How Much Do Investors Pay for Houses?*

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Abstract

I combine housing sales from the England and Wales Land Registry with online rental listings from property portal Zoopla to identify buy-to-rent transactions—known as buy-to-let (BTL) in the UK. Comparing these transactions against all other housing sales in 2009–14 I show that: (1) investors pay less than other buyers for equivalent properties, (2) these discounts are larger in regions with less liquid housing markets, and (3) properties sold to BTL investors stay less on the market. Regressions include detailed geographical fixed effects and sale listing prices to control for local market conditions and unobserved property characteristics. Results suggest that investors facilitate market clearing when housing activity is subdued.

JEL Classification: L26, D14, G11, R21

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1 Introduction

Buy-to-rent investors—known as buy-to-let (BTL) in the UK—are taking on an increasingly important role in housing markets. In terms of *flow*, according to the Council of Mortgage Lenders (CML), BTL accounted for 13% of UK mortgage lending in 2013.[1] BTL activity is also associated to a significant share of non-mortgage house purchases, for which official estimates are not available (some estimates are provided later in this paper). In terms of *stock*, data from the Department of Communities and Local Government show that the UK stock of housing held for private renting has more than doubled in the past 15 years, from 9% of the total stock in 2000 to 19% of the stock in 2013.[2] These trends are common to the US, where home ownership is also declining (Jones and Richardson, 2014).

An important policy issue is whether BTL investors push up prices and contribute to macro-financial instability or, to the contrary, play a helpful role as buyers of last resort and contribute to market clearing (Molloy and Zarutskie, 2013). The Bank of England Financial Policy Committee has recently expressed the concern that '[t]he scale and nature of BTL activity makes it a significant potential amplifier of housing and credit cycles'.[3]

The effect of BTL activity on house prices can be *direct*, when BTL investors systematically bid more than other buyers for the same houses, or *indirect*, when the arrival of a new group of buyers pushes market prices up (without necessarily implying that the new buyers pay more on average). In this paper I focus on the direct effect of the flow of investor purchases and consider both mortgage- and non-mortgage-funded BTL.[4] A systematic pattern of investors overpaying for properties could endanger macro-financial stability by exacerbating house price rises, potentially leading to overextension of credit. Also, it is often suggested in the media that investors drive other purchasers (such as First Time Buyers, FTB) out of the market.[5]

Economic theory does not provide an unambiguous prediction on the direct effect of BTL on house prices. On the one hand, homeowners may bid higher than investors because of id-

[1] `https://www.cml.org.uk/cml/publications/newsandviews/150/585`

[2] Another 18% of the stock is classified as social renting (i.e. renting from a local authority or housing association) and the remaining is owner-occupied housing.

[3] Financial Policy Committee statement from its policy meeting, 26 September 2014, available at `http://www.bankofengland.co.uk/publications/Pages/news/2014/080.aspx`.

[4] Most non-mortgage transactions are likely to be financed by cash. However, this group can also contain transactions by large private investors with access to other financing methods (such as banks corporate credit books or capital markets).

[5] See for instance 'Wild West buy-to-let investors force first-time buyers off the housing ladder', Telegraph, 11 July 2011.

iosyncratic tastes for specific property features (as in search-and-matching models of the housing market[6]), or because ownership acts as an insurance against rent risk (Sinai and Souleles, 2005). On the other hand, investors may be more efficient than homeowners at managing and renovating properties (Linneman, 1985). To further complicate the issue, homeowners and landlords are subject to different tax regimes (Chambers, Garriga, and Schlagenhauf, 2009b) and access different types of mortgages (Chambers, Garriga, and Schlagenhauf, 2009a). In the absence of a clear theoretical prediction, the question of whether BTL investors pay more for houses must be answered by the data.

The empirical strategy of this paper is based on the increasing importance of internet portals in advertising rental properties. The key idea is that, if a flat or house is advertised for rent *shortly after* its purchase, it is a BTL property.[7] I use two data sources to implement this approach: the Land Registry, which contains all residential transactions in England and Wales, and WhenFresh.com, a company that processes the listings of Zoopla, a leading UK property portal. This method allows me to detect, at the end of the sample (2014Q1), between one quarter and one fifth of all mortgage-funded BTL purchases in the UK, and approximately the same proportion of non-mortgage BTL transactions.[8]

Because this paper is the first to study UK housing investors using micro data, I describe BTL activity in England and Wales before turning to the main research question. Zoopla went online in November 2008, therefore the sample includes the quarters from 2009Q1 to 2014Q1. The micro data show that BTL transactions have doubled in this period, consistent with aggregate data from other sources such as the CML.[9] From a cross-sectional perspective, BTL transactions are concentrated in places with a large private rented housing stock (such as dense urban areas) and in types of properties which have traditionally been associated with renting (i.e. flats rather than houses). The probability of re-selling a BTL property within the

[6]The literature on search-and-matching in the housing market includes, for instance, Wheaton (1990), Albrecht, Anderson, Smith, and Vroman (2007), and Ngai and Tenreyro (2014). However these papers do not distinguish between matches for owner-occupation, investment, and rental. Halket and Pignatti (2015) discuss the household tenure decision and draw a connection between expected duration in the property and match quality.

[7]In the paper, I identify BTL purchases as transactions where a rental advertisement follows a sale on the same property during the following 6 months. I also experimented with different thresholds (3 or 12 months), which yielded very similar results.

[8]As shown in the Data section, the CML reports that there were 24,000 BTL mortgages for house purchase issued in 2014Q1, and I am able to identify around 5,000 of them in my sample. I also show that the number of mortgage BTL transactions is approximately the same as the number of non-mortgage BTL transactions.

[9]The total number of housing transactions went up by 85% in the same period, implying an increasing share of BTL purchases.

first 6 years is lower than for other dwellings, implying that this paper focuses on long-term investors rather than short-term speculators.[10]

To answer the main research question, I run a regression of individual sale prices on a BTL indicator, controlling for available property characteristics and local market conditions (through postcode-month fixed effects). To address the challenge of unmeasured property characteristics, I restrict attention to those properties for which a sale listing exists in Zoopla and include the advertised price in the regression.[11] Together with the other controls, the advertised price captures all information related to the value of the property known by the seller. The baseline estimate shows a statistically significant 1.0% discount associated with BTL transactions, implying that BTL investors spend on average less than other buyers (or, equivalently, other buyers spend more than BTL investors). Because I do not identify all BTL transactions, I am effectively comparing BTL sales with a control group of *both* non-BTL and BTL properties. The 1.0% estimate is a lower bound for the true BTL discount and corresponds to £2,100 ($3,250) for the average transaction in the sample.[12]

English regions and Wales have experienced diverse housing market conditions over 2009-2014. London has seen robust house price growth, especially in the last part of the sample;[13] the South West and South East of England have also performed well; the remaining regions have been lagging, with some parts of the country consistently experiencing negative nominal house price growth. In a second set of regressions, I analyse how BTL discounts evolve in these heterogeneous housing market conditions: discounts are larger in regions with smaller private rented markets and in the earlier years of the sample. For instance, in 2010 houses sold to BTL investors outside London and the South of England the lower bound for the discount is 2%.

Persistent discounts for equivalent properties can exist in a market with search frictions.

[10] Quickly re-selling properties (or 'flipping' as in Bayer, Geissler, Mangum, and Roberts, 2015) is uncommon in the UK due to high transaction taxes (stamp duty)—these taxes have been studied by Hilber and Lyytikäinen (2013), who focus on their effect on mobility, and Best and Kleven (2015), who concentrate on their effect on house prices. Figure 5 in Section 3 reveal that less than 2% of properties in England and Wales re-sell within 1 year of purchase.

[11] A few recent papers that use listing prices in their empirical analysis, for example to measure the effect of foreclosures on nearby property prices (Anenberg and Kung, 2014) or the effect of credit availability on house prices (Kung, 2015).

[12] A number of investors and estate agents confirmed the existence of this discount in private conversations with the author. If anything, a few market practitioners had in mind larger discounts than those reported here, consistent with the lower bound interpretation of the results. However some of their arguments—based on the different property conditions of buy-to-let investments, for instance—were at odds with the strict like-with-like comparisons implicit in the empirical strategy of this paper.

[13] London house prices rose by 20% between August 2013 and August 2014 according to the Land Registry (`http://landregistry.data.gov.uk/app/hpi/`).

A seller that decides to reject an investor's bid can end up waiting a long time before a new offer arrives. According to this view, BTL discounts are a compensation for market clearing and should be larger when market liquidity is lower. To test this hypothesis, I measure time on market (TOM), the time it takes a property to go from a Zoopla sale listing to a registered sale. I find that properties sold to investors spend five days less on the market than other properties and TOM reductions by region and year track average BTL discounts. Interestingly, in the last part of the sample BTL discounts are hardly distinguishable from zero (especially in London), suggesting that the market-clearing contribution of BTL investors becomes less valuable once the market has resumed a sustained level of activity.

From a policy perspective, it is important to distinguish between mortgage and non-mortgage transactions, not least because the literature has highlighted the potential adverse effect of increased credit availability on investors behaviour (Haughwout, Lee, Tracy, and der Klaauw, 2014). Anecdotal evidence suggests that non-mortgage transactions are quicker because buyers do not need to obtain banks' approval. The analysis confirms that non-mortgage transactions are associated with a lower TOM. This enhanced speed may allow non-mortgage buyers to obtain higher discounts, although the data does not support this conclusion: there is no statistical difference in the price paid by mortgage and non-mortgage buyers.[14]

The contribution of this paper is twofold. First, it shows how to identify housing investors when the names of buyers and sellers are not available. This methodology can have many applications—for instance, it can be used by mortgage providers to check whether owner-occupier mortgages are being used to finance a BTL investment. Second, the paper contributes to the academic and policy debate on the role of investors in the housing market (the next section contains a brief review of the literature). By showing that BTL properties are sold at a discount in non-boom periods, it provides evidence on the market-clearing role of housing investors. At the same time the paper shows that BTL discounts tend to vanish when housing liquidity improves.

Ater examining the related literature in the next Section, I describe the data, the matching

[14]A similar hypothesis relates BTL discounts to the absence of a 'chain', i.e. BTL investors do not need to sell their current property before buying a new one (as in Rosenthal, 1997, or Anenberg and Bayer, 2013). In the Appendix of the paper, I compare the discounts obtained by BTL investors with those obtained by first-time buyers, who are also unencumbered by the need to sell a property before their next purchase. I find that first-time buyers do not enjoy a statistical significant discount, making it difficult to attribute the BTL discount to the absence of a chain.

procedure, and some preliminary statistics in Section 3. Section 4 contains the main empirical analysis, and Section 5 concludes.

2 Related literature

A few papers have studied the role of housing investors in the recent housing boom. Bayer, Geissler, Mangum, and Roberts (2015) analyse a dataset of housing transactions in the Los Angeles metropolitan area between 1988 and 2009. Through buyers and sellers names, they identify people that trade several properties at once (investors), and classify them as either *middlemen*, buying at low prices and reselling quickly, or *speculators*, targeting periods and areas characterised by fast appreciation. Speculators were more active during the recent boom and in areas that later experience house price busts. Haughwout, Lee, Tracy, and der Klaauw (2014) use credit data to identify investors as people who buy a property which is not their main residence. They show that investors represented a higher percentage of transactions and new mortgage debt in US states with more pronounced housing cycles. Similar to the analysis presented here, Haughwout et al use the difference between actual and listing prices as a proxy for investors overbidding. They find that, in general, investors pay less than other buyers, but this result is reversed when focusing on investors who misrepresented their intention to live in the purchased property. Chinco and Mayer (2014) use deeds records from 21 US cities to highlight the role of out-of-town buyers in the recent housing boom. They show that an increase in the number of out-of-town buyers predicts house price appreciation in a city during the following year, and that in 2000-2007 out-of-town buyers realised worse returns on their investments than other buyers.

These studies tend to emphasise the risks that investors pose to economic stability. To do so, they concentrate on the boom period and on particular investor groups that are more prone to herd behaviour or miscalculations. In this paper, I focus on the most recent period (2009-2014) and on long-term buy-to-rent, similar to Mills, Molloy, and Zarutskie (2015). They focus on US large institutional investors, whereas I focus on the general BTL market, which in the UK is mostly made up of small investors.[15] When big corporate players are the exception rather than the rule, tracking BTL investments through comprehensive private data sources is impossible.

[15] The UK Landlord survey (2010) shows that 78% of landlords only own one rented property.

When housing datasets do not contain buyers and sellers' names, investment properties can be identified only through indirect methods, by linking together several micro datasets.

A related literature performs the same match between sold and rented properties to measure and evaluate price-rent ratios. Bracke (2015) uses real estate agency data from Central London to study the cross-section of rental yields. He shows that larger floor size and better location are associated with higher price-rent ratios. Smith and Smith (2006) employ a user cost model to measure overvaluation in the US 2005 housing market. They collect 100 sale-rental matches for a group of 10 US cities.

The present research also relates to papers that have studied the private rental market. The literature has long emphasised the fact that different types of structures are associated to different types of tenure (Linneman, 1985; Coulson and Fisher, 2012). As Glaeser and Shapiro (2003) put it, 'There are few facts in urban economics as reliable as the fact that people in multi-family units overwhelmingly rent and people in single-family units overwhelmingly own.' Relatedly, the percentage of renters is higher in inner cities than elsewhere (Hilber, 2005).

3 Data

3.1 Sources

This paper combines two data sources: (1) the England and Wales Land Registry and (2) WhenFresh/Zoopla listings.

The **Land Registry** (LR) contains all residential transactions in England and Wales since 1995 with very few exceptions.[16] A public version of the dataset is available online. Since the WhenFresh/Zoopla dataset starts in late 2008 (see below), we restrict the Land Registry to the subsample of post-2007 sales. For each transaction, the LR contains the precise postcode, the street name, the street number, and the apartment number if the property belongs to a multi-unit building. In addition, the LR records three attributes of the property: its type (flat, terraced, semi-detached, detached), whether the property is new, and the tenure type of the

[16] The exceptions are listed at `http://www.landregistry.gov.uk/market-trend-data/public-data/price-paid-data`, where the data can be downloaded. Most of these excluded transactions refer to sales through company structures or BTL sales. Traditionally, the LR has not included, in its open micro dataset, transactions that were recognised as funded by BTL mortgage. The rationale was that such transactions would not be representative of the residential sector understood as the owner-occupied sector. As shown in this paper, however, in practice one can identify many transactions that are both BTL (because a rental listing follows the sale almost immediately) and mortgage-funded (as indicated by the LR charge variable).

property (freehold or leasehold). The LR includes a variable ('charge') that indicates the use of a mortgage to purchase the property.[17] The Date of Transfer in LR is the day written on the Transfer Deed, i.e. the date of completion, when keys and funds change hands. The moment in which the transfer of ownership becomes legally binding (the 'exchange of contracts') usually happens 1-2 weeks before completion, but can take place earlier in particular cases.

The **WhenFresh/Zoopla** dataset contains all the listings ever appeared on Zoopla. The first rental and sale listings were published in November 2008. It is now common for most agents to publicise properties on portals such as Zoopla as soon as they are instructed. According to WhenFresh, the dataset covers 70% of the whole-of-household privately rented housing stock in the UK. I restrict the analysis to the subset of listings where an address can be precisely identified. The dataset contains information on the address of properties, listing sale/rental prices, and property attributes (such as property type and number of bedrooms). The WhenFresh/Zoopla rental dataset can only reveal the *intention* to put a property on the rental market, not whether a specific property was actually rented, but this information is sufficient to identify BTL investors.

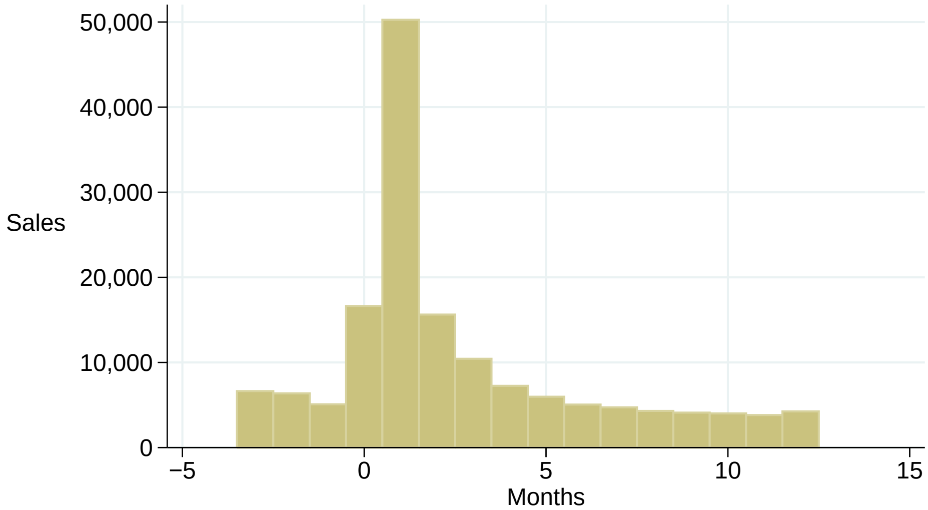
I use the WhenFresh/Zoopla sale dataset to access the listing *prices* of sold properties. Controlling for the listing price in the empirical analysis I make sure that the price differences associated with BTL purchases are not due to unobserved differences in dwelling characteristics. The assumption is that the listing price of a property reflects all the available information at the time the property was put on the market (as in Anenberg and Kung, 2014).

3.2 Matching

Matching housing datasets is a complex task, given the size of the datasets, the heterogeneity of entries and the presence of typos and different spelling conventions. A conservative approach is used where only exact matches between the three main address components (postcode, street, and number) are selected. Since the match needed for our analysis involves several data sources (LR, WhenFresh/Zoopla rentals and sales), it is convenient to first construct a reference dataset of property IDs to which all other data link. This dataset is constructed by appending together the complete addresses of all properties that appear at least once either in the LR or in WhenFresh/Zoopla data, eliminating duplicates. This reference dataset is termed the *Inventory.*

[17] This variable is not available in the public version of the Land Registry, but can be purchased.

Figure 1: Distance in months between buy-to-let purchases and WhenFresh/Zoopla rental listings
This histogram uses all sales where a match exists between a Land Registry record and a WhenFresh/Zoopla rental listing, provided that the Zoopla listing takes place somewhere between 3 months before and 12 months after the sale (which corresponds to month 0 in the chart).



Once the *Inventory* has been created, it is matched with the relevant *Events* contained in the original LR and WhenFresh/Zoopla datasets. An 'event' is any occurrence on a property such as a sale transaction or a rental advertisement. There can obviously be several events associated with one dwelling.[18]

When linking LR sales to WhenFresh/Zoopla rentals, the listing must occur either after the sale (at any time) or before the sale with a maximum of 3 months distance.[19] When linking LR sales to WhenFresh/Zoopla sales, it is required that the listing of the property happen *before* the sale in the Land Registry.

Figure 2 shows the distribution of distances between LR sales and rental adverts for matched properties, defined as rental Time-To-Market (TTM). BTL properties tend to be put on the market quickly. Conditional on the existence of a match, the most frequent rental TTM is 1 month.

[18] A major challenge is dealing with overlapping Zoopla listings that refer to the same event. For instance, two Zoopla rental listings may refer to the same property in the same month, but are two distinct entries because they were created by two different estate agents. In these cases, overlapping rows are collapsed by keeping the earliest creation date and the latest deletion date among all listings corresponding to the same event.

[19] This is to allow instances where the exchange of contracts happens several weeks before the actual completion. In practice, including or excluding these three months does not affect the results.

Table 1: Descriptive statistics, main data sources

The first two columns show data from two of the original data sources used in this paper, the England and Wales Land Registry and WhenFresh/Zoopla rental listings. The third column shows data from the subset of BTL matched properties, i.e. properties that have both a Land Registry sale and a WhenFresh/Zoopla rental listing, and the distance between the two does not exceed 6 months. To avoid outliers or wrongly-typed observation to influence the results, the bottom and the top percentile in terms of prices, rents, and yields have been removed from the data.

	Land Registry (Sales)	Zoopla (Rentals)	Matched (BTL)
Observations	4,014,482	3,676,183	100,669
Average price (weekly rent)	212,340	(244)	181,053
Median price (weekly rent)	177,000	(179)	150,000
Flat	0.19	0.46	0.30
Terraced	0.28	0.24	0.38
Semi	0.29	0.14	0.22
Detached	0.24	0.09	0.08
Other	.	0.06	.
Lease	0.24	.	0.34
Mortgage	0.68	.	0.53
New	0.10	.	0.04

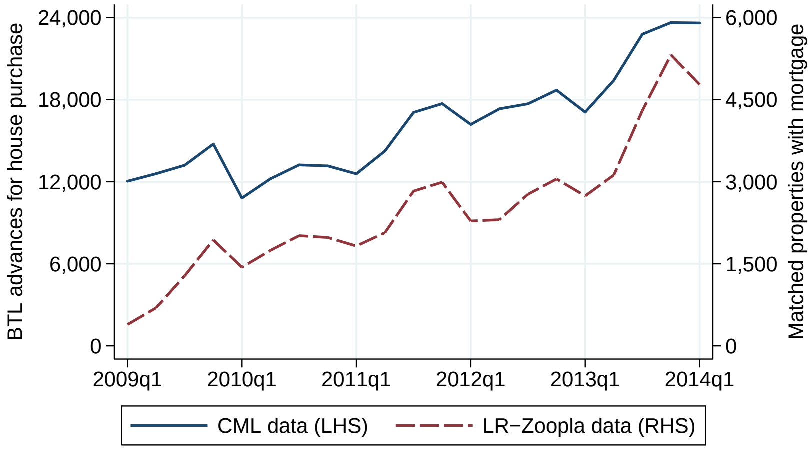
3.3 Descriptive analysis and statistics

Table 1 shows descriptive statistics for the main data sources (the Land Registry and WhenFresh/Zoopla rental listings) and the matched data. The data cover the 2009Q1-2014Q1 period. Sales properties are more likely to be single-family houses, whereas rental properties are more likely to be flats. The third column shows the descriptive statistics for the matched dataset, where characteristics are more similar to the WhenFresh/Zoopla rental dataset than the Land Registry (flats are more common).

Mortgage and non-mortgage purchases BTL investors are less likely to use a mortgage than the average buyer in the LR: 47% of BTL transactions do not involve a mortgage, whereas the percentage is only 32% for the overall LR. These figures can be used to estimate the total number of BTL non-mortgage purchases in the UK. According to the CML, in 2013 13% of all mortgages for house purchase in the UK were BTL. Considering that mortgage sales are 68% of all LR sales, then 13% * 68% = 9% of all LR sales are mortgage-funded BTL. Assuming that BTL non-mortgage transactions are roughly as many as BTL mortgage transactions (because Table 1 reports that 53% of BTL purchases are mortgage-financed), then another 9% of all LR sales are non-mortgage BTL, corresponding to 9% / 32% = 28% of all non-mortgage sales.

Figure 2: Number of buy-to-let transactions

The continuous line represents the aggregate number of BTL quarterly mortgages for house purchase in the UK as reported by the Council of Mortgage Lenders and displayed by the vertical axis on the left. The dashed line tracks the number of BTL *mortgage-funded* sales in the Land Registry-WhenFresh/Zoopla dataset used by the paper, and refers to the vertical axis on the right. Notice that the numbers on the right-hand side axis are exactly one quarter of the numbers on the left-hand side axis.

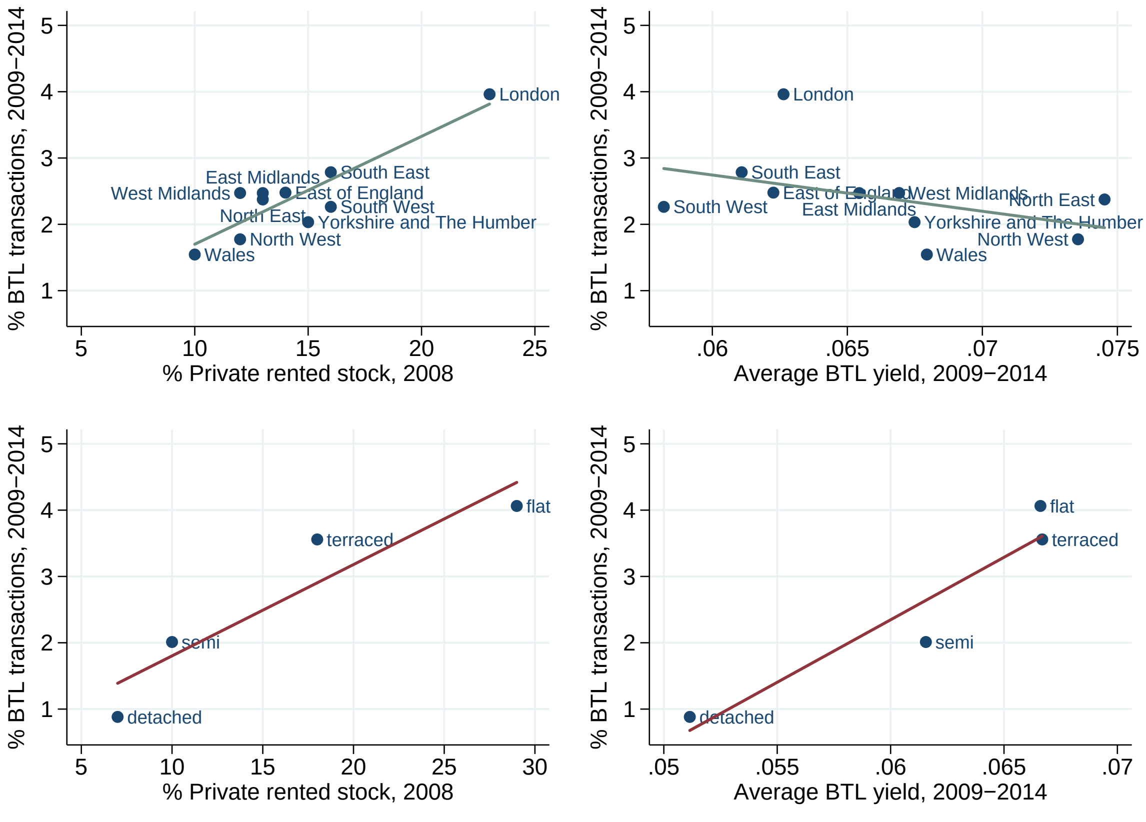


Coverage The methodology presented in this paper can only find a portion of the total number of BTL properties in the UK: not all rented properties can appear on a single dataset; moreover, as mentioned earlier, the LR excludes on purpose some transactions with a BTL mortgage. To estimate the coverage of the BTL sample, it is useful to compare the dataset with an alternative aggregate source. The solid line in Figure 2 shows the CML estimates of the quarterly number of new BTL mortgages for house purchase in the UK between 2009Q1 and 2014Q1 (included). The dashed line represents the matched properties in the LR-WhenFresh/Zoopla data (the sample is restricted to mortgage-funded sales, to make it comparable to the CML data) and refers to the right-hand-side axis (whereas the CML data refer to the left-hand-side axis). The initial coverage of the dataset was low and gradually increased. At the end of 2013, as seen by the numbers on the vertical axes, the LR-WhenFresh/Zoopla data covers approximately one quarter of the aggregate BTL mortgage market. The similarity of the solid and dashed line proves that the LR-WhenFresh/Zoopla dataset is representative of the broader BTL mortgage market.

Where and what investors buy The top-left chart of Figure 3 shows the density of BTL activity by region in the LR-WhenFresh/Zoopla data and compares it to the size of the private rented housing stock. BTL activity is more common in London and the South East, where the

Figure 3: Buy-to-let density

The top-left chart relates the fraction of the stock of housing occupied by private renters in a given region with the fraction of housing transactions identified as BTL in the Land Registry-WhenFresh/Zoopla dataset. Data on the stock of housing and its tenure composition come from the UK Department of Communities and Local Government. The top-right chart substitute the regional percentage of private rented stock with the average regional gross rental yield as computed in the Land Registry-WhenFresh/Zoopla dataset. The two charts on the bottom row replicate the analysis of the two top charts by dwelling type rather than region. The bottom-left chart shows a positive relation between the percentage of flats that are in private renting with the percentage of flat sales that are classified as BTL in the Land Registry-WhenFresh/Zoopla dataset. The bottom-right chart has average BTL gross rental yields on the horizontal axis and again shows a positive relation.



private rented sector is more developed. The bottom-left chart in Figure 3 shows the percentage of BTL purchases by type of dwelling: flat, terraced, semi-detached, detached. There is a clear correspondence between the stock of rented accommodations and what BTL investors buy, consistent with the stylised fact on rented properties mentioned in the literature section. Since one of the components of a BTL investors total return is the rental yield, it is worth checking whether BTL investors buy where rental yields are high. From a regional point of view, this does not seem to be the case: the top-right chart in Figure 3 shows that regions with high BTL density, such as London, are regions with lower average rental yields. This might be because investors tend to concentrate in regions with good fundamentals, which are associated with lower rental yields (Bracke, 2015). In terms of property types, BTL investors prefer dwellings where rental yields are high, such as flats and terraced houses.

Combining this description with information on the evolution of regional house prices over the sample period (regional indices are displayed in Figure 4), one can define three groups of regions: the first group is made of London alone, where the size of the private rented stock and the density of BTL activity are much larger than elsewhere, and house prices have grown strongly in the past couple of years. The second group is made of the Southern regions (South East and South West) and the East of England, where the private rented sector constitutes around 15% of the housing stock and nominal house prices have reached their 2007 peak or are close to doing so. The third group is made of the remaining regions and Wales, where the private rented sector is smaller and house prices are still well below their 2007 peak. This classification is used in Section 4 to distinguish between the different patterns in BTL discounts.

Do BTL investors resell quickly? To confirm that BTL investors are long-term investors, I measure the non-parametric Kaplan-Meier 'survival rate' of properties sold to different types of buyers, where 'surviving' is defined as not being sold.[20] Figure 5 shows the inverse Kaplan-Meier functions (i.e. the cumulative selling rate) for the properties in the dataset. The sample is such that we can only track properties for a maximum of 6 years. This limited time frame is

[20]More precisely, I define as 'survivor' property at time $t+1$ a property that was put on the market at time t and was not sold at time $t+1$. The cumulative survival function is estimated as

$$\hat{S}(t_j) = \Pi_{s=1}^{j}\left(1 - \frac{d_s}{n_s}\right)$$

where d_s is the number of properties that sold after s days, and n_s is the number of properties that were at risk at the beginning of the s-th day (because they did not sell before s and their spell was not censored before s).

Figure 4: Regional house price indices, 2007-2015

The indices are nominal and taken from the Land Registry website (`http://landregistry.data.gov.uk/app/hpi/`) and normalised so that the 2007 peak corresponds to 100. The first row includes London alone with its unique price increase. The second group of regions, corresponding to the second row in the Figure, includes regions whose nominal prices are either above or very close to the 2007 peak. The last two rows contain the remaining English regions and Wales.

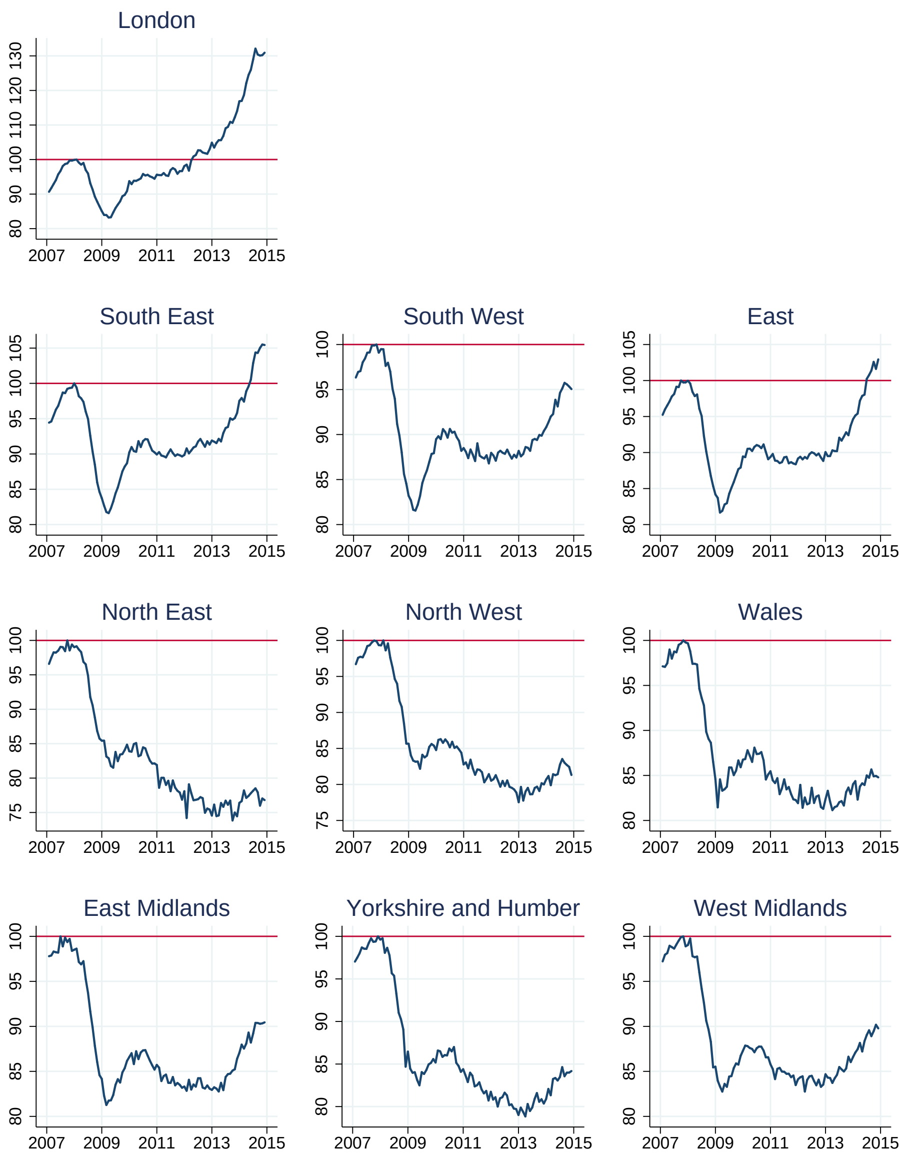
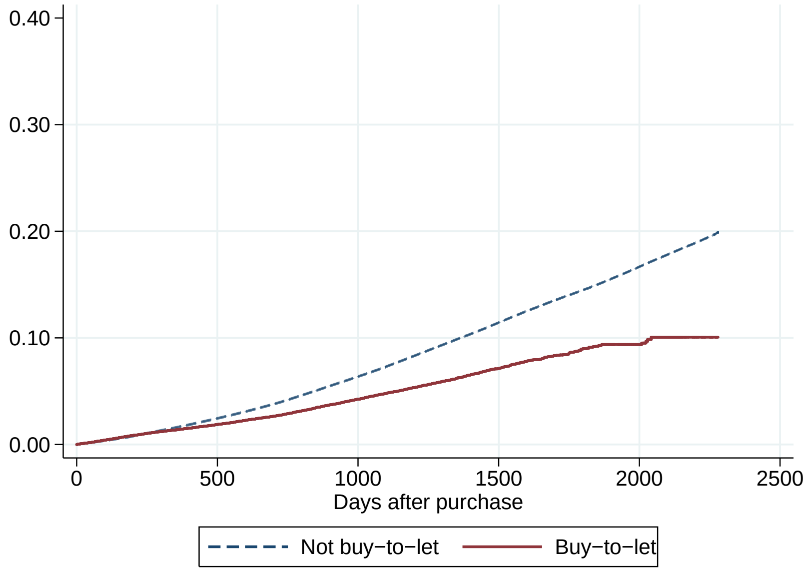


Figure 5: Cumulative fraction of re-sold properties

The figure shows the cumulative selling function of BTL and non-BTL properties in the dataset, computed as 1 minus the Kaplan-Meier survival function, where 'surviving' is defined as not being sold.



sufficient to notice that the selling rate for BTL properties is lower than for other properties.

4 Empirical analysis

4.1 The BTL discount

The baseline regression has the logarithm of the sale price as dependent variable (p_{it}) and the available characteristics of the property (X_i), the interaction between month of the sale and the postcode sector (α_{jt}), and the listing price (q_{it}) as explanatory variables, plus a BTL indicator:

$$p_{it} = \alpha_{jt} + X_i\beta + \phi q_{it} + \rho BTL_{it} + \varepsilon_{it}. \quad (1)$$

The goal of the analysis is to compare BTL purchases with other purchases, making sure that properties in the two groups are as similar as possible. The previous Section has shown that BTL investors are more likely to buy in specific areas or during specific periods. The term α_{jt} controls for these different propensities through time-location fixed effects.[21] Properties in the

[21] There are on average 15 units per individual postcode and individual postcodes in the UK have a structure like AB1 2CD. A postcode sector corresponds to all properties which share the "AB1 2" part, i.e. the same postcode district ("AB1") and a further number. There are approximately 3,000 postcode districts and 10,000 postcode sectors in the UK (`http://en.wikipedia.org/wiki/Postcodes_in_the_United_Kingdom`). The empirical strategy is therefore based on high-dimensional group effects (Gormley and Matsa, 2014).

same area might differ widely in terms of sizes and type of dwellings. The vector X contains the property attributes included in the Land Registry: type of property (whether flat, terraced, semi-detached, or detached house), construction period (whether the property is a new build), and tenure form (freehold or leasehold). It is likely that observable property characteristics do not capture all the property heterogeneity that affects prices. However, most property features that influence the price are known by the seller, who prices the property accordingly. Therefore, by including the advertised price for the property, I ensure that these factors are taken into account.

The coefficient ρ represents the percentage effect of BTL on prices once we control for observable characteristics, advertised prices, month of sale and postcode. This procedure yields an average effect of BTL in England and Wales over the entire period and for all property types. Standard errors are computed with two-way clustering on postcode and time period as described in Petersen (2009).

Table 2 shows the output of the estimation, omitting the coefficients on property characteristics for space reasons.[22] The estimation in the first column uses the entire LR sample (4m+ sales) and reveals a 10% discount associated with BTL sales. This high discount leaves open the possibility that the variables included in the regression are not enough to control for all the relevant property characteristics associated with BTL purchases. Therefore, I restrict the attention to those properties that at some point were listed on Zoopla either as a rental property or as a property to be sold. Since Zoopla almost always includes the number of bedrooms of the property, doing so allows me to have an important control for size. The results are displayed in the second column of Table 2: the discount associated with BTL purchases declines to 7%. Adding bedrooms increases the adjusted R-squared by approximately 10 percentage points.

Despite these controls, it is still possible for the BTL coefficient to be biased towards smaller properties (conditional on number of bedrooms) or properties with lower quality. The third column of Table 2 shows the results when the regression includes the log listing price without any other control. The BTL discount is reduced, and is close to half of a percentage point (statistically significant). Even if the listing price contains all relevant information on the

[22] Results are available on request. All the coefficients have the predicted signs. A new build costs on average 4% more than another property with the same characteristics. A property on a leasehold (as opposed to full freehold ownership) costs 28% less—see Bracke, Pinchbeck, and Wyatt (2014), and Giglio, Maggiori, and Stroebel (2015), for an analysis of the leasehold tenure system in England and its impact on house prices. As expected, detached houses are the most expensive property type, followed by semi-detached, terraced, and flats.

Table 2: Hedonic regression for the effect of buy-to-let on prices

The table shows results from the regression $p_{it} = \alpha_{jt} + X_i\beta + \phi q_{it} + \rho BTL_{it} + \varepsilon_{it}$, where p_{it} is the log sale price of property i at time t, α_{jt} is a postcode sector-month fixed effect, X_{it} are property characteristics (Land Registry controls: dwelling type, leasehold or freehold sale, and whether the property is newly built; WhenFresh/Zoopla information: number of bedrooms), q_{it} is the log advertised sale price, BTL_{it} is a dummy that indicates whether the sale has been identified as a BTL purchase, and ε_{it} is the error. The regression is run with double-clustered (according to postcode sector and month) standard errors, shown in parentheses. Column 5 restricts the definition of BTL to sales where the distance from the rental listing does not exceed 3 months (instead of 6 months as in the rest of the paper).

	(1) Log Price	(2) Log Price	(3) Log Price	(4) Log Price	(5) Log Price
BTL purchase	-0.103	-0.070	-0.004	-0.010	
	(0.002)	(0.001)	(0.001)	(0.001)	
Log listing price			1.009	0.980	0.980
			(0.000)	(0.001)	(0.001)
BTL (3 month)					-0.009
					(0.001)
Land Reg Controls	✓	✓		✓	✓
Bedrooms		✓		✓	✓
Pcode sector-Month	✓	✓		✓	✓
Observations	3,956,591	2,494,075	1,294,312	1,276,065	1,276,065
R2	0.69	0.80	0.99	0.99	0.99

property, the specific relation between listing and actual price changes according to area, type of dwelling, and time period (Han and Strange, 2014). Therefore, the fourth column of Table 2 shows a specification where the listing price enters the regression together with all the controls used previously: dwelling type, number of bedrooms, and postcode sector-month dummies. In this case, the discount reaches 1.0%. In a final specification, I restrict the sample of BTL properties to those with a rental Time-To-Market (TTM) up to 3 (rather than 6) months. A property that takes a long time to be advertised for rent could signal the need for substantial renovation, i.e. low quality. Column 5 of Table 2 shows that the coefficient on the restricted sample is 0.9%, which may indicate some further correction of the discount due to a better control for the quality of the property. This reduction in the discount, however, could also be due to measurement error (more BTL properties are now treated as non-BTL) and to investors anticipating some of the renovation costs and managing to obtain a higher discount than the one owner-occupiers are able to get for the same property.

The last two columns of Table 2 form the benchmark result of the paper: everything else equal, investors spend at least 0.9-1.0% less than other buyers. This number is a lower bound estimate because I only identify a fraction of actual BTL purchases—see Appendix A.3 for a discussion of the bias. The Appendix also contains two robustness checks: a regression where the dependent variable is not the property sale price but the discount between asking and achieved price[23] and an analysis limited to properties sold in the same postcode sector and month, sharing the same number of bedrooms and the same asking price.

4.2 Heterogeneity in BTL discounts

The regression results presented above reveal the average discount associated to all BTL transactions. This average could mask a quite diverse distribution; therefore, it may be useful to separate out different discounts according to region and year by running the regression:

$$p_{it} = \alpha_{jt} + X_i\beta + \phi q_{it} + \sum_s \rho_s \left(BTL_{it} \times RY_{is}\right) + \varepsilon_{it}$$

where the BTL_{it} indicator is interacted with categorical variable RY_{is}, the interaction of English regions and Wales with year dummies. Results are displayed in Figure 6.

In London, BTL investors enjoy an average discount of less than 1%, whereas in the South and East of England discounts are higher, especially in 2010-2011. In the rest of England and in Wales, estimated discounts are consistently between 1% and 2%, with a peak of almost 2% in 2010. Comparing these charts with Figure 3 reveals an inverse relation between the size of the private rented stock (or the density of BTL activity) and the discount enjoyed by BTL investors. Since regions with large private rented sectors are also the regions that experienced higher price appreciation over the sample period (see Figure 4), there is an inverse relation between BTL discounts and strength of the housing market. This relation is explored in more detail in the next subsection, where the strength of the market is measured as the time needed to sell a house.

In terms of the discounts associated with different years in the sample, the 2009-2014 period has been characterised by a recovery of the UK housing market, and correspondingly lower BTL discounts in all regions and in Wales, as shown in Figure 6.[24] Interestingly, in London the lower bound for BTL discounts is not statistically different from zero in the first part of 2014.

[23] In practice this is equivalent to assuming a unit elasticity between advertised and actual price (ϕ=1).

[24] The point estimates for 2009 sit a little outside this pattern, with lower than expected discounts and larger confidence bands. Since the Zoopla portal started its activity in November 2008, properties sold in 2009 have low TOM on average, because only properties advertised for sale after November 2008 can enter the sample. Low TOMs are associated with low discounts.

Figure 6: Buy-to-let price discounts by region-year

The figure derives from the regression $p_{it} = \alpha_{jt} + X_i\beta + \phi q_{it} + \sum_s \rho_s \left(BTL_{it} \cdot x_{is}\right) + \varepsilon_{it}$, where p_{it} is the log sale price of property i at time t, α_{jt} is a postcode sector-month fixed effect, X_{it} are property characteristics (dwelling type, number of bedrooms, leasehold or freehold sale, and whether the property is newly built), q_{it} is the log advertised sale price, and ε_{it} is the error. The term $\sum_s \rho_s \left(BTL_{it} \cdot x_{is}\right)$ represents the interactions between the BTL dummy and year dummies. The lines in the figure show these coefficients and their corresponding 95% confidence intervals, computed assuming standard errors which are double-clustered according to postcode sector and month. The point estimates for 2009 have lower than expected discounts and larger confidence bands. Since the Zoopla portal started its activity in November 2008, properties sold in 2009 have low time on market (TOM) on average, because only properties advertised for sale after November 2008 can enter the sample. Low TOMs are associated with low discounts.

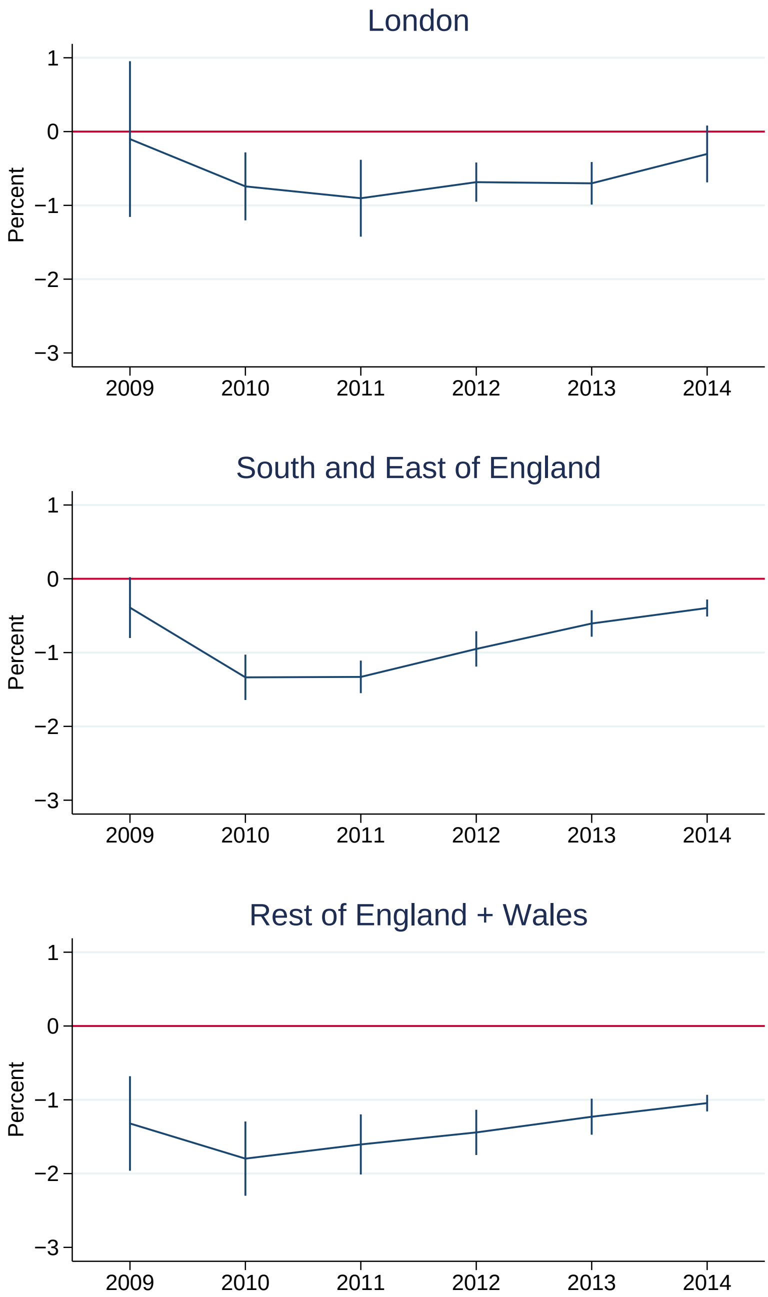
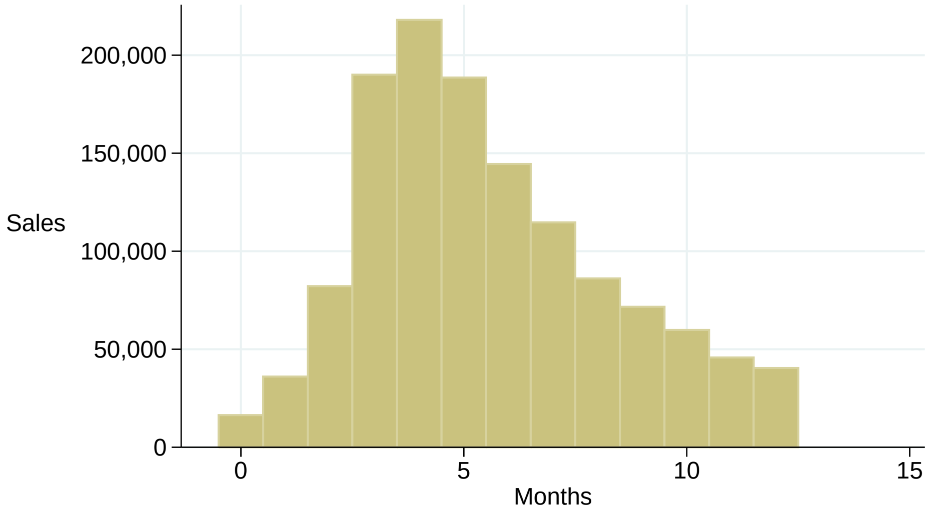


Figure 7: Months between listing and Land Registry sale
By merging the Land Registry with WhenFresh/Zoopla sale listings, it is possible to compute the distance between the month in which the listing went online and the month when the sale was completed (as recorded by the Land Registry). The maximum distance is limited to 12 months to avoid instances where the listing and the actual transaction do not correspond to the same sale event (for example, when the property was first listed and then withdrawn, then listed again). The histogram shows these distances in months, and the vertical axis reports the number of sales that fall in a given category.



4.3 Market liquidity and discounts

The housing market can be characterised as a search market (Wheaton, 1990); not accepting a potential buyer's offer may lead to a long wait for other offers. Selling to an investor at a discount may be a good idea if it entails a substantial TOM reduction.

To check this hypothesis, I analyse the TOM of properties in the dataset by measuring the distance between the first appearance of a sale listing and the actual transaction. Figure 7 shows the distribution of TOMs, expressed in months. If there are several listings referring to the same sale, TOM is computed using the first of such listings (however, the last listing provides the asking price used in the regression).[25]

The first column of Table 3 shows the main coefficients of a regression with the logarithm of TOM as the dependent variable. Consistently with anecdotal evidence, BTL transactions are associated with a 3% lower TOM. In the data, the average TOM is 5.5 months (see Figure 7); hence, this discount corresponds to a five-day reduction.[26] The remaining columns show the

[25] The matching procedure delivers a few long TOMs (above 12 months); in those cases, it is not clear whether the observations are genuine or the listing refers to a previous sale attempt. Therefore, I exclude listings with a TOM longer than 12 months—the same cutoff is used by Anenberg and Kung (2014).

[26] Running the regression on TOM levels (rather than logs) results in the same five day reduction. The 3% coefficient in the log regression underestimates the significance of this reduction, because TOM includes the time to *register* the sale, which is likely to be homogeneous across transactions. The reduction would be higher if

Table 3: Time-On-Market (TOM) regressions

The first column of the table reports results from regressions analogous to the one in Table 2, but where the logarithm of the sale Time-On-Market (TOM) is the dependent variable: $\log TOM_{it} = \alpha_{jt} + X_i\beta + \phi q_{it} + \rho BTL_{it} + \varepsilon_{it}$. Columns 2 and 3 show the usual regression with the logarithm of the sale price as the dependent variables, but including log TOM as an explanatory variable (Column 2), and also its interaction with BTL (Column 3). The last column also includes a measure of the average TOM in the regional and year when the sale took place. Other regression controls and standard errors are as described in the caption of Table 2.

	(1)	(2)	(3)	(4)
	Log TOM	Log Price	Log Price	Log Price
BTL purchase	-0.029	-0.011	-0.008	0.008
	(0.004)	(0.001)	(0.001)	(0.013)
Log TOM		-0.034	-0.034	-0.034
		(0.001)	(0.001)	(0.001)
BTL * Log TOM			-0.002	-0.002
			(0.001)	(0.001)
BTL * Log Regional TOM				-0.009
				(0.007)
Log listing price	✓	✓	✓	✓
Land Reg Controls	✓	✓	✓	✓
Bedrooms	✓	✓	✓	✓
Pcode sector-Month	✓	✓	✓	✓
Observations	1,260,027	1,260,027	1,260,027	1,260,027
Adj. R^2	0.15	0.99	0.99	0.99

effect of TOM on prices. The coefficient on the logarithm of TOM in Column 2 is -3.4%: in general, properties that stay on the market for longer sell for a higher discount. Since properties bought by BTL investors stay on the market for a shorter period of time, including TOM in the regression does not change the BTL discount by much. A better way to assess the relation between BTL discount and TOM is to insert the interaction between these two variables in the regression, as in Column 3. The negative coefficient signals that BTL are able to extract a higher discount from properties that have stayed longer on the market, which is consistent with the interpretation of the BTL discount as compensation for market clearing. The interaction is borderline significant (a coefficient of 0.2% with a standard error of 0.1%) but the baseline effect of the BTL indicator is reduced to 0.7%. The last column includes in the regression the interaction of the BTL indicator with the average TOM by region and year: it may be easier for BTL investors to extract discounts where properties take longer to sell. This seems to be the case: the insertion of this new term (which is itself not strongly significant) makes the baseline BTL discount statistically insignificant.

Figure 8 replicates Figure 6 but with TOM as the dependent variable. The data is noisier

compared to the time between web listing and sale *agreement*.

and standard errors are larger, but one can notice the same pattern of declining discounts over time. London discounts are again smaller than those in other regions, especially in 2013 and 2014.

4.4 Mortgage vs. non-mortgage BTL transactions

As shown in Table 1, only half of BTL transactions are financed with a mortgage. The potential differences between mortgage and non-mortgage transactions are important because policy makers may pay special attention to the mortgage-financed part of the market. Access to easy credit has been linked to investor behaviour that is risky for financial stability (Haughwout, Lee, Tracy, and der Klaauw, 2014).

The interpretation of results would change if BTL discounts were driven exclusively by non-mortgage investors. Table 4 shows that this is not the case. Column 1 illustrates that non-mortgage purchases are associated with 5-6% reduction in TOM—this is expected since non-mortgage buyers do not need to go through a bank's approval to purchase a property. However, when including this variable, BTL purchases still happen in at least 2% less time, implying that all BTL investors (not only those not funded by mortgages) are quicker at purchasing properties. Column 2, by including the interaction between BTL and non-mortgage purchase, demonstrates that non-mortgage BTL investors are quicker than the average non-mortgage buyer. Column 3 shows that being financed by a mortgage has virtually no effect on the price paid; the insertion of the interaction between BTL and non-mortgage in the last column illustrates that, if anything, BTL non-mortgage buyers are likely to pay slightly more than other BTL purchasers (the coefficient is borderline significant). In fact, while the greater speed of transaction could give a discount to non-mortgage transactions, there are arguments which would suggest a positive effect on prices. For instance, since these purchases are not monitored by a bank, exaggerated prices could be paid. Also, cash buyers (often recipients of inheritances or pension pots) could be less sophisticated than professional small-scale investors (who are likely to use mortgages). Finally, non-mortgage purchases include transactions by large-scale investors who have access to other sources of funds. As shown by Mills, Molloy, and Zarutskie (2015), large-scale investors tend to pay more than smaller ones.

Appendix A.4 explores the possibility that BTL discounts are driven by the absence of a

Figure 8: Buy-to-let time-on-market (TOM) discounts by region-year

The figure derives from the regression $y_{it} = \alpha_{jt} + X_i\beta + \phi q_{it} + \sum_s \rho_s (BTL_{it} \cdot x_{is}) + \varepsilon_{it}$, where y_{it} is the log TOM of property i at time t, α_{jt} is a postcode sector-month fixed effect, X_{it} are property characteristics (dwelling type, number of bedrooms, leasehold or freehold sale, and whether the property is newly built), q_{it} is the log advertised sale price, and ε_{it} is the error. The term $\sum_s \rho_s (BTL_{it} \cdot x_{is})$ represents the interactions between the BTL dummy and year dummies. The lines in the figure show these coefficients and their corresponding 95% confidence intervals, computed assuming standard errors which are double-clustered according to postcode sector and month.

Table 4: Mortgage vs. non-mortgage buy-to-let purchases

The first column of the table reports results from regressions analogous to the one reported in Column 1 of Table 3, but including an indicator variable for non-mortgage purchases. The second column adds the interaction between non-mortgage purchases and BTL. Column 3 and 4 replicate the same analysis but with the logarithm of sale price as the dependent variable. Other regression controls and standard errors are as described in the caption of Table 2.

	(1) Log TOM	(2) Log TOM	(3) Log Price	(4) Log Price
BTL purchase	-0.019	-0.010	-0.010	-0.011
	(0.004)	(0.005)	(0.001)	(0.001)
Non-mortgage purchase	-0.057	-0.056	-0.000	-0.001
	(0.002)	(0.002)	(0.000)	(0.000)
BTL * Non-mortgage		-0.018		0.002
		(0.007)		(0.001)
Log listing price	✓	✓	✓	✓
Land Reg Controls	✓	✓	✓	✓
Bedrooms	✓	✓	✓	✓
Pcode sector-Month	✓	✓	✓	✓
Observations	1,260,027	1,260,027	1,276,065	1,276,065
Adj. R^2	0.16	0.16	0.99	0.99

chain on the part of investors, i.e. BTL investors do not need to sell a property before buying a new one, which reduces uncertainty for the seller. The analysis in the Appendix shows that first-time buyers, who are also not tied by a chain, do not enjoy price discounts, which casts doubts on this explanation.

5 Conclusion

This paper presents a new way to identify buy-to-rent transactions in housing datasets where no information on buyers and sellers is available. By merging the England and Wales Land Registry with WhenFresh/Zoopla rental listings, I can spot BTL transactions where a rental listing on a sold property appears on the web in the 6 months after the sale.

In the descriptive part of the analysis, I show that the identified BTL transactions replicate the time-series pattern of aggregate BTL data, although the coverage reaches only one quarter of the total BTL market. I also show that BTL investors are less likely than other buyers to sell their property in the six years after the purchase, which confirms that BTL investments are long-term, different from short-term buy-to-sell purchases.

Comparing properties sold to BTL investors to properties sold to other buyers, this paper demonstrates that investors enjoy statistically significant discounts, whose lower bound is around 1.0%. Given high house prices in England and Wales, this is a sizeable effect, corresponding to £2,100 ($3,250) on average.[27] When analysing BTL discounts for different regions and years, I show that discounts are larger when the housing market is less liquid. BTL discounts are statistically undistinguishable from zero in London at the end of the sample, when the housing market registered increases in both prices and number of transactions.

The data show that BTL investors can accelerate property sales, and BTL discounts are the implicit compensation for this contribution. However, investors' ability to 'grease the wheels' of the housing market becomes limited when the market is already performing well. This is precisely when financial stability concerns become most important.

[27] As a comparison, Anenberg and Kung (2014) find that homes closest to a foreclosed property sell for 1.6% less when the foreclosed property is listed.

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A Appendix

A.1 Regressions with discounts as dependent variables

Starting from the regression formula in (1), one can assume $\phi = 1$ and move q_{it} on the other side to get

$$d_{it} = \alpha_{jt} + X_i\beta + \rho BTL_{it} + \varepsilon_{it}$$

where $d_{it} = p_{it} - q_{it}$ is the log difference between the actual price and the advertised price. Table A1 shows the results of this exercise. When no controls are included—i.e. we simply compare the average discount in the market with the average discount of BTL purchases (column 1)—there is no statistically significant difference between the two. However, BTL investors concentrate on areas with a strong housing market (as shown in Section 3 of this paper), which are likely to have lower discounts on average. When the regression contains controls (column 2), the BTL discount becomes statistically significant at 0.7%. These results are consistent with the discounts shown in the last two columns of Table 2. Regressions by year, type of property, and region have also been run and have confirmed the results of the main analysis. Results are available on request.

Table A1: Hedonic regression for the effect of buy-to-let on the asking price discount

The table reports results from the regression $d_{it} = \alpha_{jt} + X_i\beta + \rho BTL_{it} + \varepsilon_{it}$, where $d_{it} = p_{it} - q_{it}$ is the difference, in logarithms, between the actual price and the advertised price of a sold property. The two columns in the table replicate columns 3 and 4 of Table 2, but assuming a coefficient of 1 on the advertised sale price. Other regression controls and standard errors are as described in the caption of Table 2.

	(1) Log Discount	(2) Log Discount
BTL purchase	-0.002	-0.007
	(0.001)	(0.001)
Observations	1,583,225	1,560,640
Adj. R^2	0.00	0.15

A.2 Analysis of matched restricted sample

Given the reliance of regression (1) on postcode sector-month fixed effects, the identification of a BTL discount (coefficient ρ) depends on the presence of postcode sectors where, in the same months, both a BTL and a non-BTL purchases took place. A natural robustness check is therefore to restrict the sample only to those sales that share the same:

- postcode sector,
- sale month,
- property type,
- number of bedrooms, and
- advertised price.

Moreover, the sets of observations that share the above features must also contain at least one BTL and one non-BTL sale. This reduced dataset contains 3772 observations and shows a 1.1% discount associated with BTL properties, consistent with the regression results.

A.3 Econometric consequences of buy-to-let misclassification

Suppose that the true BTL status of a property is given by BTL^*, whereas the econometrician only observes BTL, the status derived from matching the England and Wales Land Registry with WhenFresh/Zoopla listings.

Taking the expectations of equation (1) conditional on the measured (but noisy) status BTL yields:

$$\mathbb{E}\left(p_{it}|BTL=1\right) = \alpha_{jt} + X_i\beta + \phi q_{it} + ^* \Pr\left(BTL^*_{it}=1|BTL=1\right) + \varepsilon_{it},$$

$$\mathbb{E}\left(p_{it}|BTL=0\right) = \alpha_{jt} + X_i\beta + \phi q_{it} + ^* \Pr\left(BTL^*_{it}=1|BTL=0\right) + \varepsilon_{it}.$$

The estimated coefficient ρ is equal to

$$\rho = \mathbb{E}(p_{it}|BTL=1) - \mathbb{E}(p_{it}|BTL=0) =$$

$$= \rho^* \Pr\left(BTL^*_{it}=1|BTL=1\right) - \Pr\left((BTL_i t^*=1|BTL=0\right),$$

which allows one to evaluate the attenuation bias in ρ. A reasonable assumption is that $\Pr\left(BTL^*_{it}=1BTL=1\right) \sim 1$, i.e. sales that are identified as BTL in the sample are true BTL. One can use aggregate data to estimate $\Pr\left(BTL^*_{it}=1BTL=0\right)$, the likelihood that a true BTL sale is identified as non-BTL transaction. According to the Council of Mortgage Lenders, BTL mortgages are 13% of all mortgages. In this paper, BTL transactions are 2.5% of all transactions. Assuming that the percentage of BTL transactions among cash transactions is the same as the percentage of mortgage BTL transactions among mortgage transactions, one can say that approximately 10% of all transactions are misclassified as non-BTL, i.e. $\Pr\left(BTL^*_{it}=1BTL=0\right) \sim 10\%$. The true $\rho^* = \rho/0.9=$ 1.11% if we take the ρ=1.0% estimate as starting point.

A.4 Buy-to-let and first-time buyers

To identify first-time buyers (FTB) I use the Product Sales Database (PSD), a private dataset collected by the Financial Conduct Authority (FCA). The PSD has information on UK individual mortgage transactions since 2005. Only regulated (i.e., homeowner) mortgage contracts are included—other mortgages, such as BTL loans, are not. The PSD aims at achieving universal coverage of residential owner-occupier and only collects information on new sales (mortgages or re-mortgages), excluding alterations or top-ups of the loan. Available variables include mortgage characteristics such as loan size, length in years, interest rate, and whether the borrower is a FTB. The PSD data is added on top of the matched dataset through a Land Registry-PSD probabilistic match based on sale date, price paid, and complete postcode of the property.

Similarly to BTL investors, FTB do not need to sell a property before they buy a new one. Therefore, if BTL discounts are due to the absence of these chains, FTB should enjoy them too. This analysis has the added advantage of comparing the behaviour of FTB and BTL purchasers directly as mentioned in the introduction, the media often emphasise the role of BTL in 'driving out' FTB from the market.

Columns 1 and 2 of Table A2 reproduce a couple of regressions of Table 3 adding an indicator for FTB. The regressions show that FTBs do not enjoy a price discount, despite not being part of a chain, and properties bought by FTBs spend between 1 and 2% more time on the market. In order to compare BTL investors and FTBs even more directly, Columns 3 and 4 run the same regressions as Column 1 and 2 but with a sample composed only by BTL and FTB purchases (dropping the FTB dummy). Column 3 shows that BTL buyers achieve prices that are more than 1% lower than FTBs. Column 4 shows that, after controlling for cash purchases, there is no statistically significant difference between the TOM of properties sold to investors and the TOM of properties sold to FTBs.

Table A2: Hedonic and Time-On-Market regressions, buy-to-let vs. first-time buyers

This table shows regression results that include information on whether a given sale was purchased by a First Time Buyer (FTB). The first column replicates the last column of Table 2 but includes the non-mortgage dummy and the FTB dummy. The second column reports the same regression but with the logarithm of TOM as the dependent variable. The third and fourth columns also present results from a regression on log sale price and a regression on log TOM; in this case, however, the sample is limited to BTL and FTB purchases to allow a more direct comparison between the two. Other regression controls and standard errors are as described in the caption of Table 2.

	(1) Log TOM	(2) Log TOM	(3) Log Price	(4) Log Price
BTL purchase	-0.011	0.008	-0.013	-0.004
	(0.001)	(0.005)	(0.001)	(0.010)
btl_cash	0.001	-0.070	0.001	-0.075
	(0.001)	(0.007)	(0.001)	(0.012)
Log listing price	0.980	0.172	0.973	0.163
	(0.001)	(0.011)	(0.002)	(0.024)
First time buyers	0.001	0.019		
	(0.000)	(0.003)		
Log listing price	✓	✓	✓	✓
Land Reg Controls	✓	✓	✓	✓
Bedrooms	✓	✓	✓	✓
Pcode sector-Month	✓	✓	✓	✓
Observations	1,276,065	1,260,027	253,131	252,118
R2	0.99	0.15	0.99	0.17