Accidental Landlords: Behavioral Lock-In and Rental Market Spillovers

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Abstract

Loss-averse homeowners facing nominal losses are reluctant to sell. A failed sale, however, need not keep them in place: they can list the property for rent and move, becoming "accidental landlords." Using property-level data linking sale listings, rental listings, and transaction records in the U.K., I show that paper losses relative to the original purchase price strongly predict failed-sale-to-rent conversions. Rental conversion is sensitive to losses but not to gains, with the change in slope at the original purchase price. The channel operates through the failure of the attempted sale: paper losses reduce the probability of sale, while a roughly constant fraction of failed sales spills over into the rental market. Among properties that convert, owners facing paper losses set higher asking rents. At the aggregate level, regions with higher loss shares experience lower sales volume and more rental conversions. A one-standard-deviation increase in the loss share generates additional accidental-landlord entries equal to about 7% of total annual buy-to-let purchases. Reference dependence in the ownership market therefore affects how the housing stock is allocated between the ownership and rental markets.

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1 Introduction

When house prices fall, some homeowners come to hold properties worth less than the prices they originally paid. A substantial literature shows that these historical prices serve as reference points for sellers. Owners facing potential nominal losses set higher listing prices, remain on the market for longer, and are less likely to sell than otherwise similar owners facing gains (Genesove and Mayer, 2001; Anenberg, 2011; Bracke and Tenreyro, 2021; Andersen et al., 2022). At the aggregate level, this reluctance to realize losses lowers transaction volume and slows adjustment after house-price declines (Badarinza et al., 2025). Existing work on reference dependence studies whether owners list, how they set listing prices, and whether they sell. It generally does not follow the property after an unsuccessful sale attempt. This leaves open what happens to the property afterward.

In practice, homeowners have a third option beyond selling or staying: they can retain the property, list it for rent, and move elsewhere. Selling transfers ownership and immediately realizes any nominal loss relative to the original purchase price. A rental listing does neither: the homeowner retains the property, postpones the sale, and can wait for prices to recover. This asymmetry creates a rental-market spillover from behavioral lock-in in the ownership market. A loss-exposed owner may set a high sale listing price; if the sale is unsuccessful, the same property may subsequently be listed for rent. Homeowners who would not sell instead rent out, becoming "accidental landlords." The phenomenon is not marginal. In England, 37% of private landlords originally bought their rental property to live in themselves, rather than to let it (English Private Landlord Survey, 2024).[1]

Behavioral frictions in the sales market thus generate a flow of properties into the rental market. An unsuccessful sale lowers turnover in the ownership market, while a subsequent rental listing increases rental availability. The decisions of existing homeowners therefore affect the allocation of properties across the two markets. This reallocation has welfare implications: the option to rent may allow an owner to move without immediately realizing a nominal loss, but it also changes the availability of properties to buyers and renters. Quantifying these effects across the two markets is a natural next step for this research.

This paper studies the accidental-landlord channel empirically, using linked property-level records on sale listings, rental listings, and completed transactions in the U.K. housing market. For each sale listing, I use a hedonic model to estimate the property's

[1]The survey does not identify why these owners became landlords.

fair market value and compare it with the owner's original purchase price. This comparison measures the seller's potential gain. A seller whose potential gain is negative faces a nominal "paper" loss. I then follow the property to determine whether the sale attempt succeeds and, if not, whether it is subsequently listed for rent.

Paper losses strongly predict failed-sale-to-rent conversions, and the relationship is asymmetric. In the gain domain, the conversion probability is nearly flat in the potential gain; in the loss domain, it rises steeply as losses deepen. The change in slope occurs at zero potential gain, the same kink that characterizes listing prices and sale outcomes in the ownership market. A seller facing a 20% paper loss is about 18% more likely to convert to rental than a seller at break-even. The asymmetry around the original purchase price is consistent with reference dependence and a reluctance to realize nominal losses.

The channel operates through the failure of the attempted sale. I separate the conversion into two margins: whether the sale attempt fails and, conditional on failure, whether the property is subsequently listed for rent. As potential losses deepen, the probability of an unsuccessful sale rises sharply. By contrast, among unsuccessful sale listings, the probability of a subsequent rental listing is nearly flat across the loss and gain domains. The relationship therefore does not arise because loss-exposed owners have a greater propensity to rent after a failed sale. Instead, deeper losses predict more unsuccessful sales, and a roughly constant share of those properties is later listed for rent.

A leading identification concern is unobserved property quality. If an original buyer paid a premium for a feature omitted from the hedonic model that later buyers value less, the property may both appear to face a paper loss and be difficult to sell. I proxy for such omitted quality using the difference between the price paid and the model-implied value at the purchase date. In the recent-buyer subsample for which this measure is available, the loss-domain point estimate is similar with and without the control. This check reduces the concern about unobserved quality. A second concern is that paper losses are correlated with negative home equity, which I cannot rule out directly because mortgage balances are not observed. Institutional features of the U.K. mortgage market, however, work against a simple home-equity explanation. For mortgaged owners, letting the property generally requires either temporary lender consent or a remortgage onto a buy-to-let contract, and the latter typically requires home equity of at least 25%. Financially constrained owners therefore face higher, not lower, barriers to rental conversion.

Nominal anchors remain relevant after the property enters the rental market. Among failed-sale properties that are subsequently listed for rent, owners facing paper losses set

higher asking rents relative to fair market value, consistent with reference-dependent rental pricing.[2] This anchoring is weaker for rental asking prices than for sale asking prices, so failed-sale-to-rent conversions transmit only part of the sale-side pricing distortion to the rental market.

The property-level mechanism is large enough to appear in regional housing market flows. I construct a regional loss share, defined as the fraction of the property stock whose fair market value lies below the owner's original purchase price. On the sale side, a higher loss share predicts lower transaction volume, consistent with Badarinza et al. (2025). On the rental side, regions with higher loss shares subsequently experience more failed-sale-to-rent conversions. A one-standard-deviation cross-regional increase in the loss share corresponds to roughly 6,800 additional accidental-landlord entries per year, or about 7% of annual buy-to-let purchase volume in England and Wales. Nominal anchoring therefore affects not only whether properties transact, but also how the existing housing stock is allocated between the ownership and rental markets.

These findings contribute to the literature on reference dependence and loss aversion in housing markets (Genesove and Mayer, 2001; Anenberg, 2011; Bracke and Tenreyro, 2021; Andersen et al., 2022; Badarinza et al., 2025), which studies the listing, pricing, and sale decisions of homeowners. I follow the property beyond the unsuccessful sale attempt, and show that the same nominal anchors that block transactions in the ownership market generate entry into the rental market.

The paper is also related to work on the interaction between the ownership and rental markets, where the frictions studied are financial. Han, Ngai, and Sheedy (2025) analyze transaction taxes in a search model of both markets, Greenwald and Guren (2025) estimate the degree of segmentation between them, and a growing body of work shows that mortgage rate lock-in reduces mobility and raises local rents in the United States (Fonseca and Liu, 2024; De la Roca, Giacoletti, and Liu, 2025). Relative to this work, I document a supply-side conversion channel driven by behavioral frictions, in a market where mortgage rate lock-in is largely absent. Finally, the asking-rent evidence complements Giacoletti and Parsons (2022), who document that, on the intensive margin, landlords' purchase prices carry into the rents they charge; I show that purchase prices also matter for the extensive margin of who becomes a landlord in the first place.

The remainder of the paper is organized as follows. Section 2 describes the data and the measurement of potential nominal gains and losses. Section 3 presents the

[2]Because the data record asking rather than agreed rents, this evidence reflects the pricing behavior of accidental landlords, not realized rental outcomes.

property-level results and supporting tests. Section 4 presents the regional analysis. Section 5 concludes.

2 Data

I combine three data sets: sale and rental listings from one of the largest U.K. property websites; the register of residential sales maintained by HM Land Registry; and property characteristics from the Energy Performance Certificate Register, for England and Wales. The listings record asking prices and the timing of sale and rental listings between September 2023 and December 2025. The sales register provides each seller's original purchase price and completed sales; the certificate register provides the physical characteristics. The linked records form a property-level panel that follows an initial sale listing for 400 days and records whether a sale or a rental listing occurs first, or neither is observed.

2.1 Property listings

I collect 7.0 million listings posted between September 2023 and December 2025, of which 3.88 million are listings for sale and 3.12 million are listings for rent. For each listing, the data include the asking price or asking rent, the listing date, the number of bedrooms and bathrooms, the property sub-type, and information in the property description, for example whether the property is offered at auction or with a sitting tenant. Listings display only the postcode and street name of the property, while the full address is replaced by a platform-specific address identifier. A direct address merge with the sales register is therefore not possible, but the identifier connects repeated sale and rental listings at the same address. More than half of all listings, however, display an image of the property's EPC chart, which shows the property's energy efficiency scores (Figure 1). I use these scores to match listings to properties, as described in Section 2.3.

2.2 Transactions and property characteristics

HM Land Registry records residential property transactions in England and Wales since 1995. The records contain the transaction price, date of transfer, and property address and postcode. For each linked sale listing, the most recent preceding transaction identifies the current owner's purchase price and purchase date; I use the purchase price as the

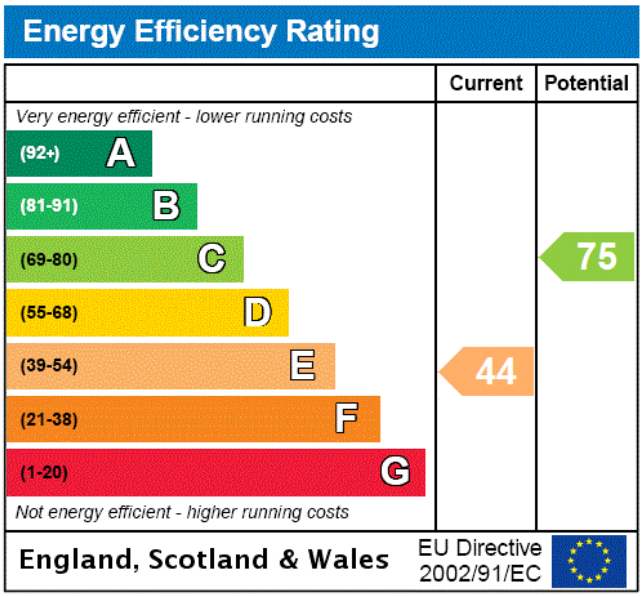


Figure 1: The EPC chart displayed on a typical listing. The chart shows the property's current and potential energy efficiency scores (here 44 and 75). I extract these scores by optical character recognition and match them to the property's certificate in the EPC Register.

seller's reference point. Subsequent transactions determine whether and when the listed property sells. Land Registry transactions matched to EPC records also provide the estimation sample for the hedonic model in Section 2.4.

The Energy Performance Certificate (EPC) Register records physical property characteristics, including floor area, property type, built form, and construction age band. Each certificate also reports the transaction type that triggered the inspection, including private rental, which allows me to identify properties with a prior rental history. The Land Registry and EPC records do not share a common property identifier, so I combine them at the property level using standardized address records and Unique Property Reference Numbers, following Chi et al. (2021).

2.3 Linking listings to properties

The EPC chart displayed on a listing reports the current and potential energy efficiency ratings; some charts also report the current and potential environmental impact ratings. I extract these scores by optical character recognition and match each listing to EPC records in the same postcode. Within a postcode, the combination of scores is close to unique. The median postcode contains 13 candidate properties, and an exact match on

the available scores identifies a unique property for 72.2% of listings with a readable chart. For listings without a readable chart, I carry an established property match across repeated listings sharing the same platform-specific address identifier, provided that the identifier maps to a single property. Together, these steps assign a property identifier to 51% of all listings.

For measuring failed-sale-to-rent conversions, the relevant match rate is conditional on the initial sale listing being linked to a property. A subsequent rental listing for the same property is then captured with probability 87.7%. This conditional rate is high because almost all linked sale listings carry the platform-specific address identifier, allowing a later rental listing with the same identifier to inherit the property match even when it does not display a readable EPC chart. Match rates are lower for flats because several flats in the same building can share a postcode and similar EPC scores. Because flats are more likely to be listed for rent, their lower match rate is likely to bias observed rental-conversion rates downward. Appendix A provides further details on the matching procedure and its performance.

2.4 Fair market values and paper gains

For each listed property, I estimate its fair market value at the listing date in two stages. The first stage follows Badarinza et al. (2025) and predicts the log transaction price using physical property characteristics and location-by-time fixed effects. I estimate the model on 8.4 million Land Registry transactions matched to EPC records:

$$\log P_{it} = \beta' X_i + \zeta_{w(i)} + \xi_{\ell(i),y(t)} + \psi_{r(i),m(t)} + \varepsilon_{it}. \tag{1}$$

Here, P_{it} is the transaction price for property i at time t, and X_i includes floor area (entering linearly, squared, and in logs), bedrooms, property type, built form, construction age band, new-build status, and tenure type. The coefficient vector β captures the contribution of these characteristics; $\zeta_{w(i)}$ are electoral-ward fixed effects; $\xi_{\ell(i),y(t)}$ are local-authority-by-year fixed effects; $\psi_{r(i),m(t)}$ are region-by-month fixed effects; and ε_{it} is the residual. The model explains transaction prices well, with an R^2 of 0.88. The fair market value $\widehat{p}_i$ of a listed property is the model prediction evaluated at the listing month. A second stage adjusts this prediction using listing-level characteristics that the registers do not record, such as the number of bathrooms and the property sub-type. Appendix B describes the adjustment.

The seller's nominal "paper" gain, or potential gain, is the percentage difference between fair market value at the listing date and the seller's original purchase price:

$$\widehat{G}_i = \frac{\widehat{p}_i - p_i^0}{p_i^0}, \tag{2}$$

where p_i^0 is the most recent purchase price observed before the sale listing. A seller with $\widehat{G}_i < 0$ faces a paper loss.

2.5 Analysis sample and outcomes

The unit of observation is the first sale listing for each linked property. I construct the sample by requiring a prior Land Registry purchase and removing properties with evidence of prior rental use, as well as listings unlikely to represent standard residential sales, including auctions, properties marketed with a sitting tenant, shared-ownership and affordable-housing schemes, nonresidential and mixed-use properties, and listings described as renovation projects or development opportunities. I identify prior rental use from an EPC inspection triggered by a private rental at any point before the sale listing; excluding these properties focuses the analysis on first observed conversions into rental rather than returns of known rental properties. Observations with missing characteristics or outside the support of the hedonic model are also excluded. Because the listing data end on December 31, 2025, I retain initial sale listings from September 1, 2023 through November 26, 2024, giving every property a complete 400-day follow-up period. The full sample contains 491,512 first sale listings.

I follow each initial sale listing for 400 days and identify the first subsequent Land Registry transaction and the first subsequent rental listing. A rental conversion occurs if a rental listing appears within this period before the first recorded Land Registry transaction. If the transaction occurs first, the property is classified as sold; if neither event occurs within 400 days, no sale or conversion is observed.

In the full sample, 12.4% of sellers face paper losses and 3.7% of properties convert to rental within 400 days. The main estimation sample retains listings for which fair market value is between 40% below and 50% above the original purchase price, leaving 266,959 observations. The restriction mainly removes long-held properties with large potential gains. Table 1 reports summary statistics for the full sample and for the main estimation sample, overall and separately in the gain and loss domains.

Table 1: Summary statistics

	Full sample	Main estimation sample		
		All	Gain domain ($\widehat{G}_i \geq 0$)	Loss domain ($\widehat{G}_i < 0$)
Sale listings	491,512	266,959	207,287	59,672
Original purchase price (median, £)	197,500	237,500	225,000	290,000
Fair market value at listing (median, £)	299,800	269,500	273,400	256,200
Potential gain $\widehat{G}_i$ (mean, %)	+83.6	+16.0	+24.0	−11.6
Potential gain $\widehat{G}_i$ (median, %)	+43.4	+16.8	+23.4	−9.5
Share with paper loss (%)	12.4	22.4	—	—
Listing premium (mean, %)	+11.6	+17.0	+12.6	+32.3
Holding period (median, years)	9.4	5.8	6.5	3.3
Floor area (median, m^2)	90	85	86	81
Flats (% of listings)	13.1	16.5	14.1	25.0
Rental conversion within 400 days (%)	3.7	4.0	3.8	4.6

Note: The full sample contains all first sale listings satisfying the restrictions in this section. The estimation sample further restricts potential gain to $\widehat{G}_i \in [-0.40, 0.50]$; the gain and loss columns partition it at zero. The potential gain is the percentage difference between fair market value at the listing date and the original purchase price; the listing premium is the percentage difference between the asking price and fair market value. A rental conversion is a rental listing within 400 days with no prior Land Registry transaction. Prices are nominal.

Within the main estimation sample, the sale listing premium averages 32.3% in the loss domain, compared with 12.6% in the gain domain. The conversion rate is also higher, 4.6% compared with 3.8%.

2.6 Regional housing market panel

For the aggregate analysis, I construct a monthly panel of 39 International Territorial Level 2 (ITL2) regions from September 2023 through December 2025. The regional loss share in a given month is the fraction of the property stock whose fair market value in that month is below the owner's most recent purchase price. The underlying stock contains 7.2 million residential properties with an EPC record and a Land Registry purchase since 2008. Because listing characteristics are unavailable for the full property stock, fair market values for the regional panel use the first-stage hedonic model in equation (1).

Monthly sale volume counts Land Registry transactions in each region, while monthly rental-conversion flow counts conversions from the listing panel. The sale panel covers

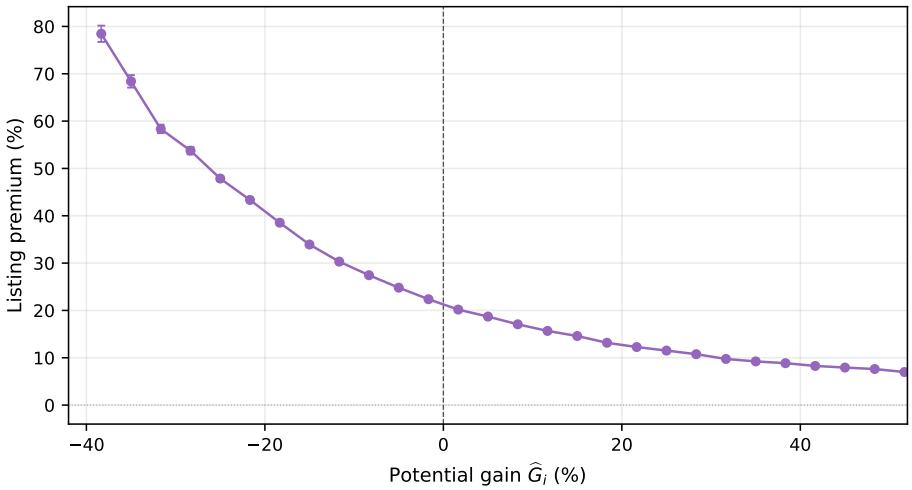


Figure 2: Listing premium by potential gain

Note: Mean listing premium, $(a_i - \widehat{p}_i)/\widehat{p}_i$, for 277,323 initial sale listings, in 3.33-percentage-point bins of potential gain. Bars show ±1 standard error. The dashed line marks zero potential gain; the dotted line, a zero premium.

all 28 months; the conversion panel begins in October 2024, the first month whose full 400-day lookback of sale listings lies within the data.

2.7 Listing behavior in the linked data

The linked data reproduce the sale-side patterns of reference-dependent listing behavior documented in the literature. Figure 2 plots the average listing premium, the percentage difference between the asking price a_i and fair market value $\widehat{p}_i$, against potential gain $\widehat{G}_i$. The premium declines gently over the gain domain and rises steeply as potential losses deepen, with the change in slope located at zero potential gain. This is the hockey-stick pattern of reference-dependent listing behavior documented by Genesove and Mayer (2001), Andersen et al. (2022), and Badarinza et al. (2025).

3 Property-level evidence

3.1 Paper losses and rental conversion

The property-level question is what happens to a property after it lists for sale. Figure 3 plots the destination shares of first sale listings within 400 days against the seller's

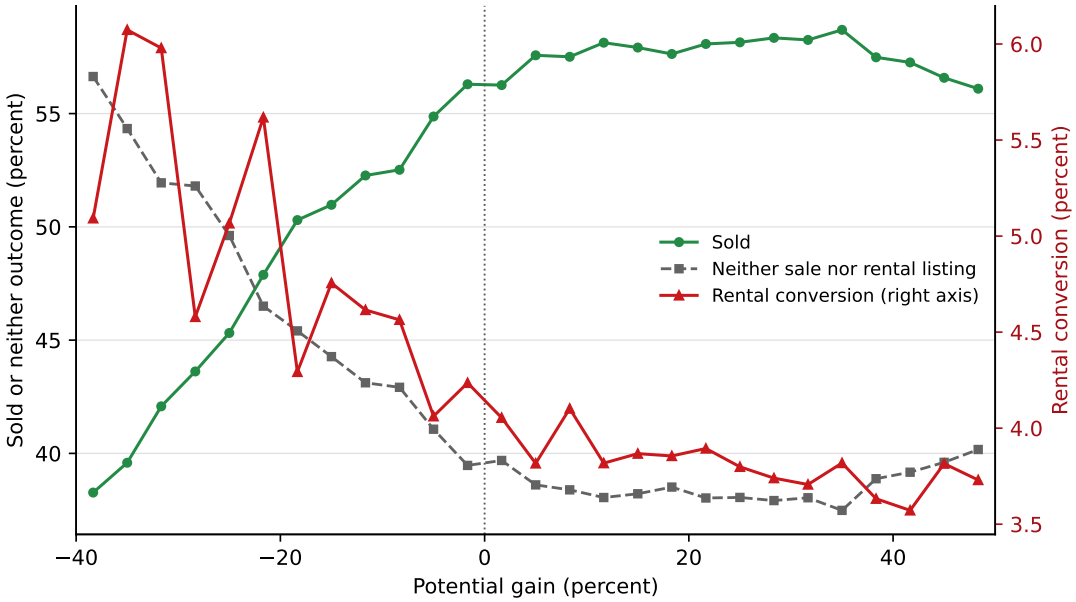


Figure 3: Destinations of first sale listings

Note: Mutually exclusive destinations within 400 days of the initial sale listing: sold (a Land Registry transaction before any rental listing), converted to rental (a rental listing first), or neither. Sale and neither shares are on the left axis; rental conversion on the right axis. Points are means within 3.33-percentage-point bins of potential gain in the estimation sample. The dotted line marks zero potential gain.

potential gain, $\widehat{G}_i$, distinguishing successful sales, no-transaction outcomes, and rental conversions.

The sale share is roughly flat in the gain domain and falls sharply as paper losses deepen, with the change in slope at $\widehat{G}_i = 0$ characteristic of reference-dependent listing behavior. The no-transaction share is the mirror image, rising as losses deepen. The rental-conversion share rises nearly in parallel, consistent with a roughly constant fraction of unsuccessful sale attempts converting to rental across the gain and loss domains.

To quantify these patterns, I estimate the following specification. For property i first listed for sale in month $q(i)$ at location $\ell(i)$:

$$y_i = \beta_L \widehat{G}_i^{\text{loss}} + \beta_G \widehat{G}_i^{\text{gain}} + \delta \log T_i^{\text{hold}} + \alpha_{\ell(i)} + \gamma_{q(i)} + \varepsilon_i, \tag{3}$$

where $\widehat{G}_i^{\text{loss}} \equiv \widehat{G}_i \mathbf{1}[\widehat{G}_i < 0]$ and $\widehat{G}_i^{\text{gain}} \equiv \widehat{G}_i \mathbf{1}[\widehat{G}_i \geq 0]$ allow separate slopes in the loss and gain domains, and T_i^{hold} is the number of years between the seller's purchase and the first sale listing. The outcome y_i equals one if a rental listing on the same property appears within 400 days with no intervening Land Registry transaction, and zero otherwise. The

specification does not add the property characteristics used to construct $\widehat{p}_i$ as controls.[3] $\alpha_{\ell(i)}$ are local-authority fixed effects and $\gamma_{q(i)}$ are listing-month fixed effects; standard errors are clustered at the local-authority level.[4]

The estimation sample restricts to $\widehat{G}_i \in [-0.40, +0.50]$. Table 2 reports the results. Column (1) reports the simple loss-indicator form on the 400-day rental-conversion outcome; column (2) allows separate slope coefficients on $\widehat{G}_i$ in the loss and gain domains on the same outcome. The loss-domain slope of the rental-conversion probability is an order of magnitude steeper than the gain-domain slope (column (2): -3.55 versus an insignificant -0.27), consistent with the change in slope visible in the rental-conversion series in Figure 3. A seller with a 20 percentage point paper loss ($\widehat{G}_i = -0.20$) has a rental-conversion probability 0.71 percentage points higher than a seller at $\widehat{G}_i = 0$, or about 18% above the baseline mean of 4.0%.

These estimates are slightly downward biased because the listing-to-property match is imperfect on the rental side, since not every rental listing carries a usable EPC chart or address ID that can be linked to the sale property. I estimate that conditional on a sale listing being in the analysis panel, a subsequent rental listing on the same property is captured with probability 87.7% (Section 2.3). Adjusting for this, the loss-domain slope rises to approximately -4.0 percentage points per unit of $\widehat{G}_i$.

3.2 Rental Conversion Conditional on Failed Sale

A rental conversion can become more likely for two reasons: the sale attempt is more likely to fail, or the property is more likely to be listed for rent conditional on failure. Let p_{rent} be the share of initial sale listings that convert to rental and $p_{\text{no txn}}$ the share for which neither a sale nor a rental listing is observed within 400 days. The probability of a rental listing conditional on a failed sale is

$$\Pr(\text{rental listing} \mid \text{sale fails}) = \frac{p_{\text{rent}}}{p_{\text{rent}} + p_{\text{no txn}}}, \tag{4}$$

and the rental-conversion probability can therefore be decomposed as

$$\Pr(\text{rental conversion}) = \Pr(\text{sale fails}) \times \Pr(\text{rental listing} \mid \text{sale fails}). \tag{5}$$

[3] Partialling out these characteristics would also remove the corresponding variation in fair market value, leaving the potential-gain coefficient identified mainly by within-cell variation in the original purchase price. Appendix B.1 reports this Frisch–Waugh–Lovell diagnostic.

[4] Potential home equity, which enters Badarinza et al. (2025) as an additional control, is omitted because mortgage balances are not observed.

Table 2: Paper losses and rental conversion

	Rental conversion (y_i), percentage points	
	(1)	(2)
Paper loss indicator ($\mathbf{1}[\widehat{G}_i < 0]$)	0.47^{***}	
	(0.12)	
Potential loss ($\widehat{G}_i \times \mathbf{1}[\widehat{G}_i < 0]$)		-3.55^{***}
		(0.88)
Potential gain ($\widehat{G}_i \times \mathbf{1}[\widehat{G}_i \geq 0]$)		-0.27
		(0.29)
Log holding period ($\log T_i^{\text{hold}}$)	0.20^{***}	0.22^{***}
	(0.07)	(0.07)
Mean conversion rate (%)	4.0	4.0
Local-authority fixed effects ($\alpha_{\ell(i)}$)	Yes	Yes
Listing-month fixed effects ($\gamma_{q(i)}$)	Yes	Yes
Test of equal slopes ($H_0 : \beta_L = \beta_G$), p-value		0.001
Observations	266,959	266,959
R^2	0.012	0.012

Note: The dependent variable equals one if a rental listing appears within 400 days with no intervening Land Registry transaction. Coefficients and standard errors are multiplied by 100. Column (1) uses a loss indicator; column (2) allows separate slopes in the loss and gain domains, continuous at zero. Both columns include the log holding period. Potential gain is restricted to $[-40\%, +50\%]$. Standard errors are clustered by local authority. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

I refer to the two terms as the failure margin and the conversion margin. Figure 3 shows that the failure margin, Pr(sale fails), moves strongly with paper losses: the sale share falls and the no-transaction share rises as losses deepen. The remaining question is whether the conversion margin, Pr(rental listing | sale fails), also rises.

Figure 4 plots the conversion margin across bins of potential gain. If loss-exposed owners had a greater propensity to become landlords after an unsuccessful sale, this conditional share would rise in the loss domain. Instead, it averages 9.1% and is flat across the loss and gain domains, with no change in slope at zero potential gain. The loss-domain asymmetry in Table 2 therefore operates through the failure margin. Paper losses cause sale attempts to fail, and a roughly constant fraction of failed sales converts to rental.

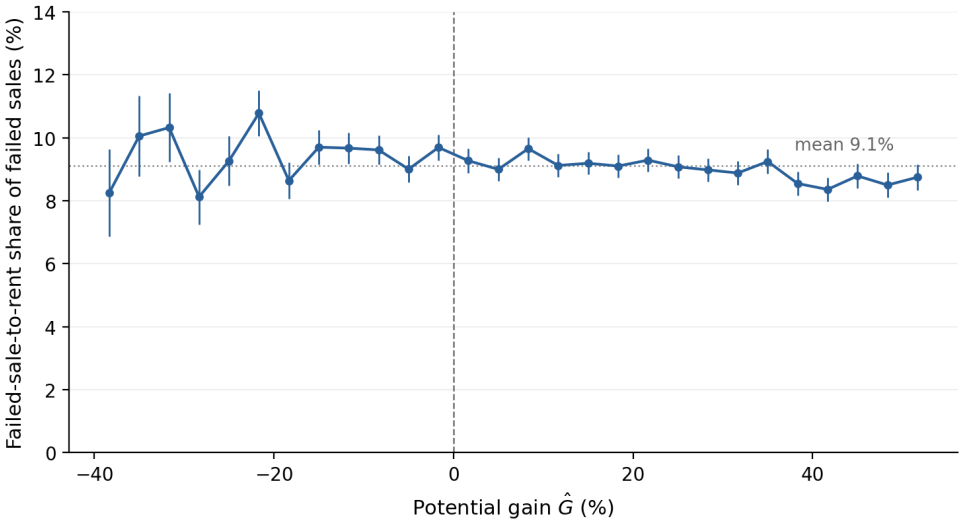


Figure 4: Rental conversion conditional on a failed sale

Note: The figure reports $p_{\text{rent}}/(p_{\text{rent}} + p_{\text{no txn}})$ within 3.33-percentage-point bins of potential gain, where p_{rent} is the share of initial sale listings converting to rental and $p_{\text{no txn}}$ the share with neither outcome within 400 days. Bars show ±1 standard error. The dotted line marks the sample mean of 9.1%; the dashed line, zero potential gain.

3.3 Unobserved property quality and home equity

A leading concern is that the relationship between paper losses and rental conversion reflects unobserved property quality. Suppose the original buyer paid a premium for a feature that the hedonic model omits and that later buyers value less. The property would then appear to face a paper loss and would also be harder to sell, generating the observed relationship without reference dependence.

I address this concern using the hedonic residual at the purchase date,

$$\widehat{\varepsilon}_i = \log p_i^0 - \log \widehat{p}_i^{\text{buy}}, \tag{6}$$

where p_i^0 is the seller's original purchase price and $\widehat{p}_i^{\text{buy}}$ is the model-implied value at the time of purchase. The residual measures the premium the buyer paid relative to model value. Potential gain can be written as

$$\log(1 + \widehat{G}_i) = \left[\log \widehat{p}_i - \log \widehat{p}_i^{\text{buy}}\right] - \widehat{\varepsilon}_i. \tag{7}$$

Conditioning on $\widehat{\varepsilon}_i$ therefore separates market appreciation since purchase from the purchase premium. Calculating $\widehat{p}_i^{\text{buy}}$ requires the purchase transaction to enter the EPC-

Table 3: Unobserved property quality and rental conversion

	Rental conversion (y_i), percentage points	
	(1) Without control	(2) With control
Potential loss ($\widehat{G}_i \times \mathbf{1}[\widehat{G}_i < 0]$)	-2.31^{***}	-3.77^{***}
	(0.88)	(1.14)
Potential gain ($\widehat{G}_i \times \mathbf{1}[\widehat{G}_i \geq 0]$)	0.89^{**}	0.09
	(0.35)	(0.55)
Purchase residual ($\widehat{\varepsilon}_i$)		-1.28^{**}
		(0.63)
Log holding period ($\log T_i^{\text{hold}}$)	-0.39^{***}	-0.24^{*}
	(0.08)	(0.12)
Mean conversion rate (%)	3.8	3.8
Local-authority fixed effects ($\alpha_{\ell(i)}$)	Yes	Yes
Listing-month fixed effects ($\gamma_{q(i)}$)	Yes	Yes
Observations	197,084	197,084

Note: Both columns use the subsample with an observed purchase residual, the difference between the log purchase price and the log model-implied value at purchase. Column (2) adds this residual to the specification in equation (3). Coefficients and standard errors are multiplied by 100. Standard errors are clustered by local authority. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

based hedonic estimation sample. The residual is therefore observed only for sellers who purchased in the EPC era, a group that accounts for about 74% of the main estimation sample.

Table 3 compares equation (3) with and without the purchase residual on the same subsample of 197,084 listings. Adding the purchase residual steepens the loss-domain slope from -2.31 to -3.77, while the gain-domain slope falls from 0.89 to an insignificant 0.09. The purchase residual enters with a coefficient of -1.28. Because a positive residual identifies a property bought above model value, this coefficient means that properties bought at larger premiums are less likely to convert. Unobserved property quality therefore masks the relationship between paper losses and rental conversion rather than generating it.

A second concern is that paper losses are correlated with negative home equity, which I cannot rule out directly because mortgage balances are not observed. Negative equity can cause a sale to fail because completing a sale below the outstanding mortgage balance requires the seller to cover the shortfall. This could link paper losses to rental conversion through the failure margin.

An equity constraint, however, binds at the outstanding mortgage balance, not at the original purchase price. This balance typically lies below the purchase price by the initial deposit and any subsequent amortization, and the resulting threshold differs across owners. Negative equity therefore does not naturally generate a change in slope at zero potential gain. Consistent with this, Badarinza et al. (2025) find in the same U.K. housing market that controlling for home equity and holding period leaves the effect of paper losses on time to sale quantitatively similar.

For mortgaged owners, rental conversion also requires either temporary lender consent or a remortgage onto a buy-to-let contract, and the latter typically requires home equity of at least 25%. Financially constrained owners therefore face higher barriers to conversion. If loss-domain failures were concentrated among owners in negative equity, these barriers should make the conversion margin fall as losses deepen. Figure 4 shows that it does not: the share of failed sales that convert is flat across the loss domain.

3.4 Rental pricing by accidental landlords

The intensive-margin question is how the asking rent is set once the property has converted. Figure 5 plots, for properties that convert within 400 days, two measures against potential gain $\widehat{G}_i$:

$$Y_i^{\text{fair}} = \frac{12r_i}{\widehat{p}_i}, \qquad Y_i^{\text{ask}} = \frac{12r_i}{a_i}. \tag{8}$$

Here r_i is the monthly asking rent on the first rental listing, $\widehat{p}_i$ is fair market value at the sale-listing date, and a_i is the asking price on the preceding sale listing. The numerator is the same in both measures. The denominators differ: Y_i^{fair} is the fair-value rental yield, while Y_i^{ask} is the sale-asking-price rental yield. Because the data record asking rather than agreed rents, both measures describe pricing behavior rather than realized rental outcomes.

The two panels move in opposite directions across the loss and gain domains. Panel A shows that the fair-value rental yield rises as paper losses deepen. Among properties that convert, owners facing larger paper losses therefore set higher asking rents relative to fair market value, consistent with reference-dependent pricing on the rental side. This result is consistent with Giacoletti and Parsons (2022), who show that landlords' purchase prices carry into the rents they charge. Panel B shows that the sale-asking-price rental yield falls as paper losses deepen.

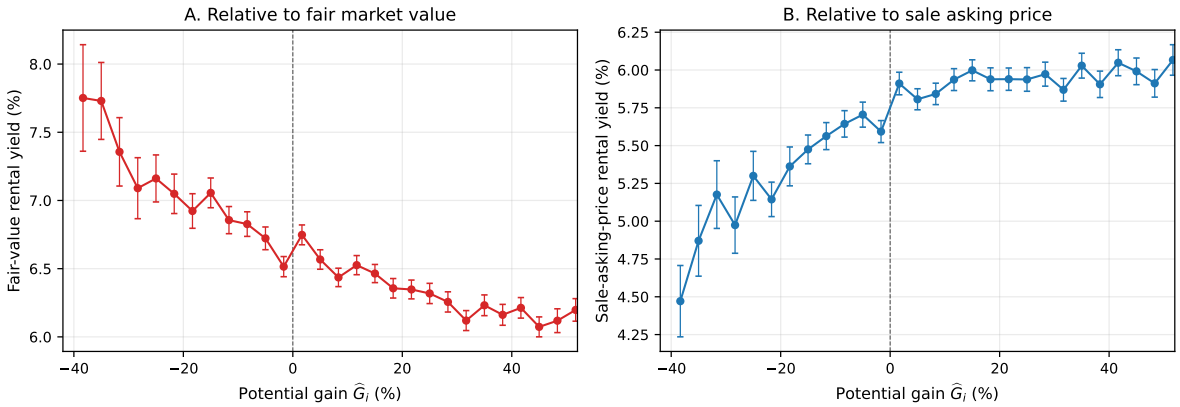


Figure 5: Asking rents after conversion

Note: Rental yields for 10,880 properties that convert within 400 days, in 3.33-percentage-point bins of potential gain: Panel A the fair-value yield, $12r_i/\widehat{p}_i$; Panel B the sale-asking-price yield, $12r_i/a_i$. Yields are trimmed at the 0.5th and 99.5th percentiles. Bars show ±1 standard error; the dashed line marks zero potential gain.

The decline in Panel B reflects the sale-side listing behavior documented in Section 2.7. Loss-exposed sellers set sale asking prices further above fair market value, which lowers the sale-asking-price rental yield.

The fair-value rental yield measures rental pricing directly, since $\widehat{p}_i$ is independent of the seller's pricing. The sale-asking-price rental yield reflects the net of sales-side and rental-side anchoring, since both the numerator and denominator can be anchored. If owners fully transmitted their sales-side anchoring into rental pricing, the higher asking rent would offset the higher sale asking price and this yield would not decline. Its decline shows that anchoring in asking rents is weaker than anchoring in sale asking prices. Conversion therefore transmits only part of the sale-side pricing distortion into the rental market.

4 Aggregate evidence

4.1 Cross-regional volume regression

The property-level evidence implies that regions with more loss-exposed owners should generate more failed-sale-to-rent transitions. I test this prediction on the regional panel of Section 2.6, estimating

$$\log V_{g,t} = \beta_p \Delta \log P_{g,t} + \beta_\ell L_{g,t} + \alpha_g + u_{g,t}, \tag{9}$$

Table 4: ITL2-month volume regression

Outcome	(1) (1) Sale $\log V^{\text{sale}}_{g,t,\text{resid}}$	(2) (2) Acc. landlord $\log(1+V^{\text{rent}}_{g,t})_{\text{resid}}$	(3) (3) Acc. landlord $\log(1+V^{\text{rent}}_{g,t})_{\text{resid}}$
$\Delta \log P$ (YoY)	1.19***	1.29	0.56
	(0.20)	(1.13)	(0.96)
Loss share	−1.66***		
	(0.31)		
Loss share$_{t-5}$		6.62***	5.54***
		(0.87)	(0.96)
log sale listings$_{t-13,t-1}$			1.84***
			(0.26)
Regional fixed effects	Yes	Yes	Yes
N ITL2-months	1,092	585	585
N clusters	39	39	39

Note: $V^{\text{sale}}_{g,t}$ is monthly Land Registry transactions in region g and month t; $V^{\text{rent}}_{g,t}$ is the monthly count of failed-sale-to-rent conversions. Both outcomes are residualized on quarter fixed effects. Column (1) uses the contemporaneous loss share; columns (2) and (3) lag it by five months. Column (3) controls for log sale listings in the preceding 13 months. Standard errors are clustered by region. * $p < .10$, ** $p < .05$, *** $p < .01$.

where g indexes the 39 International Territorial Level 2 regions and t indexes months. $V_{g,t}$ is monthly volume, $\Delta \log P_{g,t}$ is year-on-year house-price growth, and α_g are regional fixed effects. Loss share $L_{g,t}$ is the regional fraction of properties with $\widehat{p}_i(t) < p^0_i$ at t. For the sale specification, volume is the number of completed transactions. For the rental specification, it is the number of failed-sale-to-rent conversions. Both outcomes are residualized on quarter fixed effects before estimation to remove seasonality, and standard errors are clustered by region.

The sale specification uses the full 28-month panel. The accidental-landlord specification is restricted to October 2024 through December 2025, because each month's rental flow draws from sale listings in the preceding 13 months, and only from October 2024 does the full 13-month window fall within the data. The accidental-landlord specification uses the loss share lagged by five months, reflecting the median sale-to-rental conversion lag of approximately 167 days. Column (3) also controls for the log number of sale listings in the preceding 13 months, which measures the stock of listings at risk of conversion. Table 4 reports the results.

Column (1) provides a sale-side benchmark. The loss-share coefficient of −1.66 is close to the estimate of −1.73 in Badarinza et al. (2025), and confirms that regions with

Table 5: Implied annual flows from a 1 percentage point increase in regional loss share

	Sale flow	Accidental-landlord flow
Source coefficient	−1.66%	6.62%
Mean per region-month	1,271	29.2
Panel-implied annual flow	−9,900	905
Coverage capture rate	82%	51%
Adjustment factor	×1.22	×1.9
Coverage-adjusted annual flow	−12,000	1,770
vs external benchmarks:		
HMRC residential transactions, England 2023 (858k/yr)	1.4%	—
Hamptons buy-to-let purchases, England & Wales 2024 (∼101k/yr)	—	1.8%

Note: The sale benchmark is 858,000 residential transactions in England in 2023. The accidental-landlord benchmark is approximately 101,000 buy-to-let purchases in England and Wales in 2024 (Hamptons, 2025). Appendix C describes the coverage adjustments and benchmark construction.

higher loss shares have lower transaction volume. Columns (2) and (3) report the rental conversion channel. A 1 percentage point increase in regional loss share predicts a 6.6% increase in failed-sale-to-rent conversions five months later. The estimate falls to 5.5% after controlling for the number of sale listings at risk of conversion, and both estimates are significant at the 1% level.

4.2 Economic magnitude

Table 5 translates columns (1) and (2) of Table 4 into annual property flows for England and Wales. A 1 percentage point increase in regional loss share corresponds to approximately 9,900 fewer sales and 905 additional accidental-landlord entries per year in the observed data. Adjusting for coverage raises these estimates to approximately 12,000 fewer sales and 1,770 additional entries.

The coverage-adjusted estimates imply approximately 15 rental conversions for every 100 lost sales. This ratio is of the same order as the 9.1% property-level conversion rate conditional on a failed sale in Figure 4; the difference reflects the larger coverage adjustment on the rental side and the stronger aggregate loss-share elasticity. One cross-regional standard deviation of the loss share is 3.83 percentage points. A one-standard-deviation increase therefore generates roughly 6,800 additional accidental-landlord entries per year, or approximately 7% of annual buy-to-let purchase volume in England and

Wales. The accidental-landlord channel is thus a quantitatively meaningful source of entry into the private rental market, distinct from intentional buy-to-let purchases.[5]

5 Conclusion

Reference-dependent sellers are less willing to sell their homes at a nominal loss. A failed sale, however, does not necessarily leave the owner in place. The owner can retain the property, list it for rent, and move. This paper studies this accidental-landlord channel using linked sale listings, rental listings, and property transactions in the U.K. I find that paper losses strongly predict rental conversion after an unsuccessful sale. The relationship is asymmetric around the original purchase price: conversion rises sharply as losses deepen but is nearly flat in the gain domain.

The channel operates through the failure of the sale attempt. Paper losses make a sale less likely; a roughly constant fraction of failed sales flows into the rental market, so the sellers whom losses push out of the sales market are carried into the rental market. Nominal anchors also remain relevant after conversion. Accidental landlords facing paper losses set higher asking rents relative to fair market value, although the anchoring in rents is weaker than the anchoring in sale asking prices. At the aggregate level, the regional loss share predicts flows into the rental market as well as sales volume. A one-standard-deviation cross-regional shift in the loss share generates roughly 6,800 additional accidental-landlord entries per year, about 7% of annual buy-to-let purchase volume in England and Wales. Behavioral lock-in in the ownership market is therefore not only a friction that suppresses transactions; it reallocates part of the housing stock to the rental sector and distorts the asking rents of the properties that enter.

How this reallocation affects welfare remains an open question. The rental option can allow an owner to move without realizing a nominal loss, but it also changes the availability of properties to buyers and renters. A longer panel can show whether accidental landlords sell when prices recover and how long their properties remain in the rental market. Quantifying the resulting effects on prices, rents, mobility, and household welfare is a natural next step for this research.

[5]Hamptons estimates 113,630 landlord purchases in Great Britain in 2024. Scotland accounts for approximately 10.8% of U.K. buy-to-let purchase mortgages, implying approximately 101,000 purchases in England and Wales. The Hamptons measure captures intentional buy-to-let purchases and excludes the accidental-landlord pathway studied here.

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A Matching listings to properties

The Land Registry and EPC registers are combined into a property-level panel before any listing is matched. Records that share the same standardized address are merged into a single property, and units within the same building are separated using the Ordnance Survey Unique Property Reference Number. The procedure follows Chi et al. (2021) and yields 23.2 million properties, 18.2 million of which carry at least one certificate and can anchor a chart match. Each property carries its full transaction and certificate history.

Listings are matched to this panel on the scores extracted from the EPC chart. Matching proceeds in seven tiers with increasingly restrictive keys. The first tier requires the postcode and the current and potential energy efficiency ratings; subsequent tiers add the environmental impact ratings, the property sub-type, and the number of bedrooms; a fallback path handles listings whose chart reports only environmental scores. A listing is assigned a property at the smallest tier at which exactly one candidate survives. The median postcode contains 13 candidate properties, and the 90th percentile 36, so requiring an exact match on several scores within a postcode is demanding. Listings without a readable chart inherit a match through the platform-specific address identifier, provided the identifier corresponds to a single unit and maps to a single matched property; identifiers shared by a building or a street are not used.

Figure A1 summarizes the cascade over all 7.0 million listings. The chart tiers match 3.13 million listings, or 45%; address-identifier propagation raises the total to 3.56 million, or 51%. The analysis panel retains 2.33 million of these listings; the difference reflects the standard-sale filters, listings whose property has no prior Land Registry transaction, and sanity checks on characteristics.

Table A1 reports match rates by property type. Flats match least often, at 47.7%, because several flats in the same building share a postcode and can carry similar scores.

Figure A2 decomposes the conditional capture rate. Of the 1,322,984 panel sale listings collected from March 2024 onward—the period in which nearly all of the sample's conversions occur—97.7% carry an address identifier. For these, a subsequent rental listing is captured with probability 89.0%: 86.1% of the rental listings carry the same identifier and are matched through propagation, and the remaining 13.9% must be matched through their own chart, which succeeds at a rate of 20.6%. For the 2.3% of sale listings without an identifier, only a chart match is possible, and the capture rate is 32.9%. The weighted average is 87.7%.

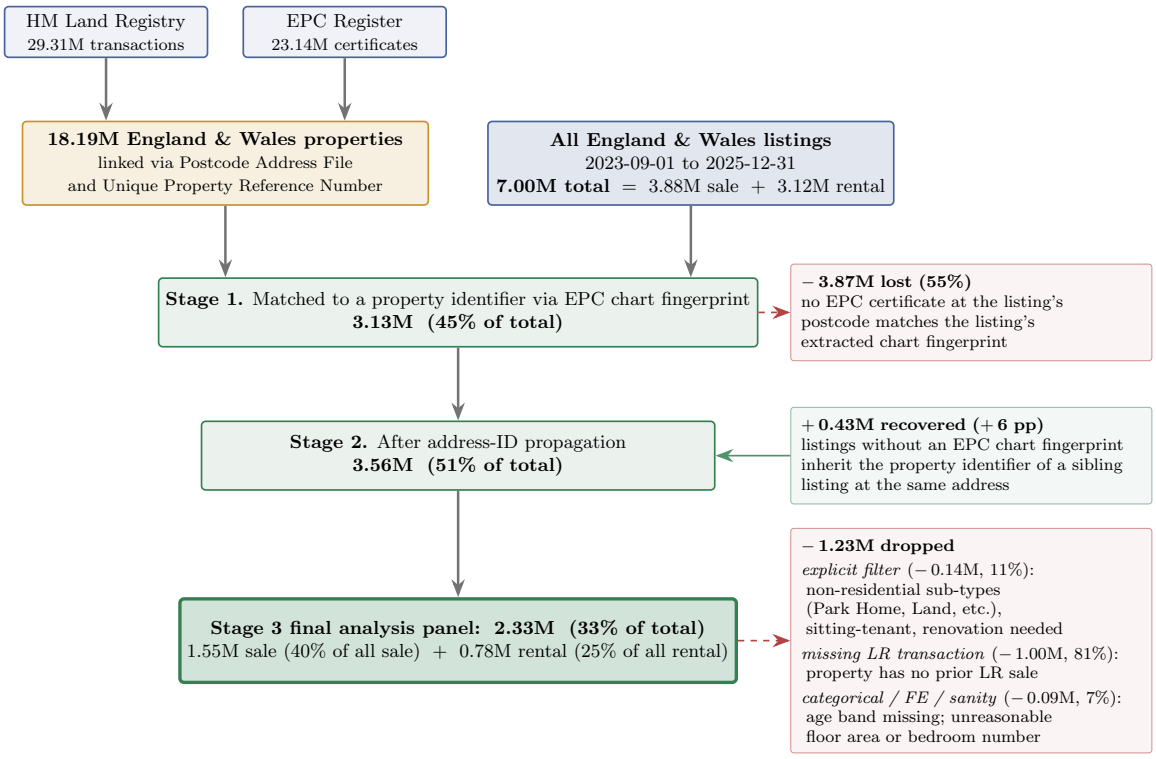


Figure A1: The listing-to-property matching cascade. Counts are for all listings collected between March 2024 and December 2025.

Table A2 traces the attrition from the raw sale listings to the analysis sample. Each row applies the restrictions of the preceding rows.

Table A1: Match rates by property type

	Listings	Matched	Rate
Terraced	771,513	529,305	68.6%
Semi-detached	838,230	536,578	64.0%
Detached	827,358	487,432	58.9%
Flat	844,734	402,922	47.7%
Bungalow	292,655	224,556	76.7%
Other	305,174	151,232	49.6%
All	3,879,664	2,332,025	60.1%

Note: Sale listings collected between September 2023 and December 2025. A listing counts as matched if it is linked to a property through the EPC chart tiers or through address-identifier propagation.

Table A2: From raw sale listings to the analysis sample

	Listings
Sale listings collected	3,879,664
Linked to a property	2,332,025
First sale listing of the property, prior purchase observed, standard-sale filters, and model support	1,108,647
Listed September 1, 2023 to November 26, 2024	574,146
No rental certificate before the sale listing (final sample)	491,512

Note: The filters are described in Section 2. Rows are cumulative.

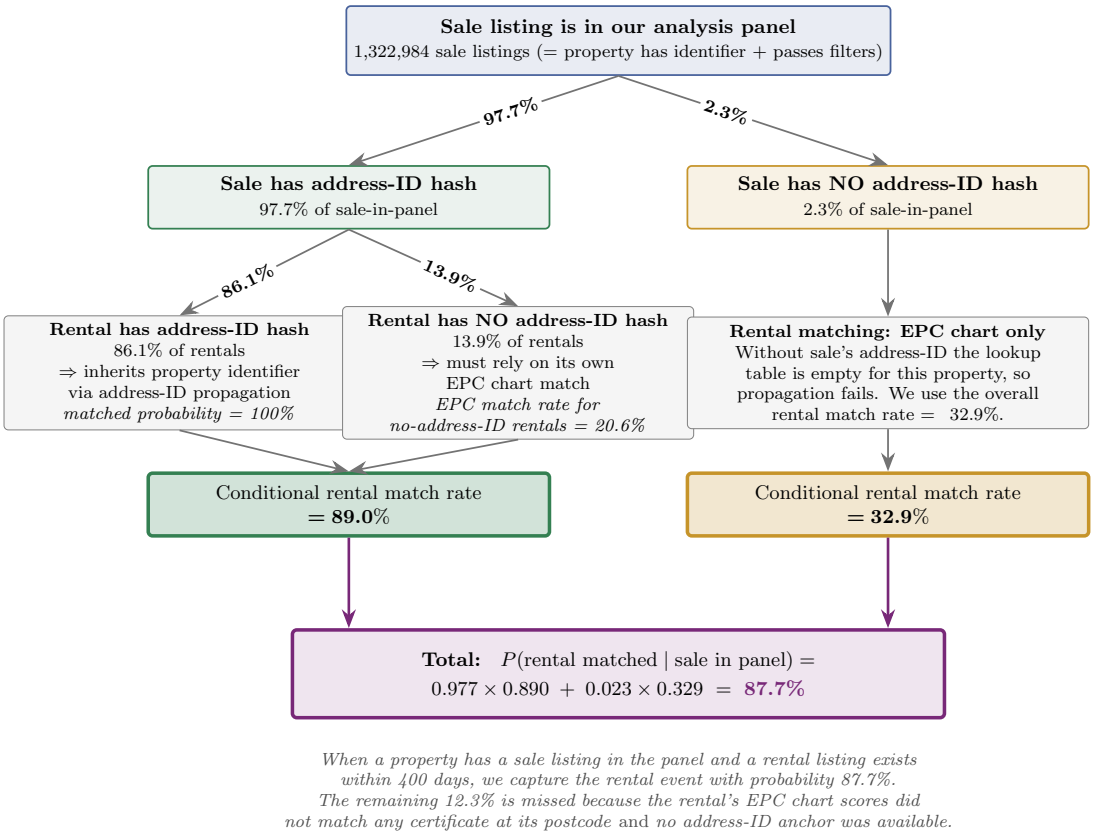


Figure A2: Decomposition of the conditional rental capture rate. The rate conditions on the initial sale listing being in the analysis panel; shares are computed on listings collected from March 2024 onward, the period in which nearly all of the sample's conversions occur.

B The hedonic second stage

The second stage incorporates listing characteristics that the registers do not record. Among sale listings followed by a Land Registry transaction within 365 days, I regress the difference between the log transaction price and the first-stage prediction on the number of bathrooms, twenty property sub-type indicators, and ten indicators for features mentioned in the listing description, with local-authority-by-sale-year and property-type fixed effects. The fitted combination of listing characteristics is then added to the first-stage prediction for every listing, after centering within property type. The intercept and fixed effects of the second stage are not carried over, because they absorb the selection of the estimation subsample into quickly sold listings. Without centering, the adjustment would shift the level of fair market values and mechanically change the share of sellers classified as facing losses; centered, it reallocates value within property types and leaves the loss share essentially unchanged. Neither stage uses the seller's asking price. The prediction at the listing month is formed by replacing the year and month fixed effects estimated at the sale date with those of the listing month, holding property characteristics fixed.

The purchase premium $\widehat{\varepsilon}_i$ used in Section 3.3 is the first-stage residual of the seller's purchase transaction, adjusted by the property's second-stage term so that the decomposition of the potential gain into market appreciation and the premium also holds for the adjusted measure, and winsorized at the 1st and 99th percentiles.

B.1 Property controls in the outcome regression

Equation 3 does not add the property characteristics used to construct fair market value. Adding these controls would mechanically change the source of variation in potential gain. In logs, potential gain satisfies $\log(1 + \widehat{G}_i) = \log \widehat{p}_i - \log p_i^0$. Because $\log \widehat{p}_i$ is constructed from these characteristics and the hedonic fixed effects, the Frisch–Waugh–Lovell theorem implies that partialling out the same variables also removes the corresponding component of fair market value. The remaining variation in potential gain is then driven mainly by variation in the original purchase price within narrowly defined property cells.

In a diagnostic using the listing-date fair market value, the residual correlation between potential gain and the negative log purchase price is 0.85 after partialling out the hedonic property characteristics and location-by-listing-quarter fixed effects. The fitted values from otherwise identical outcome regressions using the two measures have a

correlation of 0.998. The equivalence is not exact because equation 3 uses potential gain in levels and fair market value includes the second-stage adjustment, but the diagnostic shows that adding the hedonic characteristics changes the source of identifying variation rather than providing an independent control for property quality. I therefore treat specifications with these controls as diagnostics. Section 3.3 instead addresses unobserved quality using the purchase residual.

C Coverage rates and benchmarks

The aggregate sale outcome counts Land Registry transactions over properties in the panel universe, the 7.2 million properties with an EPC certificate and a Land Registry purchase since 2008. Of the 1,380,775 transactions in the sample window, 1,135,191, or 82.2%, involve a property in this universe; the remainder lack a certificate or last transacted before 2008. The adjustment factor is $1/0.822 = 1.22$.

The conversion flow faces two further layers of coverage. A sale listing enters the panel with probability $0.60 \times 0.97 \approx 0.58$, the product of the listing-to-property match rate and the share of matched listings within the support of the hedonic model. Conditional on the sale listing being in the panel, the rental listing is captured with probability 87.7% (Appendix A). The joint coverage is $0.58 \times 0.877 \approx 51\%$, and the adjustment factor is 1.96. These adjustments correct only for data coverage. Restrictions that define the scope of the analysis, such as requiring a prior purchase, are not coverage gaps, and no adjustment is applied for them.

The sale benchmark is the 858,000 residential property transactions recorded by HM Revenue and Customs for England in 2023. The buy-to-let benchmark starts from the 113,630 landlord purchases that Hamptons (2025) reports for Great Britain in 2024. Scotland accounts for approximately 10.8% of U.K. buy-to-let purchase mortgages, which implies approximately 101,000 purchases in England and Wales. Because the Hamptons measure counts purchases, it excludes conversions by existing owners, and the two flows do not overlap.