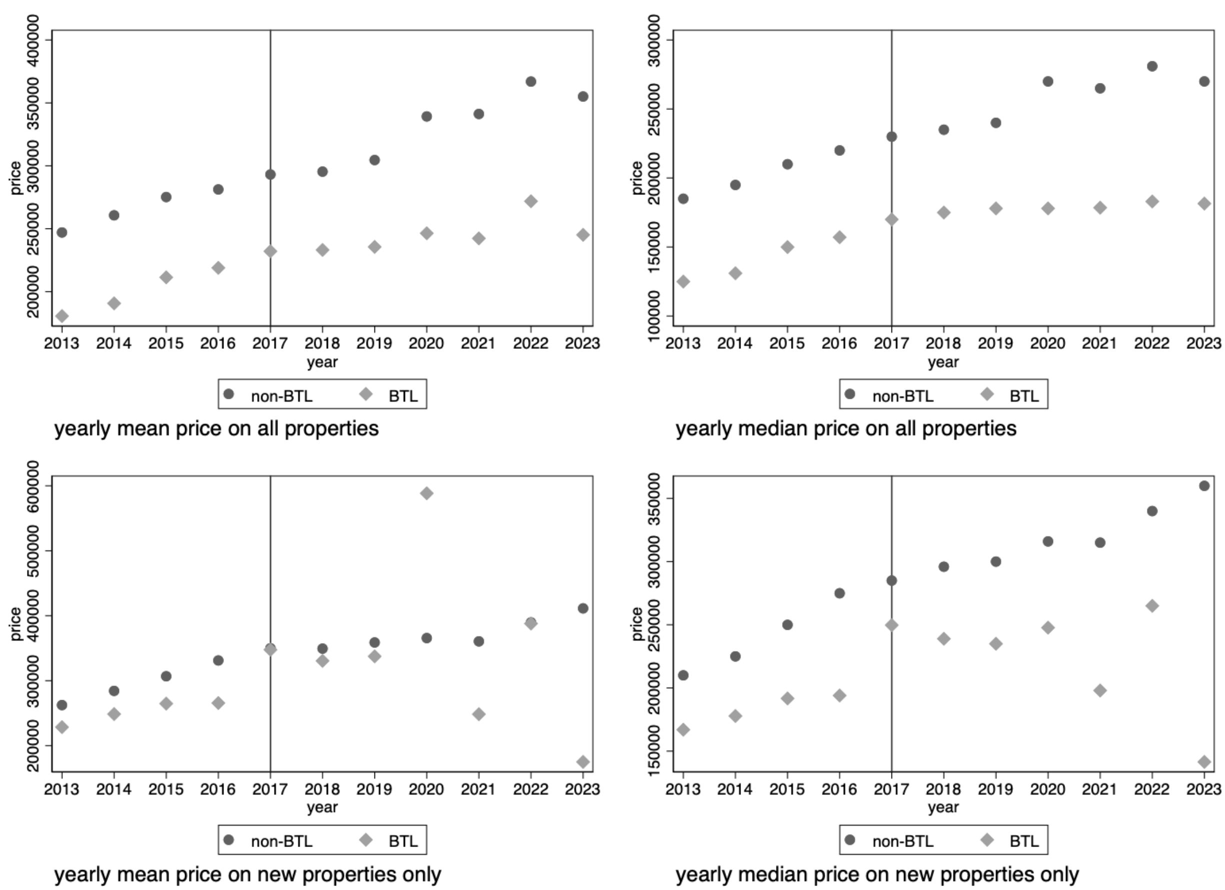
Examining the pre-intervention period is a common tactic for finding evidence to refute this assumption. If the parallel trend assumption holds, both the treatment and control groups should follow parallel trends prior to intervention and might diverge afterward. Without the intervention, the two groups should continue on their pre-intervention paths.

If different pre-trends emerge, the parallel trend assumption is violated. To examine the accuracy of the parallel trend assumption in relation to Eq. 1, two different approaches are used.

- Graphical parallel trend test

To test for parallel trends prior to intervention, typical Difference-in-Differences graphs are created. Both the treatment and control groups' average prices are plotted against time. As buy-to-let is binary, the graph can be readily plotted with clear divisions. Two average measurements, the mean and median, are used to account for the various price spreads in both samples. Means are used because the OLS estimation relies on minimising the deviation from the mean. Medians are used to account for the skewness of the prices, as is evident from the early exercises in the data portion describing the data in Table 5 and Figure 3.

Figure 5: Parallel trend test



The results are depicted in Figure 5. Prior to the implementation of the treatment in 2017, the mean and median prices trends for both buy-to-let and non-buy-to-let properties are parallel in both samples. This indicates the validity of the assumption of a parallel trend for regression in Eq.1. The similarity between the mean and median plots for the sample of all properties suggests that the parallel trend will continue past 2017 and through 2020. Intriguingly, the post-treatment trends for new properties vary significantly. For instance, the mean price of newly constructed buy-to-let properties is extremely high at £588,529; a manual check reveals that this is due to the sale of several multimillion-pound, ultra-luxurious central London apartments in 2020. Because it is unaffected by extreme values in this scenario, the median plot is preferable. This triggers a median regression to be performed later in this chapter. Nonetheless, there is clear evidence that the average price of new-construction rental properties is decreasing substantially after 2020 as the sample period comes to a close.

- Lead test

The periods in $t < 0$ can be used as leads for treatment timing because the main regression allows t to vary for all years in the sample. According to Roth, 2022, determining whether the leads are statistically significant is the most popular way to evaluate pre-trends in the literature. In this context, the leads for $t < 0$, i.e. 2013-2016, are set to 1 in the relevant pre-2017 years and are interacted with the buy-to-let indicator to generate DiD estimators. The results in Table 7 and 8 from the main regression can be used for this test.

All coefficients on the interaction terms for the all properties sample are significant for years 2013–2015. This is inconsistent with the graphical test; it is likely due to outliers or a large dispersion of observations, as the graphical test only uses the average values. The lead test shows a violation of the parallel trend assumption in the sample of all properties. For the sample with only new properties, coefficients on the interaction terms are not significant for 2014 and 2015. This is in line with the graphical test and suggests that the parallel trend assumption holds for the sample with only new properties. The reasons for the coefficient on $BTL \times 2013$ being significant are most likely due to some extreme prices in 2013 not shown in the average plots. Observations in 2013 are only available for the second half of the year; prices may be influenced by seasonal trends (Ngai and Tenreyro, 2014), which are not reflected in the averages graphs. The lead test reveals that the assumption of a parallel trend holds true only for samples with new properties but not for samples with all properties. There is a possibility that the sample of all properties contains repossessions that deviate from the parallel trend.

Since it appears that BLT and non-BLT prices move somewhat differently both before and after reform, the validity of the parallel trend assumption should be viewed with caution. It should be noted that newly built properties with controls pass the common trend test.

5.2.3 Quantile regression

To resolve the issues discovered with outliers in Figure 5, the Least Absolute Deviations (LAD) regression is used to estimate the median for the DiD specification in Eq. 1. Table 9 contains the results for this specification with time-fixed effects only. The specification includes individual and regional controls that fail to converge and are thus not reported. Even though all interaction terms are positive and significant and roughly agree with the OLS results, the insight they provide is limited due to the lack of controls.

5.2.4 Logit

Interesting results are obtained from the logistic regressions. In Table 10, coefficients and marginal effects at means are reported. The results for the sample with all properties are essentially consistent with those of the DiD. The coefficients and marginal effects for the years 2015 through 2019 are significant and positive, but of a small magnitude, followed by a significant negative coefficient in 2020 and an insignificant coefficient in 2021. They indicate an increasing proportion of buy-to-let transactions from 2015 to 2019, both before and after the initial intervention period, and a fall afterwards. Specifically, the likelihood

Table 9: Median regressions

	all	new only
	log(price)	log(price)
BTL	-0.3665***	-0.3511***
	(0.0061)	(0.0086)
year		
2013	-0.1733***	-0.2600***
	(0.0000)	(0.0056)
2014	-0.1155***	-0.1938***
	(0.0017)	(0.0044)
2015	-0.0465***	-0.0951***
	(0.0000)	(0.0015)
2017	0.0445***	0.0392***
	(0.0000)	(0.0030)
2018	0.0660***	0.0738***
	(0.0000)	(0.0035)
2019	0.0953***	0.0872***
	(0.0017)	(0.0015)
2020	0.2048***	0.1423***
	(0.0012)	(0.0034)
2021	0.2048***	0.1296***
	(0.0000)	(0.0049)
BTL×year		
1 2013	-0.0664***	0.2723***
	(0.0086)	(0.0352)
1 2014	-0.0833***	0.0931***
	(0.0098)	(0.0176)
1 2015	0.0166***	0.0700***
	(0.0064)	(0.0176)
1 2017	0.0343***	0.1820***
	(0.0061)	(0.0225)
1 2018	0.0464***	0.1204***
	(0.0054)	(0.0174)
1 2019	0.0423***	0.1111***
	(0.0064)	(0.0154)
1 2020	-0.0672***	0.1137***
	(0.0064)	(0.0254)
1 2021	-0.0672***	-0.1455***
	(0.0070)	(0.0196)
Year FE	yes	yes
Controls	no	no
Pseudo R^2	0.0226	0.0334

Standard errors in parentheses

of a transaction being a buy-to-let increases by 0.17 % points in 2017, 0.18 % points in 2018, and 0.62 % points in 2019, with a decrease of 0.16 % points in 2020 and no change in 2021 at the mean values of all other control variables, relative to the reference year 2016, one period prior to the intervention. This is consistent with Figure 4, which indicate that the proportion of buy-to-let properties is increasing but comparatively flat after 2016 and decreasing dramatically after 2020.

This time, the results for the sample containing only new properties are notably different from those for the sample containing all properties. The likelihood of a transaction being a buy-to-let is lower by 0.62 % points in 2017, 0.62 % points in 2018, 0.89 % points in 2019, 1.4 % points in 2020, and higher by 1.1 % points in 2021 at the mean values of all other control variables, compared to reference year 2016. All results are significant, which indicates that the share of buy-to-let has steadily decreased by a small but significant amount post-intervention until 2021.

5.2.5 External validity

In theory, the all properties sample consists of the entire population of relevant transactions affected by Section 24, excluding the ones missed out during data matching, but it also includes unwanted repossession transactions, and buy-to-let properties without mortgages are unidentifiable. The results are different for the two samples. This could be because repossession was not effectively removed from the data set or because the new properties are fundamentally distinct from the others. Their property characteristics are different, as seen in the descriptive Table 6; for example, ultra-luxury properties are often newly built or newly renovated, such as the London multimillion-pound apartments; with a small sample size of new build, these transactions at the high end of the price range also give a larger spread of price distribution. The findings from the sub-sample of new properties may not accurately reflect the entire population of buy-to-let transactions for the aforementioned reasons.

Table 10: Logistic regression

	all		new	
Year	BTL coefficient	ME	BTL coefficient	ME
2013	-0.1051***	-0.0037***	-0.8309***	-0.0128***
	(0.0094)	(0.0003)	(0.041)	(0.0005)
2014	-0.0077	-0.0003	-0.3901***	-0.0073***
	(0.0074)	(0.0003)	(0.0268)	(0.0005)
2015	0.249***	0.0104***	0.0724***	0.0017***
	(0.0068)	(0.0003)	(0.0219)	(0.0005)
2017	0.0454***	0.0017***	-0.3215***	-0.0062***
	(0.0073)	(0.0003)	(0.0241)	(0.0005)
2018	0.047***	0.0018***	-0.3198***	-0.0062***
	(0.0074)	(0.0003)	(0.0243)	(0.0005)
2019	0.1553***	0.0062***	-0.4984***	-0.0089***
	(0.0073)	(0.0003)	(0.0261)	(0.0005)
2020	-0.0432***	-0.0016***	-0.94***	-0.0138***
	(0.0076)	(0.0003)	(0.0316)	(0.0004)
2021	0.0000	0.0000	0.4102***	0.0112***
	(0.0078)	(0.0003)	(0.029)	(0.0009)
Year FE	yes		yes	
Controls	yes		yes	
Pseudo R^2	0.0395		0.1536	
Observations	7318913		808720	

The coefficients and marginal effects on the years are reported
Robust Standard errors in parentheses

6 Summary and Conclusion

This study looks at the introduction of Section 24, a change to taxation for residential landlords that came into effect on 6th April 2017, and was phased in over the next four years until 2020. It limits the tax deductions that residential landlords may claim, which means higher-earners will pay more tax. The government maintains that the change will have little effect on prices and rent levels since the market segment impacted is tiny (HM Revenue & Customs, 2017). Independent groups, however, hold a different viewpoint (National Property Buyers, 2023; National Residential Landlords Association, 2023). Through price and quantity, this work examines the two opposing claims on demand. The creation of a novel data set has taken a significant amount of time and effort for this analysis.

The DiD model shows that buy-to-let properties have gained in price since the policy's adoption, despite their lower prices in general. The price increases are small yet statistically significant. When the sample just contains new properties, similar patterns are displayed. The results suggest that prospective landlords continue to be willing to pay more each year to acquire a buy-to-let property, which is consistent with survey findings in the literature review that landlords continue to believe property investment is the strongest. Because repossessions taint the sample of all properties, the assumption of a parallel trend may not be valid.

The Logit results for all properties show that the likelihood of the transaction being a buy-to-let transaction increases after intervention, with the exception of 2020, which agrees with the DiD results. However, for new properties, the likelihood of a buy-to-let transaction decreases after intervention. This could be due to the fact that new properties are not economically profitable for buy-to-let, rather than the intention of buy-to-let being discouraged in general.

The results are mixed, but in general, after the reform, buy-to-let prices rose marginally more than non-buy-to-let prices before the descent in 2020. Repossession was not fully eliminated from the sample for all properties, and new properties are possibly distinct from England and Wales' general property profile. This study only looks at mortgaged buy-to-let transactions, which account for the majority of buy-to-let transactions; it is difficult to say how this policy affects the estimated 40% of landlords who do not have mortgages. Simple DiD and Logit may not adequately account for other events that occur within the same time period as this research, such as the additional stamp duty and COVID-19. Due to these restrictions, causal interpretations should be taken with caution, and this analysis remains descriptive.

6.1 Implications

Caldera and Johansson, 2013 provide empirical evidence that the housing supply in the United Kingdom is not particularly sensitive to price. In this case, the negative income effect of the additional tax did not successfully deter investors from buying to let.

The findings largely support the government's point of view and contradict that of the independent agencies. By collecting more taxes and redistributing them in other ways, the policy may have been successful in increasing equality. However, with the possible exception of new properties, it has not reduced the demand for or price of buy-to-let properties. This is likely due to the lack of alternative investment opportunities, particularly considering that the majority of second-home buyers are retirees who prefer to invest their pension in properties (Scanlon and Whitehead, 2016). A survey by Laycock, 2022, February found that property investment (including buy-to-let) is the most popular investment choice among British people and that 30% of participants believe that properties will have the best performance in 2022.[3] It is possible that the negative wealth effect from this reform is insufficient for the landlord to abandon buy-to-let investments. The government estimates that 82% of landlords do not pay additional taxes as a result of the reform as their total taxable income does not exceed the basic rate band (HM Revenue & Customs, 2016a); half of buy-to-let landlords pay annual mortgage interest of £5,000 or less (Scanlon and Whitehead, 2016).

A potential negative externality of this reform is that landlords may pass on this tax loss to tenants, thereby making it more difficult for tenants to locate affordable housing. The average weekly rent for private tenants has increased after this intervention (ONS, 2023; Statista, 2023). Given that the tax reform has not discouraged landlords from purchasing buy-to-let properties (with the possible exception of newly constructed properties), whether or not this additional tax has been passed on to tenants could be the subject of future research.

[3] Note that this survey was done in 2021, before the Bank of England base rate started to climb.

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Appendix A. Full description of variables used from data sources

This section provides tables of full description of variables used from data sources

Table 11: Description of the Price Paid Data

Variable	Description	Value type
Transaction ID	An unique reference number generated automatically for each transaction.	Nominal
Price	Sale price stated on the transfer deed.	Continuous
Date	Date when the sale was completed, as stated on the transfer deed.	Date
Postcode	The postcode of the property used at the time of the transaction.	Nominal
Property Type	D = Detached, S = Semi-Detached, T = Terraced, F = Flats/Maisonettes, O = Other*	Nominal
Old/New	Y = a newly built property, N = an established residential property	Nominal
Tenure	F = Freehold or L= Leasehold	Nominal
PAON	Primary Addressable Object Name. Typically the house number or name.	Nominal
SAON	Secondary Addressable Object Name. Where a property has been divided into separate units (for example, flats), the PAON (above) will identify the building and a SAON will be specified that identifies the separate unit/flat.	Nominal
PPD Category	A = Standard Price Paid entry B = Additional Price Paid entry**	Nominal

* where the property does not belong to the previous group. (can be multiple properties or parcels of land)
** including transfers under a power of sale/repossessions, buy-to-lets (where they can be identified by a Mortgage), transfers to non-private individuals and sales where the property type is classed as 'Other'.

Table 12: Description of the EPC data

Variable	Description	Value type
LMK key	Unique identifier for individual lodgement	Nominal
Address 1	Frist line of the address	Nominal
Address 2	Second line of the address	Nominal
Postcode	The postcode of the property	Nominal
Energy Rating	Current energy rating converted into a linear 'A to G' rating. (A being the most efficient)	Nominal
Lodgement date	Date lodged on the Energy Performance of Buildings Register	Date
Total Floor Area	The total useful floor area is the total of all enclosed spaces measured to the internal face of the external walls. (m^2)	Continuous
Number of habitable rooms	Habitable rooms include any living room, sitting room, dining room, bedroom, study and similar; and also a non-separated conservatory.	Integer
Main fuel	The type of fuel used to power the central heating e.g. Gas, Electricity*	Nominal
Construction age band	Age band when building part constructed. One of: before 1900; 1900-1929; 1930-1949; 1950-1966; 1967-1975; 1976-1982; 1983-1990; 1991-1995; 1996-2002; 2003-2006; 2007-2011; 2012 onwards.*ˆ	Nominal

* Missing data has been grouped into "Other"

ˆ Smaller groups are created

Table 13: Description of the CCOD and the OCOD data

Variable	Description	Value type
Title number	Unique identifier of the lodgement	Nominal
Property address*	Address of the property	Nominal
Post code	Post code of the property	Nominal
Price paid	Price paid for the transaction	Continuous

* Several properties with consecutive address numbers could be registered under one title.

Appendix B. Complete regression results

This section provides tables of complete regression results

Table 14: Complete regression results on DiD

	All properties			New properties only		
log(price)	Coefficient	Robust SE.	P>t	Coefficient	Robust SE.	P>t
BTL	-0.1857	0.0022	0	-0.1813	0.0064	0
Year (default 2016)						
2013	-0.1823	0.0007	0	-0.1977	0.0018	0
2014	-0.1216	0.0005	0	-0.138	0.0014	0
2015	-0.0585	0.0005	0	-0.0755	0.0013	0
2017	0.0335	0.0005	0	0.0422	0.0013	0
2018	0.0551	0.0005	0	0.0672	0.0013	0
2019	0.0704	0.0005	0	0.0884	0.0014	0
2020	0.1290	0.0005	0	0.1186	0.0013	0
2021	0.1865	0.0005	0	0.2087	0.0023	0
BTL $\times$ year (default 2016)						
1 2013	-0.0329	0.0041	0	0.0764	0.0179	0
1 2014	-0.0227	0.0031	0	-0.0001	0.0111	0.9900
1 2015	0.0121	0.0029	0	0.0003	0.0093	0.9720
1 2017	0.0087	0.0030	0.0050	0.0718	0.0095	0
1 2018	0.0139	0.0030	0	0.0597	0.0097	0
1 2019	0.0078	0.0030	0.0100	0.0470	0.0109	0
1 2020	-0.0264	0.0032	0	0.1261	0.0134	0
1 2021	-0.0373	0.0032	0	-0.1218	0.0097	0
Total floor area	0.0050	0	0	0.0074	0.0001	0
EPC (default above D)						
below average (D)	-0.0087	0.0004	0	-0.0505	0.0069	0
Age band						
before 1900	-0.1190	0.0008	0	-0.1624	0.0117	0
1900-1949	-0.1861	0.0004	0	-0.1505	0.0093	0
1950-1982	-0.1709	0.0007	0	-0.2282	0.008	0
1983-2002	-0.1467	0.0008	0	-0.235	0.0181	0
2003 onwards	-0.1225	0.0006	0	-0.0750	0.0022	0
Main fuel (default gas)						
Electricity	-0.1031	0.0006	0	-0.0469	0.0017	0
Other	0.0423	0.0009	0	0.1764	0.0018	0
Type (default detached)						
Semi-Detached	-0.1847	0.0019	0	-0.1065	0.0027	0
Terrace	-0.3428	0.0024	0	-0.1392	0.0026	0
Flat	-0.3465	0.0032	0	-0.0774	0.0032	0
Tenure (default Freehold)						
Leasehold	-0.1191	0.0008	0	-0.0456	0.0019	0
Regions (default East of England)						
West Midlands	-0.3470	0.0005	0	-0.2311	0.0014	0
South West	-0.1383	0.0005	0	-0.1307	0.0014	0
North West	-0.4964	0.0005	0	-0.3596	0.0013	0
South East	0.0764	0.0005	0	0.0772	0.0012	0
Greater London	0.6035	0.0008	0	0.4718	0.0020	0
Wales	-0.5493	0.0007	0	-0.3705	0.0018	0
East Midlands	-0.5122	0.0006	0	-0.3715	0.0014	0
North East	-0.5502	0.0006	0	-0.4166	0.0014	0
Demographics (default Rural)						
Cosmopolitans	0.2943	0.0009	0	0.2395	0.0021	0
Ethnicity Central	0.0982	0.0012	0	0.1164	0.0024	0
Multicultural Metropolitans	-0.1408	0.0007	0	-0.0879	0.0014	0
Urbanites	0.0204	0.0005	0	0.0381	0.0009	0
Suburbanites	0.0387	0.0005	0	0.0334	0.0008	0
Constrained City Dwellers	-0.2456	0.0008	0	-0.1092	0.0018	0
Hard-Pressed Living	-0.2436	0.0007	0	-0.0927	0.0011	0
Constant	12.4276	0.0073	0	11.9682	0.0109	0
Number of observations	7318913			808720		

Table 15: Complete results on Logistic regressions

	All properties			New properties only		
BTL	Coefficient	Robust SE.	P>t	Coefficient	Robust SE.	P>t
Year (default 2016)						
2013	-0.1051	0.0094	0	-0.8309	0.041	0
2014	-0.0077	0.0074	0.2920	-0.3901	0.0268	0
2015	0.249	0.0068	0	0.0724	0.0219	0.0010
2017	0.0454	0.0073	0	-0.3215	0.0241	0
2018	0.047	0.0074	0	-0.3198	0.0243	0
2019	0.1553	0.0073	0	-0.4984	0.0261	0
2020	-0.0432	0.0076	0	-0.94	0.0316	0
2021	0.0000	0.0078	0.9970	0.4102	0.029	0
Total floor area (m^2)	-0.0022	0.0001	0	-0.0004	0.0003	0.1080
EPC (default D or higher)						
below average (D)	-0.0326	0.0053	0	-0.5306	0.0575	0
Age band (default Unknown)						
before 1900	0.1708	0.0081	0	-0.0329	0.0869	0.7050
1900-1949	0.3368	0.0063	0	0.2561	0.0787	0.0010
1950-1982	0.1687	0.0063	0	0.1095	0.0808	0.1760
1983-2002	0.1214	0.0073	0	0.1255	0.0773	0.1050
2003 onwards	0.3499	0.0078	0	0.1575	0.0262	0
Main fuel (default Gas)						
Electricity	0.1806	0.0064	0	1.2281	0.0192	0
Other	0.1037	0.0091	0	0.7156	0.0227	0
Type (default Detached)						
Semi-Detached	0.1868	0.0068	0	0.8131	0.0326	0
Terrace	0.6608	0.007	0	1.358	0.0321	0
Flat	0.8661	0.0111	0	2.2824	0.0441	0
Tenure (default Freehold)						
Leasehold	-0.075	0.0076	0	0.0727	0.0331	0.0280
Regions (default East of England)						
West Midlands	0.3245	0.0084	0	0.4214	0.0318	0
South West	-0.0127	0.0089	0.1520	0.1262	0.0313	0
North West	0.4079	0.008	0	0.2724	0.0307	0
South East	0.007	0.0082	0.3980	0.1437	0.029	0
Greater London	-0.0847	0.0087	0	-0.0174	0.0307	0.5700
Wales	0.2755	0.0103	0	0.6224	0.041	0
East Midlands	0.4453	0.0083	0	0.5862	0.0321	0
North East	0.5905	0.0083	0	0.4882	0.0331	0
Demographics (default Rural)						
Cosmopolitans	0.5256	0.0106	0	-0.2742	0.0305	0
Ethnicity Central	0.7517	0.0119	0	-0.3029	0.0332	0
Multicultural Metropolitans	0.8241	0.0091	0	0.0092	0.0311	0.7670
Urbanites	0.2814	0.0085	0	0.0718	0.0261	0.0060
Suburbanites	0.1197	0.0088	0	0.0903	0.0283	0.0010
Constrained City Dwellers	0.6645	0.0102	0	0.1678	0.0333	0
Hard-Pressed Living	0.5771	0.0086	0	-0.0825	0.0321	0.0100
Constant	-4.1481	0.0158	0	-5.1775	0.0528	0
Number of observations	7318913			808720		