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Behavioral lock-in: aggregate implications of reference dependence in the housing market

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Abstract

We study the aggregate implications of reference dependent and loss averse preferences in the housing market. Motivated by micro evidence, we embed optimizing homeowners with these preferences into a dynamic search and matching equilibrium model with rich heterogeneity and realistic constraints. We assess the model using large and granular administrative data tracking buyers and sellers in the UK housing market; the predictions match regional and time variation in price growth and transaction volumes. The model shows that behavioral frictions in a decentralized market can link nominal quantities with real outcomes; and reveals that the distribution of potential nominal gains in the housing market is a key policy-relevant statistic.

Key words: Reference dependence, behavioral frictions, housing.

JEL classification: D12, D91, G51, R21, R31.

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1 Introduction

How do behavioral frictions affect aggregate economic outcomes and the optimal design of economic policy? Convincing lab and field evidence exists that households' beliefs and preferences look very different from the neoclassical benchmark, and a growing literature studies the implications of behavioral agents on macroeconomic outcomes (Kaplan and Violante, 2014; Kaplan et al., 2018; Gabaix, 2020; Laibson et al., 2021; Maxted, 2023) and the transmission and design of public policy (DellaVigna et al., 2017; Taubinsky and Rees-Jones, 2018; Rees-Jones, 2018; Allcott et al., 2019).[1]

We investigate these questions in the setting of residential housing markets, motivated by micro evidence from a range of countries that homeowners are reference dependent and loss averse, focusing on the nominal gains and losses that they expect to make when they sell their houses (Genesove and Han, 2012; Bracke and Tenreyro, 2021; Andersen et al., 2022). Housing is generally the single largest asset on household balance sheets, and mortgages are the largest liability (Campbell, 2006; Gomes et al., 2021; Goetzmann et al., 2021). In the aggregate, housing and mortgage markets are among the most important venues for the transmission of monetary policy, and housing-related taxation is an important component of government revenue around the world.[2]

To facilitate the analysis of optimal policy in this setting, we develop a dynamic equilibrium search and matching model of the housing market populated by reference-dependent and loss-averse agents, and featuring rich heterogeneity in the shocks that affect both buyers and sellers. The model delivers a number of predictions about the housing market which we verify using large and granular administrative data that covers the entire U.K. housing market and tracks the behavior of both buyers and sellers.

We first use the U.K. data to verify that observed behavior at the micro level is strongly consistent with reference-dependent preferences, confirming previous research from a range of other economies. In the data, we observe substantial and sharp bunching of realized transaction prices at the original nominal purchase price of properties, as well as diffuse bunching above this level, consistent with homeown-

[1] Chetty (2015); Mullainathan et al. (2012); Farhi and Gabaix (2020) provide overviews of the broader field of "behavioral public economics".

[2] Housing-related taxes accounted for \$708bn (3% of GDP) in the U.S., and £60bn (2% of GDP) in the U.K. in 2022, according to the OECD.

ers reluctance to transact below this level.[3] The evidence is also consistent with behavioral motivations operating *ex ante*: when prospective sellers list their houses, their initial listing prices trace out a "hockey stick" pattern in which prices are set closer to hedonic values when sellers face nominal gains relative to the reference point, and sharply increase in the domain of nominal paper losses. We show that this effect is distinct from the effect of mortgage leverage, which affects sellers' list prices similarly, consistent with the "downsizing aversion" channel posited by Stein (1995).

We next embed preferences and constraints consistent with these micro facts into a dynamic search and matching model. Homeowners in the model receive idiosyncratic moving shocks that motivate them to sell, but trade these off optimally against realization utility a la Barberis and Xiong (2012) from (log) gains and losses relative to the reference point, and face penalties for falling below a pre-determined level of home equity to capture the effect of down-payment constraints. This is in addition to receiving ongoing flow utility from homeownership, and utility from final (log) house sale prices. They evaluate these tradeoffs dynamically in an infinite horizon setup, optimally solving for whether or not to list in each period, as well as their pricing strategy conditional on listing. In the event of selling, homeowners subsequently become potential buyers.

Buyers in the model receive idiosyncratic taste shocks for properties when randomly matched with sellers; they also optimize dynamically, trading off transacting today against waiting for more promising outcomes in the future. When they make their decisions, they are aware that their purchase decisions encode their reference points as future homeowners in the event that they decide to purchase a property. The distribution of reference prices in the economy is thus endogenously varying, and we solve for the stationary distribution of reference prices in the equilibrium of the model.

Individual actions affect overall market conditions in the model. Two key statistics so affected are market tightness, which determines the rate at which buyers and sellers encounter one another; and the probability of sale conditional on meetings, which also varies endogenously with the pricing strategies of sellers. The optimal actions of agents in this economy are therefore affected by the actions of all other market participants. When they optimize, both buyers and sellers in the model

[3] Throughout the paper, we simply assume that the original nominal purchase price is the reference point from which homeowners evaluate gains and losses.

have rational expectations about how their decisions endogenously affect these key statistics, and we solve for the equilibrium of the model under this assumption. This source of complementarity, together with the non-linearities induced by reference dependence and mortgage constraints, and the persistent heterogeneity of individual state variables, generates a set of four empirically testable implications for aggregate quantities.

All these testable implications of the model are driven by the same underlying economic mechanism: in a setting with non-linear behavior induced by reference dependence, the standard aggregation result fails, as the current pattern of heterogeneity in the population does have a material influence on the aggregate impact of any given shock (Krusell and Smith, 1998; Lucas, 2003; Ahn et al., 2018). We note two corollaries of this broader mechanism. First—through time, nominal price appreciation can have an impact on real outcomes, as it determines the perceived gain/loss position of individuals relative to their reference points. Second—across space, different locations can exhibit different responses to shocks, depending on the local prevalence of homeowners for which the behavioral motive is more or less operative.

Our first prediction is that price growth rates and transaction volumes are positively correlated, as sellers with paper losses choose more aggressive listing strategies, resulting in fewer transactions that end up being realized. In a panel of U.K. regions tracked over the period 2010–2022, we find evidence of strong positive co-movement between changes in house prices and the number of completed sale transactions. We validate this observation with comparable data measured across U.S. states for the same period, and find effects that are both qualitatively and quantitatively very similar despite the very different structures of mortgages prevalent in the two countries.[4]

Second, the model predicts that the magnitude of the elasticity of housing transaction volumes to shocks affecting the utility of homeownership depends on the prevailing distribution of potential nominal gains and losses in the population of homeowners. The model predicts that this responsiveness is also asymmetric, i.e., negative shocks affecting housing values will be associated with a higher impact on transaction volumes than positive changes. In the data, we find that the positive association

[4]The U.S. market is dominated by fixed-rate mortgages or FRMs, and there is recent evidence (Fonseca and Liu, 2023) that "mortgage lock" affects homeowner mobility in this market. In contrast, the U.K. market is dominated by short-duration adjustable-rate mortgages or ARMs with a modal fixation period of two years, meaning that there are strong refinancing incentives at such short horizons (Fisher et al., 2023).

between prices and volumes is almost exclusively restricted to locations where (and periods when) the share of sellers with nominal losses is relatively higher; and that co-movement is almost absent in periods of rising house prices, while strongly evident in periods of falling prices.

Third, the model shows that the elasticity of listing volumes to price changes, i.e., the extensive margin of the listing decision (driven by the decisions of homeowners to put properties up for sale), is dampened/absorbed by the optimal pricing strategy conditional on listing, i.e., the intensive margin of the listing decision. The data strongly support this prediction, suggesting that sellers list their properties for sale at roughly similar rates in "hot" and "cold" markets, but transactions volumes conditional on listing vary widely across markets. More strikingly, the regional and time variation in these transactions volumes is tightly related to corresponding variation in the share of homeowners facing nominal losses.

Finally, the model shows that if the behavioral motive affects a large fraction of the population of homeowners, quantities absorb a large share of variation in shocks to home values that would otherwise be incorporated in prices. Tracking the time series variation of market outcomes across regions of the U.K., we confirm that transaction volumes fluctuate much more in locations where the share of losses is high, relative to locations where owners have experienced house price appreciation.

The model holds interesting implications for the impact of nominal variables on real quantities that are not directly observable in the data. Sellers that face the possibility of realizing nominal losses can become "locked-in", eschewing potentially valuable moving opportunities because of their reference dependence and loss aversion. This also means that a positive nominal change in property valuations generated by a higher rate of inflation can lead homeowners to more readily accept moving opportunities. This supports the role of "location as an asset", as homeowners internalise the potential lock-in effect of recessions, as well as the emergence of a Philips-curve type of relationship between inflation and unemployment, driven not by the rigidity of wages, but by the behaviorally-induced rigidity of house prices.

The model facilitates analysing how optimal fiscal and monetary policy design affecting the housing market should adjust in response to these behavioral frictions. In future versions of this paper, we intend to explore these questions through the lens of a calibrated model where parameters are set to match key micro-level moments in the data, and underlying shocks are identified off aggregate variation in transaction volumes and prices. For example, we hope to exploit observed variation in stamp duty taxation in the U.K. to run counterfactual simulations that allow us to gauge the fiscal consequences of wealth taxation at property level, both in terms of outcomes for the housing market as well as the impact on government revenues.

Our paper is related to the recent and growing literature that seeks to explore the role of behavioral frictions for macroeconomic and financial outcomes in a heterogeneous-agents setup with aggregate uncertainty (Krusell and Smith, 1998; Ahn et al., 2018). We emphasize the asymmetric impact of shocks across different segments of the population (Ahn et al., 2018; Huckfeldt, 2022), and the persistence of price dispersion (Burdett and Judd, 1983). Our empirical identification approach relies on a bunching estimator that separately captures strict bunching behavior at the reference point and diffuse excess mass above this point (Kleven, 2016; Allen et al., 2017; Rees-Jones, 2018; Anagol et al., 2022). We propose an equilibrium model of the housing market that is in the tradition of standard search and matching frameworks (Diamond, 1984; Merlo and Ortalo-Magne, 2004; Diaz and Jerez, 2013; Han and Strange, 2015; Allen et al., 2019), explicitly incorporating the endogenous determination of liquidity (Wheaton, 1990; Krainer, 2001; Ngai and Tenreyro, 2014; Guren, 2018; Anenberg and Ringo, 2022), the sequential nature of buying and selling decisions (Anenberg and Bayer, 2020; Moen et al., 2021; Grindaker et al., 2021), and the role of financial frictions (Stein, 1995; Fisher et al., 2023; Fonseca and Liu, 2023).

The paper is organized as follows. Section 2 describes the data sources that we employ for both our micro and aggregate empirics. Section 3 describes the micro evidence from the U.K. market that motivates our modelling assumptions. Section 4 introduces our dynamic search and matching model of the housing market. Section 5 discusses predictions of the model, provides evidence for these predictions in the data, and outlines the implications of reference dependence for real economic outcomes. Section 6 concludes.

2 Data

Our analysis uses four main data sets: address-level information on the U.K.'s residential property stock from the U.K. Ordnance Survey, the universe of residential property transactions in England and Wales from the HM Land Registry, listings for properties available for sale and corresponding online search information from Rightmove.com, and loan-level data on the outstanding stock of mortgage contracts from the Bank of England.

2.1 Residential property stock and transactions

2.1.1 Property stock

The U.K. residential property stock comprises a total of 27.3 million postal residential addresses, recorded in the Royal Mail Postcode Address File, which is released by the Ordnance Survey.[5]

2.1.2 Property transactions

We obtain the universe of residential property transactions in England and Wales from HM Land Registry. The data include details on the address of the unit (including the property postcode), the date when the contractual sale agreement was signed, the price recorded in the contract, and limited information about physical characteristics such as the building type (detached and terraced houses, vs. apartments) and an indicator of whether the construction is part of a new development. In total, 28 million transactions were recorded for the period between January 1995 and December 2022, corresponding to a turnover rate of the housing stock of around 4% per year.

For comparison, we also acquire publicly available U.S. data on residential property sales from Zillow. From this source, we construct a panel of median prices and transaction volumes, aggregated at the state level for the monthly frequency between January 2010 and December 2012.

2.2 Listings for sale

We acquire listing information for individual properties from Rightmove.com, the largest online portal for house listings in the UK. The listings data set tracks all listings on the portal that resulted in a successful transaction, as well as those that

[5] We implement our analysis at different levels of geographical aggregation. This is driven both by the availability of data as well as suitability for the specific analysis being conducted. At the very top level of aggregation, we cover two nations (England and Wales), which together account for 10 International Territorial Level 1 (ITL1) and 35 Level 2 (ITL2) regions. These regions are further disaggregated into 339 local authorities (LAD), 7862 electoral wards, and 1.49 million residential postcodes. Because each postcode includes an average of 18.4 residential addresses, it is a precise indicator of the location of housing units. The online appendix provides an overview of the composition and filtering of the data.

were withdrawn and archived. We merge these listings with the transactions registry. The merge rate is high—for example, 77% of Land Registry transactions in 2022 match with a corresponding preceding listing—consistent with the high market share of Rightmove.com and the predominant tendency of sale properties in the U.K. to be first listed online.

For each property, the data contain information on the exact address, the date of the initial listing, the listing price, and a comprehensive set of hedonic characteristics which include the number of bedrooms and bathrooms, the floor space area, and indicator variables for the construction type, whether the property is a development property, retirement home, or classified as affordable housing. The data cover 21 million listings over the period between January 2010 and December 2022.

To merge listings with final transactions, we filter both data sets by restricting the geographical coverage to England and Wales, and removing potentially misreported address units (those with either several transactions or several listings associated with a single address on the same day). We implement two different data merges using postcode-address pairs to uniquely identify properties in both data sets: (i) we match listings to a preceding transaction, which allows us to estimate the nominal gain associated with the property; and (ii) we match transactions with preceding listings to facilitate estimation of a hedonic pricing model. For the hedonic model, we constrain the set of properties which are transacted within 365 days of first listing, to avoid potential changes in hedonic characteristics from potentially "stale" listings information. We also remove auction properties, a few transactions that occur at the exact date of the first listing of the property for sale, and properties for which we do not have sufficient hedonic information in the data. These filters leave us with a final data set of 3.9 million transactions on which we estimate the hedonic model.

2.3 Search and matching

Our data also record online search activity for all Rightmove.com listings observed between January 2019 and December 2022. We distinguish between two types of engagement between an online user and a property listing.[6] The first, which we denote as a "search visit," is an instance of the user clicking the "detail view" hy-

[6]Each "online user" in our setting corresponds to a unique IP address tagged with a fully anonymized (hashed) user identifier. We filter the data to remove online users with only one search visit over the entire sample period, as well as those which search over more than 1,000 listings, as these are likely bots.

perlink on a property listing. This provides the full set of property characteristics to the user (e.g., the floor area), as well as qualitative descriptions of features that the seller/landlord deems relevant. The second layer of engagement, which we denote as a "meeting", is when an online user enters a request for direct contact with the owner of the property or the real estate agency that manages the listing. When we compute market tightness, i.e., the number of buyers divided by the number of listings, we do so using the number of online users that initiate physical meetings as our preferred measure of the number of potential buyers interested in each property.

2.4 Mortgage loans

We acquire information about the stock of mortgages issued in the U.K. from the PSD007 data set of the Financial Conduct Authority. These data cover the period between 2015 and 2022, and are available in half-yearly snapshots. To obtain information about the outstanding mortgage balance at the time of listing for listings that are eventually transacted, we identify individual properties using the postcode, the previous transacted value and the mortgage contract account opening date. The combination of these three variables is a near-unique identifier of mortgages in our sample.

We approximate the current home equity position for each listing, based on the outstanding balance from the half-yearly snapshot closest to and prior to the transaction date. In some cases, the outstanding balance from the snapshot closest to the transaction date is reported as 0 as a result of account closure; in such cases, we rely on the balances from the preceding snapshot.

In order to preserve privacy restrictions across the two data sets, we create binned versions of the home equity position of each mortgage, which are based on average values in bins of 10 observations, created from the listings data.[7] We also merge observations across mortgage-stock snapshots to estimate the average mortgage amortization schedule. To effect this merge, we track mortgages across stock snapshots based on the postcode and borrower date of birth (the latter variable also allows us to uniquely identify a borrower-property combination).[8]

[7] The online appendix describes this procedure in detail. Table A.3 shows that the binned versions of the variables have the same mean, but a lower standard deviation than their non-binned counterparts.

[8] Column 1 of Table A.2 shows the total number of observations of mortgages across different snapshots that also report property values; column 2 shows the number of observations which report

We rely on a sub-sample of mortgages originating in the first half of 2015 to construct an implied amortization schedule. Since mortgage borrowers in the U.K. may close their account at the time of moving houses or refinancing, we restrict the sample to contracts with a non-zero balance in each half-yearly snapshot between 2015H2 till 2022H2. Thus, we condition on both the particular postcode–date of birth combination being present in all subsequent snapshots, with a non-zero balance on the associated mortgage. This results in a sample of 70,000 observations with an average origination loan size of £157,500, initial interest rate of 2.95%, and a monthly payment of £776. Figure A.6 shows the corresponding estimated amortization schedule. On average, mortgages originating in 2015H1 amortize 1.85 pp of the loan balance every 6 months, and are amortized by a cumulative 30.14 pp by 2022H2.[9]

3 Motivating facts

Andersen et al. (2022) identify the nominal purchase price of a property as a quantitatively relevant reference point for sellers of residential properties in Denmark. They propose a test for reference-dependent preferences which relies on a joint set of *ex ante* and *ex post* empirical moments that capture the behavior of sellers throughout the transaction process—beginning with their initial listing decision, and ending with the realization of a successful transfer of ownership at the final sales price.

Ex ante, as initially observed by Genesove and Mayer (2001), houses with a similar current market value are listed for sale with different asking prices, depending on the individual seller's original purchase price. Andersen et al. (2022) highlight that this behavior is consistent with a model of reference-dependent sellers. In the face of nominal losses relative to the reference point, such sellers set list prices significantly higher, to "fish" for buyers that are willing to pay a high price, even if this implies

a unique combination of granular postcodes, property value, and transaction dates; column 3 shows the number of observations that report granular postcodes and borrower date of birth. The decline in the number of observations from columns 2 to 3 shows that the variable combination that we use to track mortgages across snapshots (i.e., column 3) is more restrictive than the unique combination of postcode-purchase price-date of transaction in column 2. More specifically, when moving from column 2 to 3, we drop cases in which a borrower has multiple liens on the same property, some of which are duplicate observations. We therefore rely on the sample in column 3 for all the moments computed using the mortgage data to avoid any noise generated by measurement error.

[9] In unreported results available upon request, we find that the amortization schedule is similar across origination dates and borrower types, and does not differ greatly for mortgages with different loan-to-value ratios at origination.

a much longer waiting time to sell the property.

Ex post, Andersen et al. (2022) show that the distribution of final transaction prices also exhibits patterns consistent with reference-dependent sellers steering transaction outcomes away from the domain of realized nominal losses and towards the domain of realized gains. Namely, this distribution shows significant missing mass immediately below and sharp bunching of transaction prices exactly at the reference point; diffuse bunching mass for low positive nominal gains; and a significant shift in total mass away from the domain of nominal losses.

Taken together, these observations can be rationalized in a model in which preferences exhibit reference dependence and loss aversion, with both a change in slope (a "kink") and a discontinuous jump (a "notch") at the reference point. In this paper, we first verify that these patterns in the micro housing transactions data are also evident in the U.K. housing market.

3.1 Bunching of transaction prices

For each property for which at least two transactions are recorded in the HM Land Registry data, we calculate the *ex post* nominal capital gain as the difference between the observed re-sale transaction price and the original purchase value. Plot (i) in Panel A of Figure 1 reports the frequency distribution of these nominal gains realized over the period 1995–2022, for binned percentage point intervals that are closed to the left and open to the right (i.e., the 0% bin contains gains in the interval between 0% and strictly below 1%).

Consistent with prior evidence, we find missing mass immediately below the reference point and significant bunching at exactly zero nominal gains. A build-up of additional mass is observed as diffuse bunching for nominal gains in the low positive domain, which is consistent with reference dependence in the presence of optimization frictions (Anagol et al., 2022).

Figure A.1 in the online appendix repeats the estimation for 9 ITL1 regions in England. Both strict and diffuse bunching at zero nominal gains are consistently observed in each local housing market, over and above the tendency of transaction prices to cluster at round numbers.

3.2 Counterfactual distribution: Hedonic model

To compute a counterfactual distribution of transaction prices that would prevail in the absence of any behavioral motive, we compute the estimated hedonic value of each property, i.e., the price for which a property with given characteristics and in a given location is expected to trade at a given point in time. For the part of the sample for which we have high-quality measures of hedonic characteristics, we estimate a standard hedonic pricing model, which predicts the log of the sale price P_{it} of all sold properties i in each year t:

$$\ln(P_{i,t}) = \zeta_w + \xi_{l,t} + \psi_{r,m} + \beta_{\mathbf{x}}{}'\mathbf{X_{i,t}} + \varepsilon_{i,t},, \tag{1}$$

where ζ_w are electoral ward fixed effects, $\xi_{l,t}$ are local authority district $\times$ year fixed effects, $\psi_{r,m}$ are region $\times$ month fixed effects, and $\mathbf{X_{i,t}}$ is a vector of time-varying property characteristics, namely, a second order polynomial of floor area (m^2) augmented with a logarithmic term, number of bedrooms and bathrooms, and dummy variables for property type, whether the property is a development property, retirement home, or affordable housing property. The baseline model has strong explanatory power with an R^2 of 0.87.[10]

In Panel A of Figure 1, we calculate an excess mass measure of bunching, where we subtract the counterfactual frequency of nominal gains that would occur if the properties were sold exactly at the hedonic market value, from the actually observed frequency distribution of realized nominal gains. The figure continues to show excess mass at zero nominal gains, alongside substantial diffuse mass transferred from the domain of negative nominal gains to the domain of positive nominal gains.

Panel B of the figure checks the regional variation of this excess mass measure. The horizontal axis of this figure shows the share of sellers who face nominal losses in each ITL2 region and the vertical axis shows the excess bunching mass measured between 0 and 20% realized gains in the same region. The observed strong correlation between the two measures confirms that the build-up of mass to the right of the

[10]Some of the variables used in the regression are not available in our data for all properties. Most importantly, we frequently miss information on the number of bathrooms. Therefore, we impute the number of bathrooms by regressing it as a continuous variable on floor area with fixed effects on number of bedrooms, electoral ward, and property type, and dummy variables on whether the property is a retirement home, auctioned, a development, or affordable housing property. The hedonic model that we use in our subsequent analysis uses imputed number of bathrooms to handle the missing data. The model fit across different price levels is shown in Figure A.3.

reference point is tightly linked to the mass of sellers that we would predict to be affected by loss aversion (in the absence of active seller behavior, this mass would lie below the reference point).

3.3 Seller optimization: Listing premia

To further document ex-ante seller behavior in response to the reference point, we analyse initial listing prices set by sellers on the online platform, i.e., the step preceding bilateral negotiations and contractual outcomes. We calculate the potential gain of a listing ($\widehat{G}$) as the percent difference between the hedonic valuation of the property and its initial purchase price; and the listing premium (ℓ) as the percent difference between the listing price and the corresponding hedonic valuation.

Panel A of Figure 2 shows that the listing premium is negatively sloped in potential gains, and that there is a change in this slope around zero potential gains. The negative slope is consistent with reference dependence and the non-linearity with the presence of loss aversion: as sellers face nominal losses, they are more likely to engage in"fishing" behavior, i.e., to list for higher prices relative to a measure of fair market value; this strategy becomes more aggressive, the higher the magnitude of the negative potential gain. Online appendix Figure A.2 shows that this *ex ante* pattern is robust across geographical locations, consistent with the observed bunching of transaction prices *ex post*.

Table 2 explores this relationship quantitatively, and isolates the response of sellers to their nominal gain position from their level of home equity, attributing the bulk of the effect to the former. Another way to see that the effect of losses exists over and above the effects of mortgage leverage is in Panel A of Figure 2, which reports the mean listing premium in each potential gain percentage point bin, for two different samples. The first is a sample of listings for which a mortgage contract is outstanding at the time of listing ("Mortgage sample"), and the second is listings where the mortgage has either been completely repaid, or the seller's ownership is outright.[11]

Plot (i) in Panel B of Figure 2 shows the potential gain distribution for the full set of listings in the data—approximately 25% of sellers face nominal losses if they

[11] As Stein (1995) highlights, mortgage leverage also generates a desire to "fish" as it magnifies the effects of losses on home equity, which in turn reduces the expected downpayment on the next house thus increasing the likelihood of painful downsizing.

were to sell at hedonic value. The positive slope of the listing premium profile, and especially the non-linearity around zero potential gains thus reflects the behavior of a sizable fraction of the population.

For properties that are financed with a mortgage, plot (ii) shows the distribution of the potential home equity position of the seller, calculated as the difference between the outstanding mortgage amount and the hedonic value at the time of listing. In the U.K. mortgage market, interest costs start to increase for loan-to-value ratios above 80-85% (Liu, 2022). This implies that a seller with home equity below 20% will find it relatively more difficult to afford a loan for a property of similar value to the one they are selling, and may have to consider downsizing. Online appendix Figure A.5 shows that a sizable number of mortgages are issued with initial LTVs that are above 80%, which suggests that for most mortgage borrowers downsizing is only expected to be a material possibility when they are close to being underwater. In the data, only a tiny fraction (3%) of all mortgage contracts are in this situation, and only a relatively small share (16%) have a home equity level below 20%.

Despite these apparently low magnitudes, there is a theoretically distinct role for down-payment constraints for both seller strategy and final transaction outcomes (Stein, 1995). We therefore incorporate such downsizing/credit financing frictions explicitly in our theoretical analysis.

3.4 Buyer optimization: Matching outcomes

In addition to the share of properties for which the behavioral motive may have particular relevance, a second critical determinant of aggregate effects is how buyers respond to reference dependent sellers' listing strategy. Plot (i) of Figure 3 shows the probability that a given property is sold within 6 months (180 days) post-listing. The average probability is 33%; but, more importantly, the probability of a quick sale varies strongly with the price premium that the seller chooses at the point of listing the property. The greater the difference between the initial asking price and the estimated hedonic value at the time of listing, the lower the probability that the sales occurs within six months. Plot (ii) of Figure 3 how final sales price premia (sales price less hedonic value) track listing premia. There is a strong positive relationship between the two, consistent with sellers trading off longer time-on-the-market for eventually higher transaction prices arising from meeting buyers with higher willingness-to-pay.

Overall the picture that emerges is of a downward-sloping demand curve. Higher listing premia from aggressive "fishing" by sellers with low potential gains or low home equity reduces the likelihood of eventual sale or at a minimum, increases the property's pre-sale time-on-the-market.

4 The Model

Motivated by these facts, we develop a dynamic heterogeneous agent search and matching model of the housing market where homeowners are reference dependent and face financial constraints. Seller decisions are conditional on heterogeneous realizations of shocks to mobility, heterogeneous levels of reference prices, and heterogeneous outstanding mortgage amounts. Buyer decisions are conditional on heterogeneous realizations of housing matching quality shocks. The participation and pricing decisions of homeowners in the search and matching process determine aggregate housing market outcomes including prices and transactions volumes.

4.1 Environment

Consider a discrete-time formulation of an economy with a housing stock N_H potentially available for sale, and a mass N_B of interested buyers. Current homeowners choose whether to list their houses for sale, and buyers randomly search over the outstanding stock of available listings. We denote the endogenous number of sellers in a generic period t by N_{St} and the resulting market tightness by $q_t = N_B/N_{St}$, [12] The probability that a seller meets a buyer is assumed to be given by a constant returns to scale matching function $\chi(q_t)$. The probability that a buyer meets a seller is then equal to $\chi(q_t)N_{St}/N_B = \chi(q_t)/q_t$. Upon a successful transaction, the buyer becomes a homeowner and the seller begins their search for a new home as a buyer, which implies that the overall number of buyers N_B remains constant through time.

4.2 Homeowners

Owning a home generates flow utility u_t. At the beginning of period t, each homeowner i draws a mobility shock $\theta_{it} \sim F_\theta(\cdot)$, which represents a newly available outside

[12] The market becomes "tighter" when the number of buyers searching actively increases relative to the number of sellers, and is less tight when the opposite is true.

opportunity with a payoff that only gets realized if the house is successfully sold. Given the draw, the homeowner either lists the property for sale and pays a one-time cost $\phi \geq 0$ for doing so, or they ignore the opportunity, and take another independently distributed draw during the next period. If the homeowner chooses to list, they choose a take-it-or-leave-it log asking price p_{it}.

With probability $\alpha_t(p_{it})$, the sale transaction completes successfully, the seller receives a one-time utility payoff $U(p_{it}, r_i, m_{it})+\theta_{it}$, where r_i denotes the log *reference price* for which they originally purchased their property, and m_{it} their log mortgage balance; and they start searching for a new property, from the position of a new buyer. With probability $1 - \alpha_t(p_{it})$, the homeowner is unable to sell their property for the price p_{it}, and they draw another independent and identically distributed realization of the mobility shock in the next period.

We denote the homeowner's value function by $V_t^h(r_i, m_{it})$ and define it through the following Bellman equation:

$$\begin{aligned} V_t^h(r_i, m_{it}) = u_t - \tau^h + \mathbb{E}_\theta \max\{\max_{p_{it}} &\underbrace{\alpha_t(p_{it})[U(\cdot) + \theta_{it} + \beta\mathbb{E}_t[V_{t+1}^b]]}_{\text{Listing success}} \\ &+ \underbrace{(1-\alpha_t(p_{it}))\beta\mathbb{E}_t[V_{t+1}^h(\cdot)]}_{\text{Listing failure}} - \phi, \underbrace{\mathbb{E}_t[\beta V_{t+1}^h(\cdot)]}_{\text{No listing}}\}, \end{aligned} \tag{2}$$

where $\tau^h = \ln\left(\frac{1}{1-\text{property tax}}\right)$.

4.2.1 Seller utility

We assume the seller utility function includes reference dependence and loss aversion, and set:

$$U(p_{it}, r_i, m_i) = p_{it} + \underbrace{W(p_{it}, r_i)}_{\substack{\text{Reference}\\\text{dependence}}} - \underbrace{\mu(\gamma - (p_{it} - m_i))_+^2}_{\substack{\text{Downsizing}\\\text{penalty}}}, \tag{3}$$

where:

$$W(p_{it}, r_i) = \begin{cases} \eta(p_{it} - r_i), & \text{if } p_{it} \geq r_i, \\ \lambda\eta(p_{it} - r_i), & \text{if } p_{it} < r_i. \end{cases} \tag{4}$$

The function $W(\cdot)$ describes reference dependent ($\eta > 0$) and loss averse ($\lambda > 1$) preferences. We also include a convex downsizing penalty as mentioned above, motivated by Stein (1995) and Andersen et al. (2022). If the seller's home equity is lower than the exogenously set threshold γ, they expect to face additional costs to finance another house of similar size or quality after selling their home. Therefore, they dislike the prospect of selling at a price that reduces home equity beneath the threshold, because that would require either painful down-sizing if they cannot acquire financing, or costly financing to bridge the gap.

4.2.2 Homeowners' extensive margin decision

Conditional on listing, the maximization problem for the price p produces an optimal price $p_t^*(r, m, \theta)$ for each pair of state variables r and m, and for each draw of θ. The extensive margin decision is governed by a threshold rule, where homeowners list their property for sale if and only if:

$$\alpha_t(p_t^*(r_i, m_{it}, \theta_{it}))\left[U(p_t^*(r_i, m_{it}, \theta_{it}), r_i, m_{it}) + \theta_{it} + \beta\mathbb{E}_t[V_{t+1}^b] - \beta\mathbb{E}_t[V_{t+1}^h(r_i, m_{it})]\right] \geq \phi.$$

This yields a threshold rule for listing:

$$\theta_{it} \geq \frac{\phi}{\alpha_t(p_{it}^*)} - \left[U(p_{it}^*, r_i, m_{it}) + \beta\mathbb{E}_t[V_{t+1}^b] - \beta\mathbb{E}_t[V_{t+1}^h(r_i, m_{it})]\right] = \theta_{it}^*(r_i, m_{it}), \quad (5)$$

where we have denoted $p_{it}^* \equiv p_t^*(r_i, m_{it}, \theta_{it}^*)$. Notice that the equality in (5) is a consistency condition for θ_{it}^*. Together with the optimal price setting condition from the seller's optimization problem these constitute two equations on two unknowns p_{it}^* and θ_{it}^* for each (r_i, m_{it}) pair.

4.3 Mortgage amortization

After a transaction between a seller and a buyer at price R_i, the buyer draws a random mortgage balance $M_{i,t+1} \sim F_M([0, R_i])$ and enters the economy as a homeowner with state $= (\ln R_i, \ln M_{i,t+1}) = (r_i, m_{i,t+1})$. Afterwards, we assume the mortgage loan-to-value ratio (relative to the original purchase price), denoted $\widetilde{m}_{i,t+1}$, reduces deterministically: $\widetilde{m}_{i,t+2} = \widetilde{m}_{i,t+1} - \delta_m$, for a constant δ_m. This implies that the mortgage amortization rate is independent of the original purchase price or issuance LTV.

4.4 Buyers

Each period, buyers search for houses randomly. Upon a meeting with a seller i, buyer j draws an idiosyncratic taste shock $\varepsilon_{jt} \sim F_\varepsilon(\cdot)$, which leads them to accept the asking price and to purchase the property, if and only if:

$$\beta \mathbb{E}_t[V_{t+1}^h(p_{it}, m_{j,t+1})] + \varepsilon_{jt} \geq p_{it} + \tau^b + \beta \mathbb{E}_t[V_{t+1}^b],$$

where V_t^b is the buyer's value function at time t, p_{it} is the log transaction price of the sale (set by the seller i), τ^b is the log of (one plus) the stamp duty tax rate on the purchase, and $m_{j,t+1}$ is the log mortgage amount taken to purchase the property. The transaction price becomes the buyer's reference price as they become a new homeowner upon sale completion.

The buyer's optimal choice is thus also governed by a threshold rule:

$$\varepsilon_{jt} \geq p_{it} + \tau^b + \beta \mathbb{E}_t[V_{t+1}^b] - \beta \mathbb{E}_t[V_{t+1}^h(p_{it}, m_{j,t+1})] \equiv \varepsilon_t^*(p_{it}). \tag{6}$$

Note that the taste shocks and seller and buyer values are measured in units of log price. Therefore, the model implicitly assumes log utility on transaction prices for buyers and sellers.

The buyer's Bellman equation can then be expressed as:

$$V_t^b = \left[1 - \frac{\chi(q_t)}{q_t}\right] \underbrace{\beta \mathbb{E}_t[V_{t+1}^b]}_{\text{Not meeting a seller}} \tag{7}$$

$$+ \frac{\chi(q_t)}{q_t} \int_p \int_{\varepsilon_t^*(p)}^{\infty} \underbrace{\left[\varepsilon + \beta \mathbb{E}_t[V_{t+1}^h(p, m_{t+1})] - p - \tau^b\right]}_{\text{Value of the surplus}} d\Phi_\varepsilon(\varepsilon)\, d\Omega_t(p). \tag{8}$$

where $d\Omega_t(\cdot)$ is the endogenous density of available listing prices.

4.5 Aggregation and model dynamics

We denote the (time-varying) density of homeowners by $f_t(\cdot, \cdot)$ over reference prices r and mortgages m_t. At each (r, m_t) pair, each existing homeowner draws a mobility shock θ_t, they choose whether to list the property for sale, and choose the corresponding asking price $p_t^*(r, m_t, \theta_t)$. These optimal choices induce an endogenous listing price distribution, which we denote by $d\Omega_t(p) = \omega_t(p)\, dp$.

At each reference price r and mortgage balance m_t, we denote the share of existing homeowners who decide to list their property for sale as $1 - F_\theta(\theta_t^*(r, m_t))$; with probability $\alpha_t(p_t^*(r, m_t, \theta))$, sales go through. This is endogenously determined by the number of meetings and the probability of buyers accepting their offers, conditional on a meeting:

$$\alpha_t(p) = \underbrace{\chi(q_t)}_{\substack{\text{Probability that} \\ \text{seller meets a buyer}}} \times \underbrace{[1 - F_\varepsilon(\varepsilon_t^*(p)]}_{\substack{\text{Probability of acceptance} \\ \text{conditional on a meeting}}} . \tag{9}$$

On the other hand, after a successful transaction, the new homeowner draws a random log mortgage balance and enters the economy with reference price r and mortgage balance $m_{t+1} \sim F_m(\cdot)$. The mass of new homeowners with reference price r and mortgage balance m_{t+1} is

$$\underbrace{N_{St}\omega_t(r)}_{\substack{\text{Number of sellers} \\ \text{who list at} \\ \text{price } r}} \times \underbrace{\alpha_t(r)}_{\substack{\text{Probability of} \\ \text{sale conditional} \\ \text{on listing}}} \times \underbrace{f_m(m_{t+1})}_{\substack{\text{Density of new} \\ \text{homeowners with} \\ \text{mortgage } m_{t+1}}} .$$

Taken together, it follows that the law of motion for the homeowner distribution is given by:

$$\begin{aligned} f_{t+1}(r, m_{t+1}) &= \text{Existing homeowners not selling} + \text{New homeowners} \\ &= \underbrace{f_t(r, m_t)}_{\text{Existing homeowners}} \times \underbrace{\left[1 - \int_{\theta_t^*(r,m_t)}^{\infty} \alpha_t(p_t^*(r, m_t, \theta))\, d\Phi_\theta(\theta)\right]}_{\text{Non-sellers and failed sellers}} \\ &\quad + \underbrace{N_{St}\omega_t(r)\alpha(r)f_m(m_{t+1})}_{\text{New homeowners}}, \end{aligned} \tag{10}$$

where $m_{t+1} = \ln(M_{t+1})$ and $M_{t+1} = M_t - R \cdot \delta_m$, i.e., the mortgage is reduced by a constant fraction of the purchase price R.

Finally, we close the model with

$$N_{St} = \int_{r,m} \int_{\theta^*(r,m)}^{\infty} f_\theta(\theta)\, d\theta\, dF_t(r, m), \tag{11}$$

which constitutes a fixed point problem, since the optimal threshold rule for listing depends on aggregate equilibrium outcomes.

4.6 Equilibrium

We specify the distribution of shocks as normal distributions $F_\theta(\cdot) = \Phi(\cdot; \mu_\theta, \sigma_\theta)$ and $F_\varepsilon(\cdot) = \Phi(\cdot; \mu_\varepsilon, \sigma_\varepsilon)$ and consider aggregate valuation shocks

$$u_{t+1} = \bar{u} + \rho_u(u_t - \bar{u}) + \epsilon_{u,t+1}, \tag{12}$$

which affect the value of the house both for buyers and sellers.[13] The valuation shocks encompass consumption and marginal utility, risk premia associated with home ownership (e.g., relative to renting, which is unmodeled), and shocks to inflation, which directly affect the nominal house value.

Definition. An equilibrium consists of:

- buyer and seller value functions $V_t^b, V_t^h(r, m)$ defined through the Bellman equations (7) and (2), respectively;
- buyer policy function $\varepsilon_t^*(p)$ satisfying (6);
- seller price setting policy $p_t^*(r, m, \theta)$, which solves the seller's price setting problem, and extensive margin policy function $\theta_t^*(r, m)$, which solves (5);
- aggregate transaction probability $\alpha_t(p)$ satisfying (9);
- distribution of reference prices and mortgage balances $F_t(r, m)$, whose law of motion satisfies (10);
- distribution of listing prices $\Omega_t(p)$, which arises endogenously from the sellers' extensive and intensive margin decisions;
- market tightness q_t satisfying (11); and
- all agents' rational expectations that u_t evolves according to (12).

[13] In future versions of the paper, we will also consider aggregate taste shocks

$$\mu_{\varepsilon,t+1} = \bar{\mu}_\varepsilon + \rho_\varepsilon(\mu_{\varepsilon,t} - \bar{\mu}_\varepsilon) + \epsilon_{\varepsilon,t+1}, \tag{13}$$

which can be considered demand shifters and aggregate mobility shocks

$$\mu_{\theta,t+1} = \bar{\mu}_\theta + \rho_\theta(\mu_{\theta,t} - \bar{\mu}_\theta) + \epsilon_{\theta,t+1}, \tag{14}$$

which correspond to supply shifters.

4.7 Model features

4.7.1 Endogenous disagreement

The value of a property for a homeowner is $V_t^h(r, m)$. This consists of the utility flow u from owning the property and the option value associated with good outside opportunities θ.

When a buyer considers buying a property, they compare the price p_{it} to the expected property value $\beta\mathbb{E}_t[V_{t+1}^h(p_{it}, m_{t+1})]$ and their idiosyncratic taste ε_{jt} for the property. The seller in turn considers the price p_{it} they receive, their value $\beta\mathbb{E}_t[V_{t+1}^h(r_i, m_{it})]$ for keeping the property, and their idiosyncratic mobility shock θ_{it}.

Apart from idiosyncratic buyer taste ε_{jt} and seller outside option θ_{it}, the trade-offs the buyer and seller face are between the price p_{it} and the buyer and seller property valuations $\beta\mathbb{E}_t[V_{t+1}^h(p_{it}, m_{t+1})]$ and $\beta\mathbb{E}_t[V_{t+1}^h(r_i, m_{it})]$, respectively. This difference in the property valuations between the buyer and the seller generates disagreement in terms of what constitutes property "fair value". In other words, there is no mutually agreed fair price for the property. Despite this gap between WTA and WTP, the buyer's individual taste and the seller's outside option can facilitate trade; i.e., the gap between the property valuations is closed by the individual circumstances of the agents. Put differently, the seller may be willing to accept a lower price because of a good outside option, or the buyer may accept a higher price due to their idiosyncratic taste for the particular property even if they consider it to be overpriced.

In the empirical tests of the model predictions in section 5, we define *listing premium* in the model as the difference of the listing price and *average* transaction price without taking a stance on the "fair value". In the data, this corresponds to interpreting the hedonic valuation as an average price for the particular property with given hedonic characteristics.[14]

4.7.2 Rational behavioralism

The difference of opinion stems from two sources. On the one hand, sellers' valuations depend on their reference prices, which are unique to each seller. On the other hand, buyers understand that whatever price p they pay for the property will become their

[14] In the model all properties are considered identical, whereas in the data the properties have heterogeneous hedonic characteristics. In our empirical tests, we construct price indices using the time fixed-effects from the hedonic model. These can be considered as average valuations cleaned of heterogeneity in property characteristics.

reference point. This will affect their future sales behavior, should they ever want or need to sell the property. In other words, when paying a high price, the buyer understands that it will be challenging to sell the property at that price later, and they incorporate this prospect in their decisions *ex-ante*. Thus, buyers anticipate their future reference-dependent behavior and discount future outside options (i.e., mobility shocks θ) accordingly.

When facing a positive demand shock that drives prices upwards, sellers have better prospects on the market but they also anticipate the need to pay higher prices when they become buyers in the future. Therefore, the quantitative effect of a positive demand shock depends on the relative magnitude of each of these forces. Given that purchasing a property is always the buyer's free choice, and a seller is never forced to buy another property in the future, we expect sellers to respond positively to positive demand shocks. However, the quantitative effect is reduced by their expectations of higher purchase prices in the future. In case of a negative shock, the response is also asymmetric since, due to loss aversion, sellers dislike the nominal losses from selling the property more than they like the prospect of buying cheap in the future. In conclusion, all agents in the model have rational expectations, and the behavioral component is only due to the preference structure that we assume, a situation that we label as *rational behavioralism*.

4.7.3 Implicit bargaining

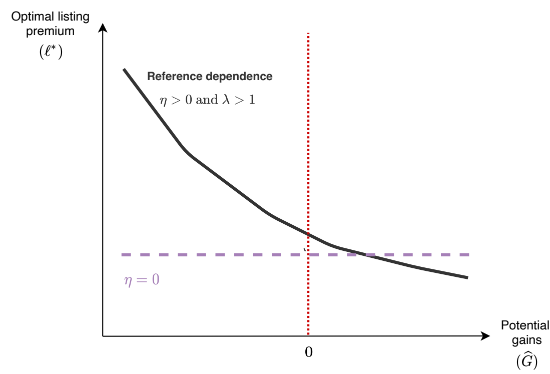
In terms of realized sales prices, the model assumes that sellers have all the bargaining power, through take-it-or-leave-it offers. However, this does not necessarily imply the absence of price negotiation, but rather that sellers can fully anticipate the result of any such negotiation and set prices accordingly. Buyers exercise their market power in terms of the extensive margin of accepting a seller's offer, as opposed to the intensive margin of bargaining over the final prices.

Moreover, while the model does not consider an endogenous bargaining process explicitly, we note that the sellers' listing prices depend on their outside options: the optimal price is a function of θ_{it} as $p^*_t = p^*(r_i, m_{it}, \theta_{it})$. Sellers with good outside options set lower prices, since the opportunity cost of being unable to sell is higher than for those sellers with a relatively poorer outside option.

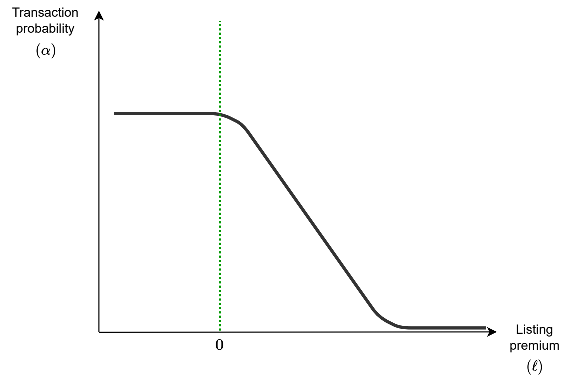
5 From Micro to Macro: Model vs. Data

5.1 Positive price-volume correlation

In this section, we develop a set of stylized predictions from the model solution and discuss empirical tests that validate these predictions in the data. First, consider the optimal pricing strategy of the seller, which is given by a non-linear pricing schedule that depends on the location of the reference point. A higher accumulated potential gain makes the seller list for a lower price, in an attempt to attract more buyers and ensure that this gain will be realized. This generates a negative slope between the listing price premium over hedonic value, and the level of the potential gain. On the other side, if the property value appreciation since purchase is small or negative, loss-averse sellers want to avoid the possibility of realizing a loss, so they have an incentive to "fish" for higher prices. The diagram below summarizes this behavior, and shows that the model-predicted optimal listing premium matches the shape observed in the data only when sellers are both reference dependent and loss-averse:



Consider now the effect of a positive valuation shock (i.e., a positive shock in ϵ_u), which increases property values relative to all reference points. This leads all sellers to be less "aggressive", i.e., to list with lower listing premia, prioritizing lower times on the market. These decisions have effects on buyers' behavior in the model, as summarized in the diagram below, which also matches the shape of the relationship between transaction probabilities and listing prices observed in the data:



Lower listing premia lead to increases in buyers' likelihood of accepting sellers' offers; this in turn generates a higher number of transactions.

This mechanism generates an observed positive correlation between aggregate prices and realized transaction volumes. We test this prediction in the data at the level of ITL2 regions of the U.K. and states of the U.S. at the monthly frequency, for the period between January 2010 and December 2022. For the U.K., we construct a price growth series using the location $\times$ month fixed effects from the hedonic pricing model in equation (1), and compute the corresponding number of transactions from HM Land Registry for each month and location. For the U.S., we use the median transaction price and the reported number of residential property sales in each state and month. For each location-month observation, we express the volume series as a relative deviation to the location-specific mean, and price growth as a relative percent difference to the location-specific mean.

Using these data, Figure 4 shows a robust positive price-volume relationship in both markets. The estimated magnitude of the co-movement is economically very significant, with an 8% location-month-specific price increase associated with a 20% increase in corresponding location-month-specific transaction volume in the U.S. In the U.K., an 8% price decrease is associated with a corresponding 30% drop. Interestingly, the price–volume correlation is highly asymmetric in both locations, but more so in the U.K.

To more precisely quantify the size of the co-movement, we estimate the following panel regression:

$$\ln V_{i,t} = \gamma_i + \beta_P \Delta \ln P_{i,t} + \varepsilon_{i,t}, \tag{15}$$

where $V_{i,t}$ is the normalized number of transactions, $\Delta \ln P_{i,t}$ is the year-over-year growth rate of log prices in location i and month t, and γ_i is a location-specific fixed effect. The second and third columns in Table 1 confirm the presence of an economically high and statistically significant positive co-movement between transaction volumes and price growth in both countries. We now turn to analyzing the link between this effect and the distributions of reference points in the model and the data.

5.2 Distribution of reference points

The non-linearity of the listing premium along the dimension of potential gains implies that the strength of the mechanism described above depends on the aggregate distribution of reference prices at each point in time. For example, in one limiting case in which the housing market has appreciated substantially and consistently over a number of periods, all homeowners will have positive nominal gains, the slope of the listing premium will be relatively flat, and the response of volumes to a price shock will be negligible. In contrast, when house values have declined, homeowners face the possibility of realizing losses and the listing premium slope will be very steep, meaning that a change in value can lead to a dramatic adjustment of listing prices, and significant variation in observed transaction volumes. Thus, a central prediction of the model is that the share of sellers who face nominal losses is a key aggregate statistic to explain the overall response of transaction volumes to valuation shocks.

To evaluate this in the data, in Figure 5 we calculate the share of sellers with nominal losses in each month in each ITL2 region of the U.K. We then compare the price-volume relationship in region-months where the share of nominal losses lie above the in-sample mean ("High" in the plot's legend), with those region-months where the share of nominal losses lies below the in-sample mean ("Low" in the plot's legend). We lag the classification of region-months by one month relative to the time at which we measure price growth and volumes to avoid any mechanical correlation. The figure shows, consistent with the model prediction, that the elasticity of volumes to prices is much more pronounced when the share of homeowners facing nominal losses is high, and much more muted when a relatively lower fraction of the population faces nominal losses relative to historical reference points.

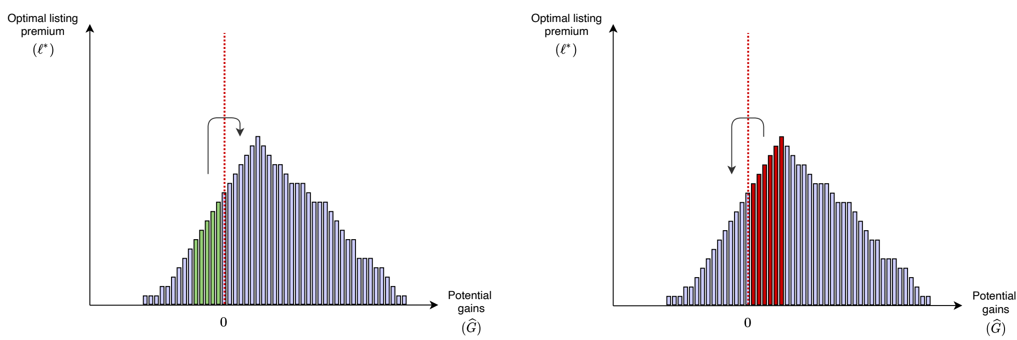
For more granularity on this result, in Panel A of Figure 6 we estimate the price–volume relationship in equation (15) for each ITL2 region separately:

$$\ln V_{i,t} = \gamma_i + \beta_{i,P} \Delta \ln P_{i,t} + \varepsilon_{i,t}, \tag{16}$$

and plot the estimated location-specific coefficients $\beta_{i,P}$ against the average share of properties that face nominal losses in that region. The plot shows a positive association, with a univariate $R^2 = 0.30$. We interpret this as further suggestive evidence for the aggregate implications of behavioral lock-in, as the elasticity of volumes with respect to price growth rates is more pronounced in regions where a large number of prospective house sellers face nominal losses.

5.3 Asymmetric responses and path dependence

While the size of the volume response depends on the mass of homeowners affected by a change in property values, it also depends on the *direction* of the change. The diagram below illustrates this phenomenon, under the assumption that housing prices are generally on an upwards trend, and a relatively larger share of the property stock has appreciated since the initial purchase. In this case, a shock leading to a value increase will trigger a volume response primarily because owners that would have seen a modest nominal loss now see a nominal gain, and are more likely to realize a sale. But this response is more muted than that corresponding to a situation where values decrease, which is triggered by owners that see a potential gain turning into a potential loss—simply because the mass of the latter group of owners is larger than the mass of the former.



More generally, the implication of the model is that after a prolonged period of house price appreciation, the market responds more strongly to a price decrease than to a price increase, because there is more mass in the positive than the negative nominal gain domain; while after a prolonged period of house price depreciation, the market responds more strongly to a price increase, because this triggers a nonlinear adjustment for a larger share of the housing stock.

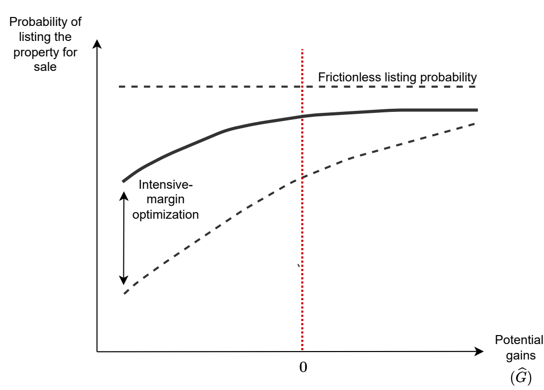
Given the asymmetry in the utility function from loss aversion and the mortgage constraint, the model predicts that positive and negative shocks affecting house values induce asymmetric volume responses. The results reported in Figure 5 are consistent with this prediction.

Overall, the path dependence described above is an important feature of our model. A positive valuation shock which increases both prices and volumes leads more owners to reset their reference point to a high level. An eventual negative valuation shock then has a larger impact than in the initial state. Reference dependence therefore generates significant non-linearity in housing market liquidity: The more unusual a "hot market" episode with high liquidity and high prices, the higher the number of owners that lock into a reference point that has a high level, and the deeper the fall in liquidity if valuations later decrease. In terms of policy interventions, the model implies that the transmission of monetary policy to the housing market, for example, will depend to a critical degree on the (recent) history of transactions, with the key conditioning variable being the distribution of reference points prevailing at the time when a policy intervention is rolled out.

5.4 Extensive vs. intensive margin

The effects described above occur along the intensive margin, i.e., they are driven by sellers' listing price strategy and buyers WTP when encountering property sale listings. In parallel to these responses, the model implies that changes in valuation also have an impact on the extensive margin, i.e., when faced with the possibility of realizing a loss, homeowners also have a lower incentive to list the property for sale.

The response of listing volumes is more muted because it is partially absorbed by the optimal choice of the listing premium, as the following diagram illustrates:



The degree to which this absorption occurs depends on the cost associated with listing (ϕ in the model). If putting a property up for sale incurs a zero cost, all homeowners with a positive realization of the moving shock (θ) list their properties for sale, and the magnitude of the potential gain just determines how aggressive the "fishing" strategy is. In contrast, when listing costs are very high, e.g., because of estate agent fees, hassle factors, lengthy negotiations with prospective buyers, or multiple property inspections that are physically invasive, listing only occurs when it is clearly worth paying the high transaction cost; and conditional on listing, sellers are much more conservative, prioritizing a low listing premium and a quick sale.

In column 1 of Table 1, we report the elasticity of listing volumes (i.e., the extensive margin) to year-on-year price growth rates in the U.K. This is small in comparison to the elasticity of transaction volumes conditional on listing to price growth rates shown in column 2 of the table. This result is in accordance with the model, suggesting that the majority of the price-volume relation comes from faster turnover of already listed properties in response to price growth shocks, whereas the response of listing volumes is more muted. Put differently, the intensive margin appears to be the dominant channel through which price-volume correlation arises, while the listing volume response is relatively flat across different levels of price shocks.

To explore this further, Panel B of Figure 6 considers the role of extensive and intensive margins in explaining the price–volume relationship within each ITL2 region. The figure shows that the cross-sectional variation in the conversion rate of sales listings to actual transactions explains most of the variation in the elasticity of volumes to price changes across regions.

5.5 Quantities absorb price impact

Next, consider the response of the market to a negative shock to the value of the property. This opens a gap between the buyers' willingness-to-pay and the loss-averse sellers' willingness-to-accept (again, as a consequence of the latter group's "fishing" behavior). Since sellers have the option to defer the transaction and only sell to willing buyers, the realized price distribution will be truncated and only reflect transactions where relatively higher prices have been achieved. Prices therefore decrease by less than they would in a situation where sellers are not reference-dependent, and volumes decrease by more, absorbing part of the effect of the valuation shock. More generally, for the case of both positive and negative exogenous variation in fundamental quantities, the model predicts that the more the behavioral lock-in motive is operative, the larger the volatility of volumes, and, all else equal, the lower the volatility of prices.

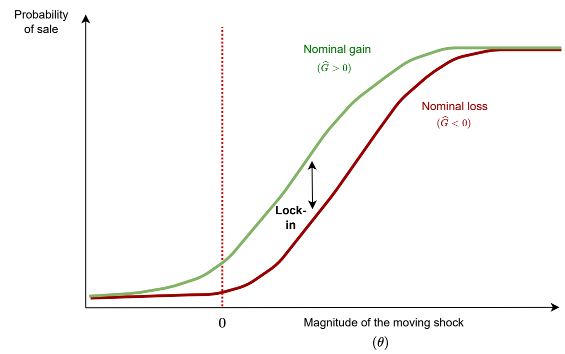
Thus, our model with reference dependence predicts that in regions with a higher loss share volumes respond more and prices respond less to fundamental economic shocks. For example, when regions with high nominal loss shares face negative demand shocks, the model predicts that many sellers will be unwilling to reduce prices, which in the data should show up as a dampened price response; correspondingly, the volume response will be amplified.

To check this, Figure 7 reports the time-series variance of volumes and price growth rates across ITL2 regions, plotted against the regional share of potential nominal losses. The cross-sectional correlation of potential losses with these variances aligns with our theory's predictions. In regions where the potential loss share is high, the volume response is amplified, reflected in a high observed time series volatility of volumes.

5.6 Real effects of nominal shocks

The analysis has thus far focused on model quantities that are observable in the data. But the benefit of the model is that it also allows us to quantify the response to unobservable factors. One important factor of this type is the moving opportunity shock θ. The model predicts that reference-dependent sellers that face the possibility of realizing nominal losses on selling their homes will change their response to positive opportunity shocks. More specifically, reference dependence and loss aversion will make these sellers act in such a way as to lower the probability that sale transactions will successfully complete, and therefore potentially miss out on valuable moving opportunities.

To summarize, the model predicts that the nominal gain/loss situation of the owner will affect their mobility. The diagram below uses the calibrated version of the model to illustrate this effect:



We calculate the average probability of sale implied by the model, for different realizations of θ. Sellers in the nominal gain domain are generally more likely to move, but the impact is asymmetric, and most pronounced when the magnitude of the moving opportunity is in an intermediate range.

For low values of θ, the moving probability is low, irrespective of the position of the reference point, because the gains from moving are low. At the opposite end of the distribution, for sufficiently high values of θ, owners have a strong incentive to realize sales regardless of the behavioral motive, meaning that the marginal impact of reference dependence is minimal in this region as well. It is the sellers who face values of θ in an intermediate range that are most likely to fail to realize a sale when facing a nominal loss on selling—they become behaviorally locked in, and reject moving opportunities that would otherwise be valuable. This channel is separate and distinct from both home equity lock-in a la Bernstein and Struyven (2022) and interest-rate lock-in a la Fonseca and Liu (2023).[15]

A related implication is that changes in property valuations accompanying fluctuating rates of consumer price inflation can lead homeowners to more readily accept or reject moving opportunities (such as. e.g., job offers from other locations), depending on their nominal gain/loss situation. Since labor mobility is a material driver of the level of unemployment (Head and Lloyd-Ellis, 2012), this generates a link between inflation and the real economy resembling a Phillips-curve relationship, which emerges in the absence of any other source of real rigidity.

[15] The U.K. mortgage market is dominated by short fixation period ARM instruments (Badarinza et al., 2018), meaning that the interest-rate lock-in channel is less operative in this market. Despite this, there is a strong similarity in the relationship between prices and volumes between the two markets.

5.7 Location as an asset

Finally, we note that the value $V_t^h(r, m)$ of a house from the perspective of the homeowner includes the expectation of receiving high outside options in the future. From the buyers' perspective, these options are available only if a property is purchased. Therefore, we can interpret the choice of a property as the choice of a city/location with good outside options, similar to Bilal and Rossi-Hansberg (2021). Conversely, sellers understand that selling their property could lead to utility gains through improved potential future matching outcomes, captured by the shock ε.

6 Conclusions

Careful experiments have documented the presence of reference dependence and loss aversion in a wide variety of settings and countries. But do such non-standard formulations of preferences generate observable behavioral biases in actual field settings with real stakes? A large strand of current literature confirms that this is the case—from marathon running, to job search, the filing of income taxes, and financial investment (Ingersoll and Jin, 2013; Kleven, 2016; Allen et al., 2017; DellaVigna et al., 2017; Rees-Jones, 2018).

Do these individual biases also have a material impact on economic outcomes at aggregate level? We explore this question in the market for residential real estate, which is the largest asset for most households. Using large and granular data that cover the entire U.K. housing market, we first document empirical evidence that is strongly consistent with reference dependent preferences affecting the house selling decision, in line with previous findings by Andersen et al. (2022) for Denmark.

Embedding reference dependence in a dynamic equilibrium model of the housing market with search and matching frictions and financial constraints, we derive a range of predictions which we verify in the data. Consistent with the model, we find that the distribution of nominal reference points in the population is tightly linked to the dynamics of aggregate quantities. We show that (i) prices and transaction volumes co-move positively, (ii) the co-movement is asymmetric, and more pronounced when property values are decreasing, (iii) a simple statistic to characterize the magnitude of aggregate effects is given by the share of the population that faces the possibility of realizing a nominal loss, and (iv) the volatility of housing transaction volumes is substantially more pronounced in regions where higher share of sellers face a nominal loss and the behavioral preferences are thus more operative.

The model has two additional important implications. The first is that nominal shocks affect real outcomes, as homeowners' moving decisions are directly impacted by their anticipated gains or losses relative to their reference points. The second is that higher property valuations lead new homeowners to set their reference points to high levels, making the housing market more fragile and vulnerable to potential future downturns.

How do these mechanisms affect the design of public policy? In the next version of the paper, we plan to understand the appropriate design of housing taxation policies in a housing market populated with behavioral agents, and to understand the impacts of inflation on mobility in this economy. To do so, we will estimate the parameters of the model to match micro-level facts, and to extract structural shocks from the observed historical paths of prices and transaction volumes. This will allow us to evaluate the effects of counterfactual fiscal and monetary policies.

References

Ahn, SeHyoun, Greg Kaplan, Benjamin Moll, Thomas Winberry, and Christian Wolf, "When inequality matters for macro and macro matters for inequality," *NBER macroeconomics annual*, 2018, *32* (1), 1–75.

Allcott, Hunt, Benjamin B Lockwood, and Dmitry Taubinsky, "Regressive sin taxes, with an application to the optimal soda tax," *The Quarterly Journal of Economics*, 2019, *134* (3), 1557–1626.

Allen, Eric J, Patricia M Dechow, Devin G Pope, and George Wu, "Reference-dependent preferences: Evidence from marathon runners," *Management Science*, 2017, *63* (6), 1657–1672.

Allen, Jason, Robert Clark, and Jean-François Houde, "Search frictions and market power in negotiated-price markets," *Journal of Political Economy*, 2019, *127* (4), 1550–1598.

Anagol, Santosh, Benjamin B Lockwood, Allan Davids, and Tarun Ramadorai, "Diffuse Bunching with Frictions: Theory and Estimation," Technical Report, Working Paper 2022.

Andersen, Steffen, Cristian Badarinza, Lu Liu, Julie Marx, and Tarun Ramadorai, "Reference dependence in the housing market," *American Economic Review*, 2022, *112*, 3398–3440.

Anenberg, Elliot and Daniel Ringo, "The propagation of demand shocks through housing markets," *American Economic Journal: Macroeconomics*, 2022, *14* (3), 481–507.

_ **and Patrick Bayer**, "Endogenous Sources Of Volatility In Housing Markets: The Joint Buyer–Seller Problem," *International Economic Review*, 2020, *61* (3), 1195–1228.

Badarinza, Cristian, John Y Campbell, and Tarun Ramadorai, "What calls to ARMs? International evidence on interest rates and the choice of adjustable-rate mortgages," *Management Science*, 2018, *64* (5), 2275–2288.

Barberis, Nicholas and Wei Xiong, "Realization utility," *Journal of Financial Economics*, 2012, *104* (2), 251–271.

Bernstein, Asaf and Daan Struyven, "Housing lock: Dutch evidence on the impact of negative home equity on household mobility," *American Economic Journal: Economic Policy*, 2022, *14* (3), 1–32.

Bilal, Adrien and Esteban Rossi-Hansberg, "Location as an Asset," *Econometrica*, 2021, *89* (5), 2459–2495.

Bracke, Philippe and Silvana Tenreyro, "History dependence in the housing market," *American Economic Journal: Macroeconomics*, 2021, *13* (2), 420–443.

Burdett, Kenneth and Kenneth L Judd, "Equilibrium price dispersion," *Econometrica: Journal of the Econometric Society*, 1983, pp. 955–969.

Campbell, John Y, "Household finance," *The journal of finance*, 2006, *61* (4), 1553–1604.

Chetty, Raj, "Behavioral economics and public policy: A pragmatic perspective," *American Economic Review*, 2015, *105* (5), 1–33.

DellaVigna, Stefano, Attila Lindner, Balázs Reizer, and Johannes F Schmieder, "Reference-dependent job search: Evidence from Hungary," *The Quarterly Journal of Economics*, 2017, *132* (4), 1969–2018.

Diamond, Peter A, *A search-equilibrium approach to the micro foundations of macroeconomics*, Vol. 1982, MIT press, 1984.

Diaz, Antonia and Belén Jerez, "House prices, sales, and time on the market: A search-theoretic framework," *International Economic Review*, 2013, *54* (3), 837–872.

Farhi, Emmanuel and Xavier Gabaix, "Optimal taxation with behavioral agents," *American Economic Review*, 2020, *110* (1), 298–336.

Fisher, Jack, Alessandro Gavazza, Lu Liu, Tarun Ramadorai, and Jagdish Tripathy, "Refinancing cross-subsidies in the mortgage market," Technical Report, Working Paper 2023.

Fonseca, Julia and Lu Liu, "Mortgage Lock-In, Mobility, and Labor Reallocation," Technical Report, Working Paper 2023.

Gabaix, Xavier, "A behavioral New Keynesian model," *American Economic Review*, 2020, *110* (8), 2271–2327.

Genesove, David and Christopher Mayer, "Loss aversion and seller behavior: Evidence from the housing market," *The quarterly journal of economics*, 2001, *116* (4), 1233–1260.

_ **and Lu Han**, "Search and matching in the housing market," *Journal of Urban Economics*, 2012, *72* (1), 31–45.

Goetzmann, William N, Christophe Spaenjers, and Stijn Van Nieuwerburgh, "Real and private-value assets," *The Review of Financial Studies*, 2021, *34* (8), 3497–3526.

Gomes, Francisco, Michael Haliassos, and Tarun Ramadorai, "Household finance," *Journal of Economic Literature*, 2021, *59* (3), 919–1000.

Grindaker, Morten, Artashes Karapetyan, Espen Moen, and Plamen Nenov, "Transaction Sequence Decisions and Housing Market Volatility: Evidence from Norway," Technical Report 2021.

Guren, Adam M, "House price momentum and strategic complementarity," *Journal of Political Economy*, 2018, *126* (3), 1172–1218.

Han, Lu and William C Strange, "The microstructure of housing markets: Search, bargaining, and brokerage," *Handbook of regional and urban economics*, 2015, *5*, 813–886.

Head, Allen and Huw Lloyd-Ellis, "Housing liquidity, mobility, and the labour market," *Review of Economic Studies*, 2012, *79* (4), 1559–1589.

Huckfeldt, Christopher, "Understanding the scarring effect of recessions," *American Economic Review*, 2022, *112* (4), 1273–1310.

Hyvärinen, Aapo, "Estimation of Non-Normalized Statistical Models by Score Matching," *J. Mach. Learn. Res.*, dec 2005, *6*, 695–709.

Ingersoll, Jonathan E and Lawrence J Jin, "Realization utility with reference-dependent preferences," *The Review of Financial Studies*, 2013, *26* (3), 723–767.

Kaplan, Greg and Giovanni L Violante, "A model of the consumption response to fiscal stimulus payments," *Econometrica*, 2014, *82* (4), 1199–1239.

_ **, Benjamin Moll, and Giovanni L Violante**, "Monetary policy according to HANK," *American Economic Review*, 2018, *108* (3), 697–743.

Kleven, Henrik Jacobsen, "Bunching," *Annual Review of Economics*, 2016, *8*, 435–464.

Krainer, John, "A theory of liquidity in residential real estate markets," *Journal of Urban Economics*, 2001, *49* (1), 32–53.

Krusell, Per and Anthony A Smith Jr, "Income and wealth heterogeneity in the macroeconomy," *Journal of Political Economy*, 1998, *106* (5), 867–896.

Laibson, David, Peter Maxted, and Benjamin Moll, "Present bias amplifies the household balance-sheet channels of macroeconomic policy," Technical Report, National Bureau of Economic Research 2021.

Liu, Lu, "The demand for long-term mortgage contracts and the role of collateral," Technical Report, Working Paper 2022.

Lucas, Robert E Jr., "Macroeconomic priorities," *American economic review*, 2003, *93* (1), 1–14.

Maxted, Peter, "A macro-finance model with sentiment," *Review of Economic Studies*, 2023, p. rdad023.

Merlo, Antonio and Francois Ortalo-Magne, "Bargaining over residential real estate: evidence from England," *Journal of Urban Economics*, 2004, *56* (2), 192–216.

Moen, Espen R, Plamen T Nenov, and Florian Sniekers, "Buying first or selling first in housing markets," *Journal of the European Economic Association*, 2021, *19* (1), 38–81.

Mullainathan, Sendhil, Joshua Schwartzstein, and William J Congdon, "A reduced-form approach to behavioral public finance," *Annu. Rev. Econ.*, 2012, *4* (1), 511–540.

Ngai, L Rachel and Silvana Tenreyro, "Hot and cold seasons in the housing market," *American Economic Review*, 2014, *104* (12), 3991–4026.

Rees-Jones, Alex, "Quantifying loss-averse tax manipulation," *The Review of Economic Studies*, 2018, *85* (2), 1251–1278.

Stein, Jeremy C, "Prices and trading volume in the housing market: A model with down-payment effects," *The Quarterly Journal of Economics*, 1995, *110* (2), 379–406.

Taubinsky, Dmitry and Alex Rees-Jones, "Attention variation and welfare: theory and evidence from a tax salience experiment," *The Review of Economic Studies*, 2018, *85* (4), 2462–2496.

Wheaton, William C, "Vacancy, search, and prices in a housing market matching model," *Journal of Political Economy*, 1990, *98* (6), 1270–1292.

Winberry, Thomas, "A method for solving and estimating heterogeneous agent macro models," *Quantitative Economics*, 2018, *9* (3), 1123–1151.

Figure 1

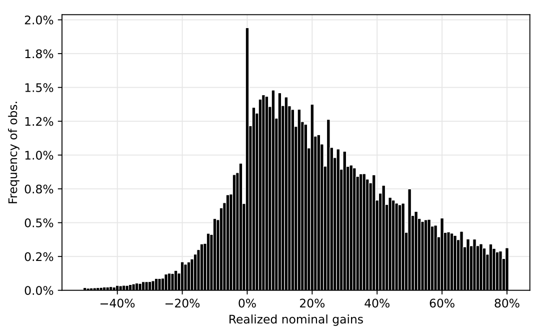
Reference dependence and loss aversion

Plot (i) reports the distribution of differences between the realized price in a given sale transaction and the price for which the property has been initially purchased (the nominal realized gain). Plot (ii) reports the difference between this distribution and a counterfactual version of it, obtained under the assumption that all transactions occur at the estimated hedonic value (excess mass). Panel B calculates the total relative excess mass for nominal gains between 0% and 20% for each ITL2 region separately, and plots this quantity against the average share of owners for which the hedonic property value is below the initial purchase price, i.e., they face a potential loss.

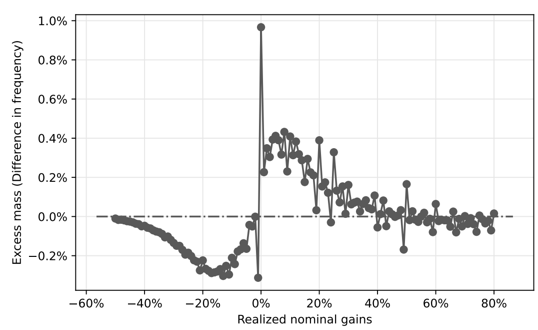
Panel A

Bunching at the nominal reference point

(i) Distribution of transaction prices



(ii) Excess mass



Panel B

Validation of the link between potential gains and realized gains

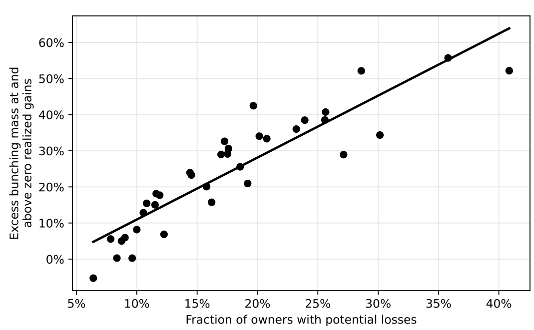
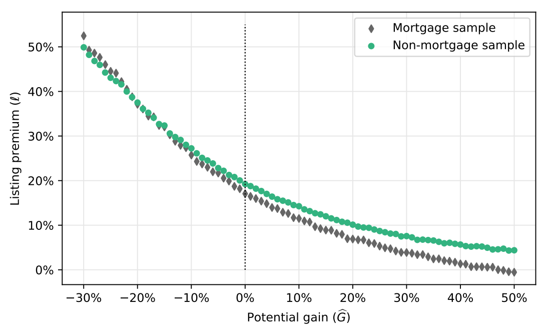


Figure 2
Reference dependence, loss aversion and financial constraints

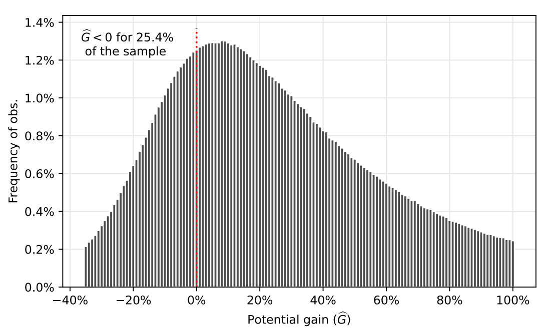
Panel A plots average listing premia, i.e., the percent differences between the listing price and the hedonic property value at the time of listing, for different values of potential gains. We restrict the horizontal axis, for a more convenient graphical representation of effects around zero potential gains. Panel B reports histograms for potential gains, i.e., the percent differences between hedonic property values measured at the time of listing and initial purchase prices, and potential home equity, i.e., the percent differences between hedonic property values and outstanding mortgage amounts.

Panel A
Sellers' listing premium



Panel B
State variables

(i) Potential gains



(ii) Potential home equity

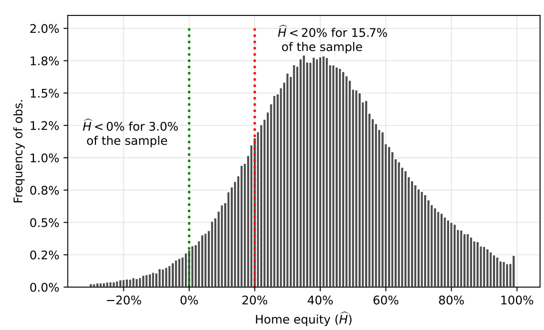
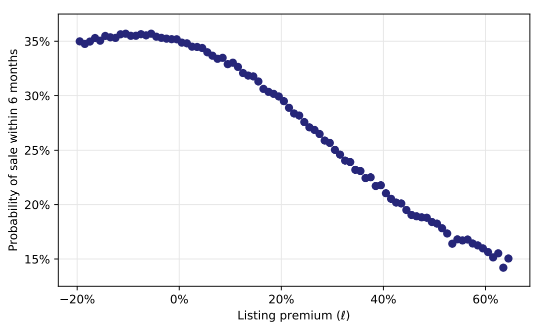


Figure 3
Search and matching outcomes

The figure reports outcomes of the search and matching process, for different levels of the sellers' chosen initial listing premium. Plot (i) shows the average probability that a given listing results in a successful sale within 6 months. Plot (ii) shows the average realized sale price, relative to the estimated hedonic value of the property, i.e., the realized premium.

(i) Transaction probability



(ii) Transaction price

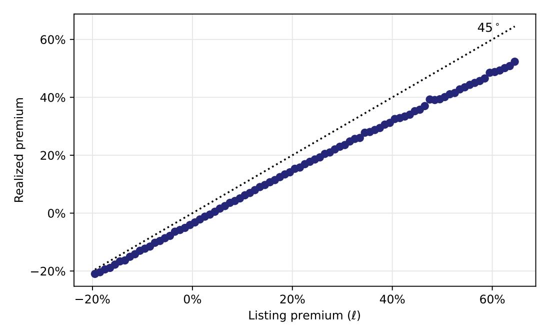


Figure 4
Price-volume correlation

The figure reports the correlation between year-over-year changes in housing prices and the volume of realized transactions. We calculate prices and volumes at the level of ITL2 regions (U.K.) and the level of states (U.S.), respectively; measured at monthly frequency, for the period between January 2010 and December 2022. We express the volume series as a relative deviation to the location-specific mean, and the price growth as a relative percent difference to the location-specific mean. On the horizontal axis, we report price growth rate bins, constructed by rounding to the second decimal, for a domain restricted to [-8%, 8%], for comparability. Online appendix Figure A.4 shows the corresponding frequency distribution. Error bars indicate 95% confidence intervals for bin-specific means.

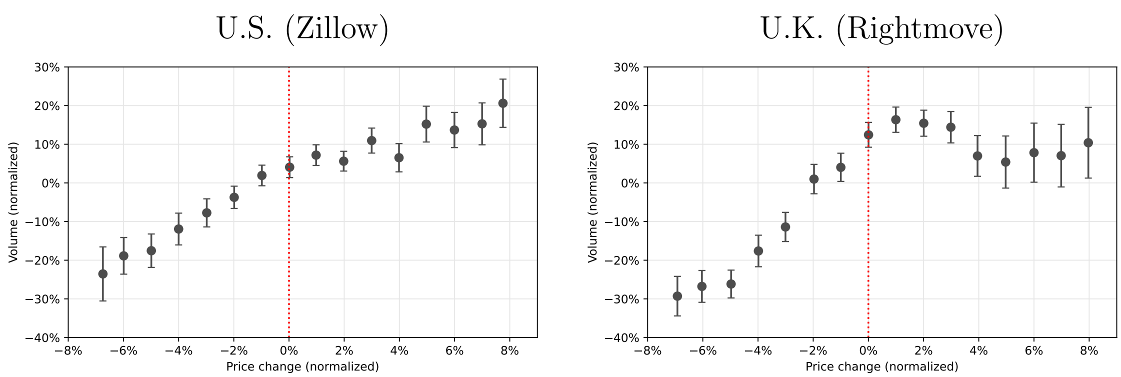
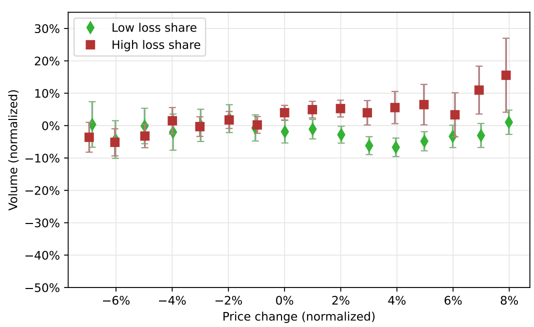


Figure 5

Decomposition of the price-volume correlation

The figure reports the correlation between year-over-year changes in housing prices and the volume of listings (i) and realized transactions (ii). We calculate prices and volumes at the level of ITL2 regions, at monthly frequency, for the period between January 2010 and December 2022. We express the volume series as a relative deviation to the location-specific mean, and the price growth as a relative percent difference to the location-specific mean. We distinguish between periods during which the share of sellers that face the possibility of a loss is below/above the median in the sample ("Low/High loss share"), respectively. Error bars indicate 95% confidence intervals for bin-specific means.

(i) Listing volume



(ii) Transaction volume

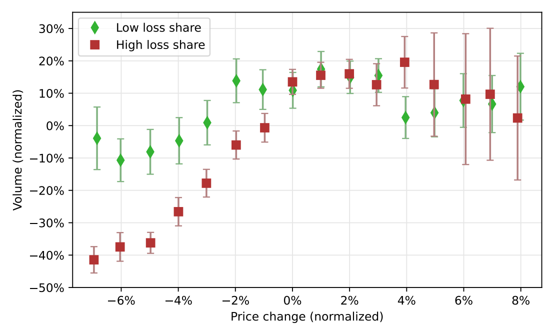


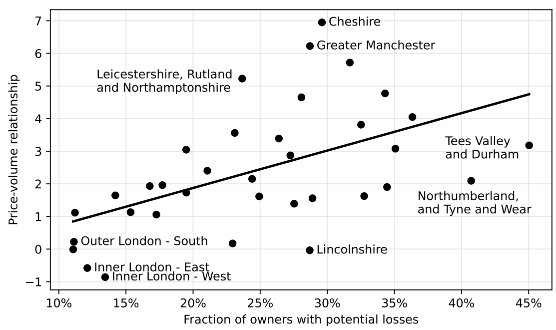
Figure 6

Cross-regional variation in the price-volume relationship

Panel A plots regression coefficients from regressions of the realized transaction volume on the year-on-year price change in each ITL2 region, for the period between January 2010 and December 2022. The horizontal axis indicates the share of owners that list a property for sale, for which the estimated hedonic value of the property is below the initial purchase price. Panel B calculates corresponding region-specific regression coefficients where the dependent variable is, respectively, (i) the listing volume, and (ii) the ratio between the transaction volume and the listing volume, i.e., the transaction probability.

Panel A

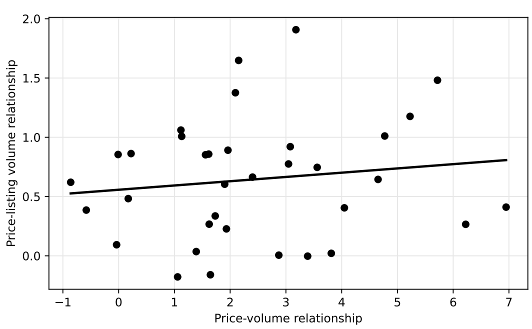
The role of the local loss share



Panel B

Decomposition

(i) Extensive margin:
Listing volume



(ii) Intensive margin:
Transaction probability

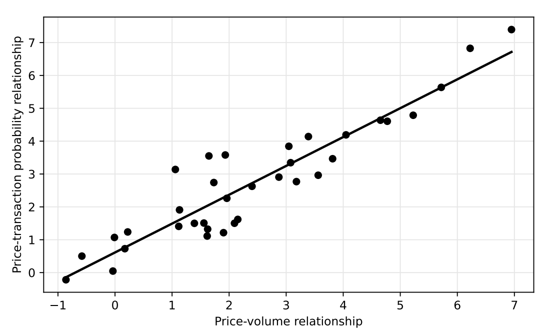
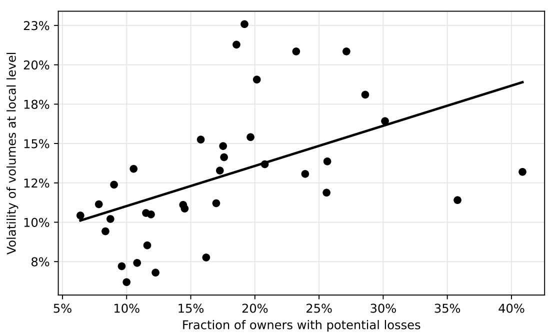


Figure 7
Cross-regional variation in volatilities

The figure reports region-specific volatilities of transaction volumes, measured as the standard deviation of realized sales volume in each ITL2 region over the period between January 2010 and December 2022. The horizontal axis indicates the share of owners that list a property for sale, for which the estimated hedonic value of the property is below the initial purchase price.

(i) Transaction volume



(ii) Transaction price

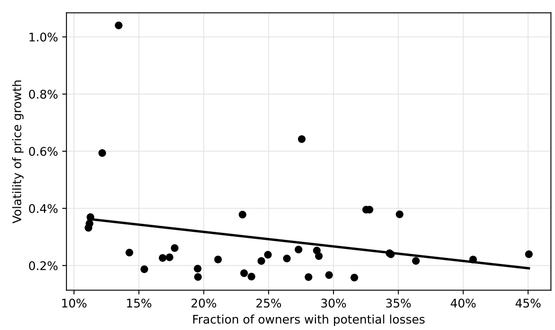


Table 1
Price-volume correlation: International comparison

The table reports estimated coefficients from the following regression specification:

$$\ln V_{it} = \gamma_i + \beta\Delta \ln P_{it} + \varepsilon_{it},$$

where i is an $ITL2$ region, t is a month and Δ is a year-over-year difference operator. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, based on standard errors clustered at the level of ITL2 regions.

	U.K.		U.S.
	Listing volume	Realized volume	Realized volume
Price change (YoY)	0.318***	2.270***	3.072***
	(0.119)	(0.283)	(0.14)
No. of obs.	4,871	4,871	4,752
R^2	0.669	0.301	0.906

Table 2
Listing premia: Conditional "Hockey stick" patterns

The table reports estimated coefficients from the following regression specification:

$$\ell_j = \beta_1 1_{\widehat{G}_j<0}\widehat{G}_j + \beta_2 1_{\widehat{G}_j\geq 0}\widehat{G}_j + \beta_3 1_{\widehat{H}_j<0}\widehat{H}_j + \beta_4 1_{\widehat{H}_j\geq 0}\widehat{H}_j + \epsilon_j,$$

where j indexes an individual listing. We restrict the sample to listings which are successfully merged between the Rightmove listing data, transaction records in the Land Registry, and the Bank of England mortgage balance data. *, **, *** indicate statistical significance at the 10%, 5% and 1% level.

Dependent variable: Listing premium (ℓ)		
Potential gain ($\widehat{G}$)	-0.48***	
	(0.005)	
$\times\ \widehat{G} \leq 0$		-1.081***
		(0.009)
$\times\ \widehat{G} > 0$		-0.357***
		(0.005)
Potential home equity ($\widehat{H}$)	-0.434***	
	(0.007)	
$\times\ \widehat{H} \leq 20\%$		-0.125***
		(0.010)
$\times\ \widehat{H} > 20\%$		-0.098***
		(0.008)
No. of obs.	150,587	150,587
R^2	0.416	0.444

Behavioral Lock-In: Aggregate Effects of Reference Dependence in the Housing Market

Online Appendix

Cristian Badarinza, Tarun Ramadorai,
Juhana Siljander, Jagdish Tripathy

January 9, 2024

A Appendix

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A.1 Additional tables and figures

Figure A.1
Bunching consistently observed across regions

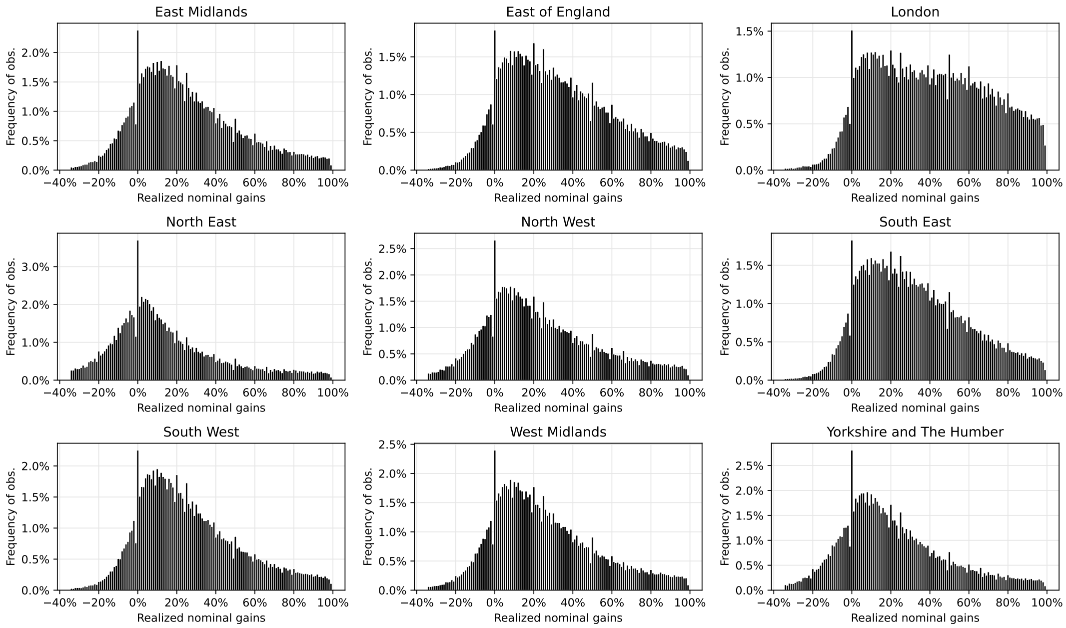


Figure A.2
“Hockey stick” pattern consistently observed across regions

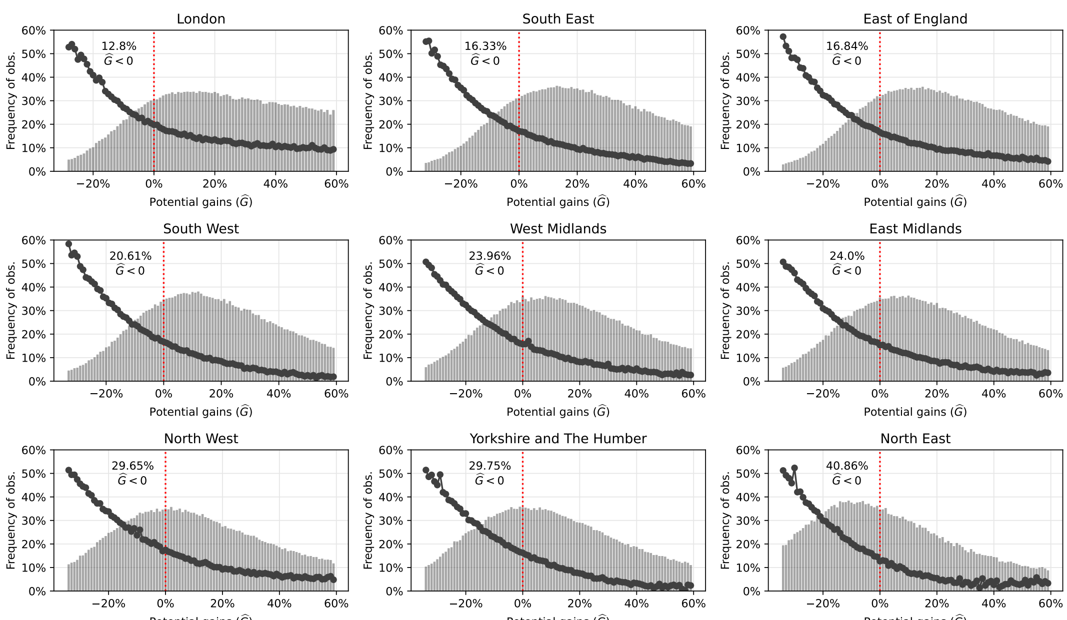


Figure A.3
Actual price vs. hedonic price

The figure illustrates the in-sample fit of our hedonic model. The horizontal axis shows the realized log transaction price, and the vertical axis the predicted log price from the hedonic model. We report a bin-scatter plot based on 20 frequency bins.

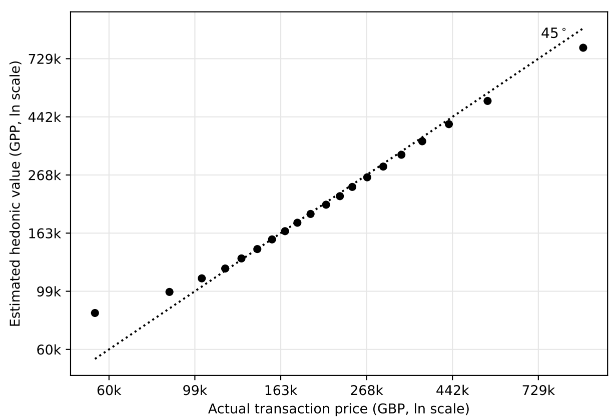


Figure A.4
Price-volume correlation in U.S. data

The figure reports year-over-year changes in housing prices and the correlation with the volume of realized transactions, at the level of U.S. states, for the period between January 2010 and December 2022. We express the volume series as a relative deviation to the location-specific mean, and the price growth as a relative percent difference to the location-specific mean. Error bars indicate 95% confidence intervals for bin-specific means.

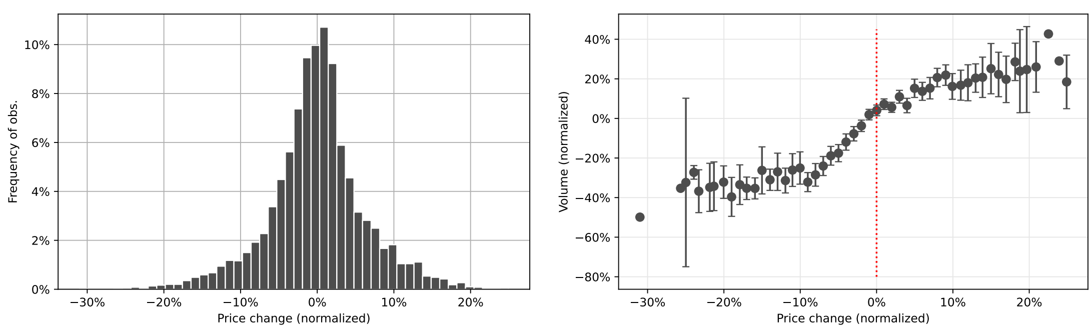


Table A.1
Transactions and listings data: sample description and cleaning, 2010 – 2022

Rightmove listings data		HM Land Registry Price Paid data	
All unique listings	**21,014,152**	**All transactions**	**28,012,267**
		Transactions before 2010	-16,228,143
Ambiguous addresses	-2,019,206	Ambiguous addresses	-964,799
Not in England or Wales	-908,193		
Total	18,086,753		10,819,325
Development prop.	1,130,725		
Non-development prop.	16,956,028		
Listings/transactions match			
Unmatched to a preceding transaction	-10,015,534	Unmatched to a preceding listing	-4,308,913
Development prop.	-1,102,693	Transaction over 365 days after listing archiving	-868,231
Non-development prop.	-8,912,841		
	8,071,219		5,642,181
Development prop.	28,032		
Non-development prop.	8,043,187		
Hedonic sample			
Auction properties	-80,670		-76,766
Transaction within 30 days of first listing	-56,635		
Incomplete hedonic characteristics	-2,141,343		-1,635,494
Final listings data	**5,764,539**	**Hedonic model data**	**3,929,921**

Table A.2
Total number of observations across mortgage-stock snapshots

The table shows the number of observations in the U.K. mortgage stock associated with a property value (column 1), with a unique combination of property value, transaction date and granular postcodes (used to merge to the U.K. land registry, column 2), and with a unique combination of granular postcodes and borrower date of birth (used to track mortgages over snapshots, column 3).

Snapshot	Total	Unique combination for merge	
		with LandReg	across snapshots
2015H1	6,804,852	6,727,027	6,547,065
2015H2	6,903,364	6,819,688	6,625,624
2016H1	6,966,672	6,880,262	6,655,600
2016H2	7,118,232	7,025,876	6,792,460
2017H1	7,195,250	7,098,368	6,854,541
2017H2	7,457,215	7,354,596	7,064,382
2018H1	7,481,944	7,375,001	7,064,379
2018H2	7,517,354	7,410,966	7,052,391
2019H1	7,769,324	7,652,926	7,284,116
2019H2	7,768,736	7,654,581	7,284,871
2020H1	6,897,770	6,811,842	6,485,018
2020H2	8,103,209	7,979,305	7,669,896
2021H1	8,273,139	8,142,959	7,835,923
2021H2	8,121,613	7,990,651	7,649,971
2022H1	8,288,562	8,154,020	7,771,863
2022H2	8,488,874	8,351,212	7,950,613

Table A.3
Summary statistics on listings sample merged with mortgage data

The table shows summary statistics for our listings sample that are merged with the mortgage data based on unique combinations of property value, transaction date and granular postcodes. We further condition the sample to only consider listings that are eventually transacted, and have non-zero home equity close to the listing date.

	mean	sd	p10	p25	p50	p75	p90
Previous price (£)	204,468	138,251	97,000	125,000	170,000	240,000	340,000
Hedonic price (£)	250,533	167,267	110,150	145,200	205,815	302,212	438,074
$\hat{G}$	0.19	0.24	-0.11	0.03	0.18	0.34	0.49
$\hat{H}$	0.42	0.25	0.13	0.27	0.42	0.58	0.74
$\hat{H}$ (Binned)	0.42	0.16	0.21	0.32	0.43	0.53	0.62

Table A.4
Price-volume correlation: intensive vs. extensive margins

The table reports estimated coefficients from the following regression specifications in the Rightmove listings sample:

$$\begin{aligned}\ln(V_t) &= \gamma + \beta P_{\Delta,t} + \varepsilon_t,\\ \ln(L_t) &= \gamma_L + \beta_L P_{\Delta,t} + \varepsilon_{t,V},\\ \ln(V_t/L_t) &= \gamma_{VL} + \beta_{VL} P_{\Delta,t} + \varepsilon_{t,VL},\end{aligned}$$

where t is a month and $P_{\Delta,t}$ is a de-seasonalised year-over-year price growth index in the U.K.. *, **, *** indicate statistical significance at the 10%, 5% and 1% level.

	Transaction volume $\ln(V_t)$ (β)	Supply of listings $\ln(L_t)$ (β_L)	Conversion rate $\ln(V_t/L_t)$ (β_{VL})
Price growth index ($P_{\Delta,t}$)	3.395***	1.321*	2.074***
	(1.053)	(0.745)	(0.635)
Number of obs.	132	132	132
R^2	0.074	0.024	0.076

Table A.5
Summary statistics on mortgages originated in 2015 tracked across snapshots

The table shows summary statistics for mortgages originated in the first half of 2015 (2015H1) that have a non-missing balance in each snapshot until 2022H2. We observe the original loan and subsequent balance in half-yearly snapshots over 7 years for this sample, and use it for the amortization schedule shown in Figure A.6 used to fit the model.

	mean	sd	p10	p25	p50	p75	p90
Original Loan (£)	157,564	128,993	52,813	81,464	127,547	195,725	289,995
Balance (£)	154,386	126,774	51,652	80,008	125,117	191,876	283,556
Interest Rate (%)	2.95	1.06	1.84	2.29	2.79	3.49	4.45
Original Term (months)	471	1,370	156	204	288	360	420
Monthly Payment (£)	766	579	287	429	641	954	1,382
Incentivised ($\mathbb{D}$)	0.94	0.24	1	1	1	1	1

Figure A.5
Initial loan-to-value ratios and costs

The figure reports the distribution of loan-to-value ratios at origination and the mortgage credit interest rate spread paid on 5-year fixed-rate mortgages across loan-to-value bands estimated by Liu (2022) for mortgage contracts issued between 2013 and 2017.

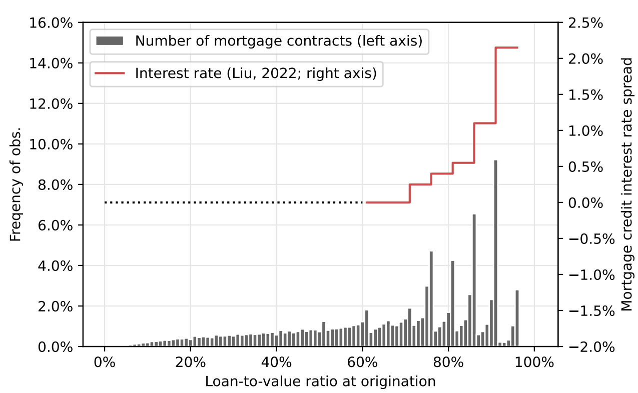


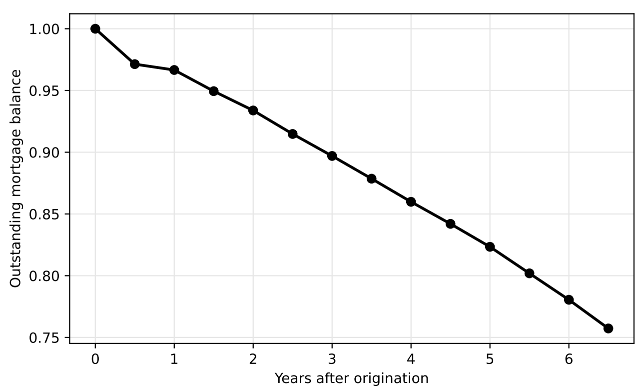
Figure A.6

Amortization and repayment of mortgage loans

The figure illustrates the evolution of outstanding mortgage balances in our data in half-yearly snapshots for a sub-sample of mortgages originated in the first-half of 2015 using regression analysis. The estimated coefficients reflect average amortization rate for half-yearly lags to origination, and based on the following specification:

$$b_{it} = \sum_t \mathbb{D}_t + \varepsilon_{it},$$

where $b_{it} = l_{it}/l_{i,2015H1}$ is based on the outstanding balance for mortgage i in half-yearly snapshot t (l_{it}) and original loan size ($l_{i,2015H1}$), and $\mathbb{D}_t$ are half-yearly dummies.



A.2 Listings vs. transaction volumes

In the listings sample, we can decompose the price – volume regression to listing volumes and transaction probabilities as

$$\ln(V_t) = \underbrace{\ln(V_t/L_t)}_{\substack{\text{Probability of transaction} \\ \text{conditional on listing}}} + \underbrace{\ln(L_t)}_{\text{Listing volume}} .$$

We implement this decomposition by considering whether listings in the Rightmove listings data are transacted within 180 days of the first listing. Leveraging this linear structure we obtain $\beta = \beta_V + \beta_{VL}$, where

$$\ln(L_t) = \gamma_L + \beta_L P_{\Delta,t} + \varepsilon_{t,V}, \tag{17}$$

$$\ln(V_t/L_t) = \gamma_{VL} + \beta_{VL} P_{\Delta,t} + \varepsilon_{t,VL}, . \tag{18}$$

The results for these price – volume regressions are shown in Table A.4. We observe that approximately 60% of the price – volume elasticity is explained by the intensive margin, i.e., the probability that sales listings convert to actual transactions.

We note that transactions volumes are obtained from the Land Registry transactions data. To consider the *additive* decomposition of transaction volumes to listing volumes and listings converting to transactions, we need to build the transaction volumes from the listings data. This restricts the sample to the set of transactions for which we observe a listing in the Rightmove listings data.

A.3 Computational appendix

Our computational strategy consists of two main components. First, we will use value function iteration to solve a deterministic steady state of the model, following the approximation strategy of Winberry (2018). Second, we use the perturbation method to consider the effects of aggregate valuation shocks.

A.3.1 Value function iteration

To implement the value function iteration, we assume a Chebyshev approximation for the seller value function. For each level of m, we look for an n'th order Chebyshev polynomial solution

$$V^h(r,m) = \sum_{j=0}^{n-1} v_{m,j} T_j(r), \tag{19}$$

where T_j is the Chebyshev polynomial of order j, and $v_{m,j}$ are the coefficients to be solved in the value function iteration. These are n_m polynomial approximations, one for each mortgage LTV $m_i, i = 1, \ldots, n_m$.

The iteration proceeds as follows. We consider a grid of $r_1, \ldots, r_{n_r}$ reference price points, which are chosen as the $n_r > n$ roots of the n_r'th order Chebyshev polynomial.

We begin with a guess (indexed by k) for market tightness q^k, the buyer value function $V^{b,k}$, and for the seller Chebyshev coefficients $v^k_{m,j}$ for each m. Using these guesses, we first define the seller's intensive margin problem as

$$\widetilde{V}^k(r_i, m, \theta_l) \equiv \max_p \alpha(p, q^k) \left[U(p, r_i, m) + \theta_l + \beta V^{b,k} - \beta \sum_{j=0}^{n-1} v^k_{m',j} T_j(r_i) \right], \tag{20}$$

where

$$\alpha(p, q^k) = \chi(q^k)[1 - F_\varepsilon(\varepsilon^k(p))]$$

and

$$\varepsilon^k(p) = p + \beta V^{b,k} - \beta \sum_{j=0}^{n-1} v^k_{m,j} T_j(p).$$

We plug these into the right hand side of the homeowner's Bellman equation to obtain in each of the Chebyshev grid points r_i that

$$\bar{y}^{k+1}_m(r_i) \equiv u + \beta \sum_{j=0}^{n-1} v^k_{m,j} T_j(r_i) + \sum_{l=1}^{n_\theta} w^\theta_l \nu \ln \left[1 + \exp\left(\frac{1}{\nu} \widetilde{V}^k(r_i, m, \theta_l) \right) \right],$$

where we have approximated the expectation over θ using a discrete sum with weights w^θ_l over n_θ grid points. Moreover, we have also approximated the maximum function $\max\{0, a\}$ by $\nu \ln\big(1 + \exp(a/\nu)\big)$ for a parameter ν to be chosen small. Note that at the limit $\nu \to 0$, this converges to $\max\{0, a\}$ pointwise. Moreover, it's derivative also converges pointwise to the derivative of the maximum function. Therefore, this specification also provides approximation to the first order conditions of the problem. This will be important in the optimal price setting problem, where we will use this approximation for the preference function U.

Notice that $\bar{y}_m^{k+1}(r_i), i = 1, \ldots, n_r$ are n_r values for each m. We now define the updated seller value function $V^{k+1}(r, m)$ as the Chebyshev approximation of $\bar{y}_m^{k+1}(r_i), i = 1, \ldots, n_r$ as

$$v_{m,j}^{k+1} = \frac{2}{n_r} \sum_{i=1}^{n_r} T_j(r_i) \bar{y}_m^{k+1}(r_i), \tag{21}$$

for $j = 2, \ldots, n$ and

$$v_{m,1}^{k+1} = \frac{1}{n_r} \sum_{i=1}^{n_r} T_1(r_i) \bar{y}_m^{k+1}(r_i). \tag{22}$$

For the buyer value, we update

$$V^{b,k+1} = \beta V^{b,k} + \sum_{i}^{n_r} w_i \frac{\chi(q^k)}{q^k} [1 - F_\varepsilon(\varepsilon^k(r_1))] \mathbb{E}_\varepsilon[\varepsilon - \varepsilon^k(r_i) \mid \varepsilon > \varepsilon^k(r_i)] \omega^k(r_i),$$

where

$$\mathbb{E}_\varepsilon[\varepsilon - \varepsilon^k(r_i) \mid \varepsilon > \varepsilon^k(r_i)] = \mu_\varepsilon + \sigma_\varepsilon \frac{\phi(z_i)}{1 - \Phi(z_i)} - \varepsilon^k(r_i), \quad z_i = \frac{\varepsilon^k(r_i) - \mu_\varepsilon}{\sigma_\varepsilon},$$

$w_i, i = 1, \ldots, n_r$ are the weights associated with Chebyshev quadrature for approximation integrals, $\phi(\cdot)$ and $\Phi(\cdot)$ are the probability and cumulative densities of the standard normal, respectively, and $\omega^k(\cdot)$ is an updated listing price distribution built from the seller problem above (described in the subsection A.3.5).

A.3.2 Mortgage grid

We characterise $F_m(\cdot)$ as a discrete distribution by assuming a discrete grid of mortgage loan-to-value (LTV) ratios relative to the original purchase price of the property: $\widetilde{m}_1 > \widetilde{m}_2 = \widetilde{m}_1 - \delta_m > \cdots > \widetilde{m}_{n_m} = \widetilde{m}_1 - (n_m - 1)\delta_m$ with weights $w_1^m, \ldots w_{n_m}^m$ at issuance. Each new homeowner i, therefore, has an issuance mortgage balance drawn from $\{R_i \cdot \widetilde{m}_1, \ldots, R_i \cdot \widetilde{m}_{n_m}\}, r_i = \ln R_i$. Moreover, given a draw $m_{it} = r_i + \log(\widetilde{m}_{l_i})$, we assume that the mortgage balance evolves along the same grid as $m_{i,t+1} = r_i + \log(\widetilde{m}_{l_i+1})$. In what follows, we will denote the log mortgage balance by $m_l \equiv m_l(r) = r + \log(\widetilde{m}_l)$, suppressing the dependence on r.

Given the discrete grid on mortgages, for the numerical implementation, we rewrite (10) as

$$
\begin{aligned}
&f^{k+1}(r, m_l) \\
&= \underbrace{f^k(r, m_{l-1})}_{\text{Existing homeowners}} \times \underbrace{\left[1 - \int_{\theta^{k,*}(r, m_{l-1})}^{\infty} \alpha^k(p^{k,*}(r, m_{l-1}, \theta))\, d\Phi_\theta^k(\theta)\right]}_{\text{Non-sellers and failed sellers}} \\
&\quad + \underbrace{N_S^k \omega^k(r) \alpha(r) w_l^m}_{\text{New homeowners}},
\end{aligned}
\tag{23}
$$

for $l = 2, \ldots, n_m$ and $f^{k+1}(r, m_1) = N_S^k \omega^k(r) \alpha(r) w_1^m$ for $l = 1$.

A.3.3 Optimal price setting

Let us consider the computational implementation of the price setting problem (20). We solve the problem by first taking analytical first order condition of the equation, and then solve the resulting FOC numerically using Matlab root finding routines. In order to produce a well-defined first order condition, we approximate the utility function as

$$
W(p_{it}, r_i) \approx \hat{W}(p_{it}, r_i) = -\nu \ln \left[\exp\left(-\frac{\eta(p_{it} - r_i)}{\nu}\right) + \exp\left(-\frac{\eta\lambda(p_{it} - r_i)}{\nu}\right) \right]
$$

and the downsizing penalty as

$$
\mu(\gamma - (p_{it} - m_i))_+^2 \approx \mu\nu^2 \ln \left[1 + \exp\left(- \frac{p_{it} - m_i - \gamma}{\nu}\right)\right]^2.
$$

Recall that mortgage m follows a grid, where $m \in \{r + \log(\widetilde{m}_1), \ldots, r + \log(\widetilde{m}_{n_m})\}$, where r and $\log(\widetilde{m})$ are the log reference price and the log LTV (relative to the reference price), respectively. Using these approximations, the first order condition for (20) can be calculated analytically. This is then solved numerically to obtain the optimal p, given $r_i, i = 1, \ldots, n_r$, $\widetilde{m}_j, j = 1, \ldots n_m$, and $\theta_l, l = 1, \ldots, n_\theta$.

A.3.4 Extensive margin decision

For each mortgage grid point m and Chebyshev root r we calculate the threshold θ, called $\theta^{k,*}(r, m)$, at which listing becomes optimal. Denote the optimal price at the threshold $\theta^{k,*}$ by $p^{k,*}$, suppressing the dependence on r and m. The threshold value

$\theta^{k,*}$ is now characterised by

$$\alpha(p^*, q^k)\left[U(p^*, r, m) + \theta^{k,*} + \beta V^{b,k} - \beta \sum_{j=0}^{n-1} v_{m',j}^k T_j(r)\right] = \phi,$$

where p^* satisfies the first order optimality condition arising from the price setting problem described in section A.3.3. For each (r, m) pair, this constitutes two equations in two unknowns $p^{k,*}$ and $\theta^{k,*}$.

We approximate the normal density of θ with a discrete grid and calibrate the grid such that $\theta_1 < \min_{k,r,\widetilde{m}} \theta^{k,*}(r, \widetilde{m})$ with $w_1^\theta = \Phi(\theta_1; \mu_\theta, \sigma_\theta)$ and

$$w_i^\theta = \frac{(1 - w_1^\theta)\phi(\theta_i; \mu_\theta, \sigma_\theta)}{\sum_{i=2}^{n_\theta} \phi(\theta_i; \mu_\theta, \sigma_\theta)}, \quad i = 2, \ldots, n_\theta,$$

setting the weights thus to represent the normal density.

We calculate the number of sellers as

$$N_S^k = \sum_j^{n_m} w_j^{m,k} \sum_i^{n_r} w_i[1 - \Phi(\theta^*(r_i, \widetilde{m}_j); \mu_\theta, \sigma_\theta)]\phi(r_i; \mu_f^k(\widetilde{m}_j), \sigma_f^k(\widetilde{m}_j)),$$

where $w_j^{m,k}$ are endogenous weights of the mortgage distribution and we have assumed a normal distribution parametrization (i.e. approximation) with endogenous mean $\mu_f^k(\widetilde{m}_j)$ and standard deviation $\sigma_f^k(\widetilde{m}_j)$ for the reference price distribution at any given mortgage level $\widetilde{m}_j$; that is, following Winberry (2018) we approximate the distribution of reference prices with a parametric distribution, which we now assume to be normal. Recall that w_i describe the Gauss-Chebyshev quadrature weights, so that the inner sum represents the Gauss-Chebyshev approximation for

$$\int_r \left[1 - \Phi(\theta^*(r, \widetilde{m}_j); \mu_\theta, \sigma_\theta)\right] \phi(r; \mu_f^k(\widetilde{m}_j), \sigma_f^k(\widetilde{m}_j))\, dr.$$

Given exogenous number of buyers N_B, we then update the guess for the market tightness as

$$q^{k+1} = \frac{N_B}{N_S^k}.$$

It remains to discuss, how the listing price distribution and distribution of reference prices is determined.

A.3.5 Approximation of the listing price distribution

Given the distributions of reference prices (assumed normal) with mean $\mu_f^k(m)$ and standard deviation $\sigma_f^k(m)$ for each mortgage level, we produce the listing price distribution from the solution of the sellers' price setting problem.

We first randomize a set of reference prices, by drawing an ordered sample $\{x_{i,\theta,m}\}$ of $n_{random} \times n_\theta \times n_m$ points from the standard normal distribution. We will consider these as fixed parameters, providing a random sample of n_{random} points for each θ and $\widetilde{m}$ grid points. This implies that $z_i(\theta, m) \equiv \mu_f^k(\widetilde{m}) + x_{i,\theta,m} \cdot \sigma_f^k(\widetilde{m})$ is a random sample drawn from the endogenous reference price distribution, which for each $\widetilde{m}$ is approximated by a normal distribution with endogenous mean $\mu_f^k(\widetilde{m})$ and endogenous standard deviation $\sigma_f^k(\widetilde{m})$.

Having solved the optimal price for (r, m, θ) triples, for each $\widetilde{m}_j, \theta_l$ we build a Chebyshev approximation of the form (19) for the optimal price $p(\cdot; \widetilde{m}_j, \theta_l)$:

$$p(r; \widetilde{m}, \theta) = \sum_{j=0}^{n-1} \tilde{p}_{\widetilde{m},\theta} T_j(r)$$

for constants $\tilde{p}_{\widetilde{m},\theta}$ solved similarly as in (21) and (22).

This allows us to solve for the optimal price, called $p_i = p(z_i(\theta, m); \widetilde{m}_j, \theta_l)$, at any of the random points $z_i(\theta, m)$. Therefore, for each pair $(\widetilde{m}_j, \theta_l)$ we now have a pseudo-random sample of optimal prices, properly weighted by the reference price distribution. We will use these to estimate the listing price distribution by standard kernel estimation techniques. We approximate the listing price distribution with normal distribution having mean μ_ω^k and standard deviation σ_ω^k. Denote $\mathbf{g} = (\mu_\omega^k, \sigma_\omega^k)$.

We proceed to implement the kenrel estimation by score matching (Hyvärinen, 2005), minimizing the square distance

$$J(\mathbf{g}) = \int_r \omega^k(r) \Big[\psi(r; \mathbf{g}) - \psi_\omega^k(r) \Big]^2 dr + \frac{\nu_g}{2} \|\mathbf{g}\|^2,$$

where $\psi(r; \mathbf{g}) = \ln[\phi(r; \mathbf{g})]$ is the score of the normal density $\phi(\cdot)$ and $\psi_\omega^k(r) = \ln(\omega^k(r))$. Hyvärinen (2005) shows that

$$J(\mathbf{g}) = \int_r \omega^k(r) \left[\frac{\partial}{\partial r} \psi(r; \mathbf{g}) + \frac{1}{2} \left(\frac{\partial^2}{\partial r^2} \psi(r; \mathbf{g}) \right)^2 \right] dr + \frac{\nu_g}{2} \|\mathbf{g}\|^2,$$

where ν_g is a small constant regularization parameter. Given our random sample $\{z_i\}_i$ from $\omega_t(\cdot)$, this yields an estimator

$$\tilde{J}(\mathbf{g}) = \sum_{l=1}^{n_m} w_l^{m,k} \sum_{j=1}^{n_\theta} \sum_{i}^{n_{random}} w_j^{\theta,*} \left[\frac{\partial}{\partial r} \psi(p_i(m_l, \theta_j); \mathbf{g}) + \frac{1}{2} \left(\frac{\partial^2}{\partial r^2} \psi(p_i(m_l, \theta_j); \mathbf{g}) \right)^2 \right],$$

which can be minimized over $\mathbf{g}$. This leads to a linear system of equations on $\mathbf{g}$.

Note that for small enough values of θ_i, the homeowner chooses not to list the property for sale. For this purpose, we adjust the weight w_j^θ above to account for the listing choice by setting

$$w_j^{\theta,*} = w_j^{\theta,*}(z_i, m_l) = \frac{w_j^\theta}{1 + \exp\left(- \frac{\theta^*(z_i, m_l) - \theta_j}{\nu} \right)}$$

for a small constant parameter ν.

A.3.6 Approximation of the reference price distribution

We approximate also the reference price distribution with a normal distribution similarly to the listing price distribution in the previous section. We use equation (23) to update the distribution and consider the squared distance as before for each m_l separately:

$$J(\mathbf{g}) = \int_r f^{k+1}(r, m_l) \left[\frac{\partial}{\partial r} \psi(r; \mathbf{g}) + \frac{1}{2} \left(\frac{\partial^2}{\partial r^2} \psi(r; \mathbf{g}) \right)^2 \right] dr + \frac{\nu_g}{2} \|\mathbf{g}\|^2,$$

where $\psi(\cdot)$ is again the score of the normal density as above. However, instead of using sampling as with the listing price density, we directly calculate the above integral using Gauss-Chebyshev quadrature:

$$J(\mathbf{g}) \approx \sum_{j=1}^{n} w_j f^{k+1}(r_j, m_l) \left[\frac{\partial^2}{\partial r^2} \psi(r_j; \mathbf{g}) + \frac{1}{2} \left(\frac{\partial}{\partial r} \psi(r_j; \mathbf{g}) \right)^2 \right] + \frac{\nu}{2} \|\mathbf{g}\|^2.$$

We solve for the parameter vector $\mathbf{g}$ again by minimizing J, which leads to a system of linear equations. Finally, we calculate new mortgage weights by integrating

$$\int_r f^{k+1}(r, m_l)\, dr$$

using the Gauss-Chebyshev quadrature and set

$$w_l^{m,k+1} = \frac{\sum_{i=1}^{n} w_i f^{k+1}(r_i, m_l)}{\sum_{l=1}^{n_m} \sum_{i=1}^{n} w_i f^{k+1}(r_i, m_l)}.$$

Having the updated guess q^{k+1} for the market tightness and updated reference price distribution $\phi(\cdot; m_l, \mu_{f,k+1}, \sigma_{f,k+1})$ with weights $w_l^{m,k+1}$, we proceed with the iteration letting $k \to \infty$, leading to convergence to the steady state.

A.4 Model calibration

A.4.1 Simplified version

To develop further intuition about the predictions of the model, we solve a version which imposes a set of restrictions and simplifying assumptions. First, we consider the distribution of reference points r_i and mortgage amounts m_i to be exogenously determined and stationary. This corresponds to a local approximation of the model around the steady state distribution of property prices and outstanding mortgage amounts.

Second, we assume that upon a successful sale, the homeowner exits the market, i.e., they do not start searching in the next period from the position of a potential buyer. The value of being a homeowner then simplifies to the following expression:

$$\begin{aligned} V_{it}^h(\theta_{it}, r_i, m_i) = u_t + \max\{ & \underbrace{\max_{p_{it}} \alpha(p_{it}, q_t) U(\cdot)}_{\text{Listing success}} \\ & + \underbrace{(1 - \alpha(p_{it}, q_t))\beta E_t[V_{it+1}^h(\cdot)]}_{\text{Listing failure}} - \phi, \underbrace{\beta E_t[V_{it+1}^h(\cdot)}_{\text{No listing}}\} \end{aligned}$$

Here, the per-period utility of housing is equal to u_t, the probability of a successful sale is $\alpha(p_{it}, q_t)$, and, for analytical tractability, mortgage contracts are assumed to have an amortization rate of zero. For each level of the reference price r_i and mortgage level m_i, the seller follows a threshold rule for listing, given by $\theta_{it} \geq \theta^*(r_i, m_i)$. If listing, they set the optimal asking price $p_{it}^*(\theta_{it}, r_i, m_i)$.

Third, on the buyer side, we assume that buyers value the property as if holding it in perpetuity with a per-period utility flow u_t, i.e.:

$$V^b_{jt}(\varepsilon_{jt}) = \frac{u_t}{1-\beta} + \varepsilon_{jt}, \text{ with } \varepsilon_{jt} \sim N(\mu_\varepsilon, \sigma_\varepsilon).$$

The buyer accepts the seller's offer if and only if $V^b_{jt}(\varepsilon_{jt}) > p_{it}$, which corresponds to a threshold rule for the matching quality shock:

$$\varepsilon_{jt} > \varepsilon^*_{jt}(p_{it}) = \underbrace{p_{it} - \frac{u_t}{1-\beta}}_{\substack{\text{Listing} \\ \textbf{premium } (\ell_{it})}}.$$

This allows for a convenient representation of premium over fundamental value. It also allows us to interpret all quantities in the model as relative to this fundamental value, which we normalize to $\frac{u_t}{1-\beta} = 1$. In this case, the aggregate demand condition faced by sellers becomes:

$$\alpha(\ell_{it}, q_t) = \underbrace{\chi(q_t)}_{\substack{\text{Meeting} \\ \text{probability}}} \times \underbrace{\left[1 - F^N_\varepsilon(\ell_{it})\right]}_{\substack{\text{Probability of a sale,} \\ \text{conditional on meeting}}} \tag{24}$$

Equation (24) illustrates the central trade-off that sellers face: A higher listing price implies a higher realized transaction value, but a lower probability of buyer acceptance. The total number of listings in each period is then equal to:

$$N_{St} = \int_{r_i, m_i} \int_{\theta^*(r_i, m_i)}^{\infty} f_\theta(\theta) d\theta. \tag{25}$$

In this simplified framework, it continues to hold that, in equilibrium, the market tightness $q_t = N_B/N_{St}$ depends on a seller's own action, as well as the actions of all other market participants. The individual decision to list affects a seller's own matching probability $\chi(q_t)$, and also imposes an externality on everyone else. Homeowners have rational expectations about market tightness and the expected matching probability, and therefore equilibrium corresponds to a fixed-point solution of equation (25) that insures consistency between the homeowners' expectations and their optimal listing decisions.

A.4.2 Numerical solution

We implement a preliminary calibration of the model, which uses a set of preference parameters consistent with previous research and targets observed demand conditions in the data. Table A.6 describes the details of this procedure. To capture cross-sectional variation in reference points and mortgage amounts, we solve two versions of the model, for two different sets of distributions, distinguishing between high and low shares of potential losses.

Panel A of Figure A.7 illustrates quantitative implications and shows equilibrium aggregate decisions on the demand and supply side. It demonstrates the ability of the model to replicate qualitatively the non-linear pattern of demand (i) and the "hockey stick" pattern of the listing premium (ii), as well as to generate a lower listing probability of listing for owners with nominal potential losses (iii).

Panel B plots impulse responses of average realized prices, listing volumes and transaction volumes after an exogenous shock to the per-period housing valuation term u_t. Plot (i) shows that in a friction-less version of the model with no reference dependence and no financial constraints, volumes are not affected by the shock, because it increases the valuations of both buyers and sellers symmetrically. In plot (ii) the situation is very different, because reference-dependent sellers now have an additional benefit from an increased valuation, which is that it increases the distance to the reference point, and therefore makes them more inclined to realize the transaction. Since, if the sale gets realized, the property is now marginally more valuable for a seller than for a buyer, owners are both more likely to list properties for sale, and to aim for a low time on the market. As expected, the price responds less in this case, compared to the friction-less version.

Finally, plot (iii) contrasts effects in two locations, which differ with respect to the share of nominal losses in the stock of properties. Consistent with the intuition and empirical evidence described above, in the region where more owners have experienced price appreciation, the response of volumes is lower and the response of prices is higher, i.e., the price-volume relationship is more muted, and volumes are less volatile.

Table A.6
Calibration of structural parameters

The table reports calibrated and estimated parameters. We estimate the parameters q and α_1 assuming a Cobb-Douglas specification with constant returns to scale. (Genesove and Han, 2012; Badarinza, Balasubramaniam, Ramadorai, 2023). Defining market tightness $q_{it} = N_{Bit}/N_{Sit}$, we have:

$$\chi(q_{it}) = \alpha_0 q_{it}^{\alpha_1},$$

where market outcomes are defined in terms of the observed bilateral contact rate ("meetings") between online searchers and the available number of listings. The parameters pertaining to the demand side are estimated to insure consistency with the observed concave demand pattern in the data.

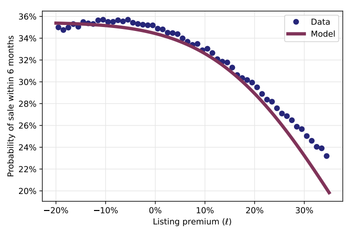
Notation	Description	Value
V	Steady state seller value function	1
β	Discount rate	0.98
ζ	Market tightness (Buyer/Seller ratio)	3.27
α_0	Demand function	0.59
α_1	Elasticity of matching function	0.57
u	Per-period utility of owning	0.02
θ_μ	Distribution of mobility shocks	-4
θ_σ		2
ε_μ	Distribution of buyer valuation shocks	0.38
ε_σ		0.20
ϕ	Listing cost	0.01
η	Reference dependence	0.7
λ	Loss aversion	2.5
μ	Financial constraint	0.6
γ	Down-payment requirement	0.2

Figure A.7
Moments in the model

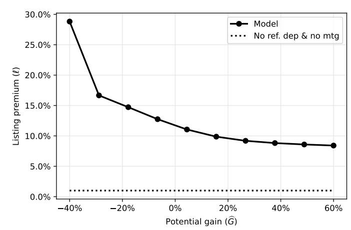
The figure shows results from the calibrated version of the model. Panel A shows quantities in steady state. Panel B shows responses of aggregate model variables in response to a 10% innovation in the valuation process u_t.

Panel A
Micro-level decisions in steady state

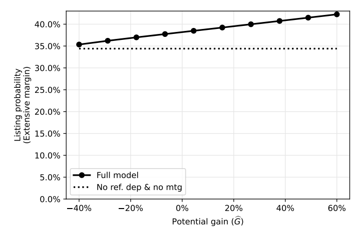
(i) Concave demand



(ii) Listing premium

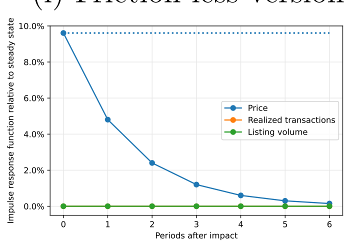


(iii) Extensive margin

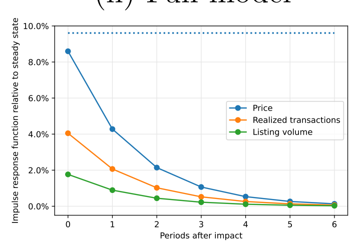


Panel B
Impulse response analysis

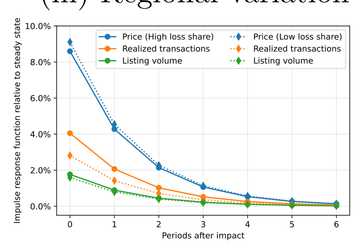
(i) Friction-less version



(ii) Full model



(iii) Regional variation



Panel C
Real effects of nominal shocks