Behavioral Lock-In: Housing Market Taxation with Reference Dependent Agents

Cristian Badarinza, Tarun Ramadorai,
Juhana Siljander, Jagdish Tripathy*

March 20, 2025

Abstract

We embed optimizing agents with reference-dependent and loss-averse preferences into a dynamic equilibrium search and matching model of the housing market with rich heterogeneity and realistic constraints. We estimate and evaluate the model using granular administrative data from the U.K. housing market. Behavioral frictions act as a nominal rigidity, increasing the distortions associated with transaction taxes, and generating a novel source of inefficiency for ongoing property taxes. At the aggregate level, a simple statistic, the prevalence of "paper losses" in the stock of properties, captures variation in prices and volumes across regions, and determines variation of policy impact across locations.

*Badarinza: NUS Business School, Department of Real Estate, Email: cristian.badarinza@nus.edu.sg. Ramadorai (corresponding author): Imperial College London and CEPR, Email: t.ramadorai@imperial.ac.uk. Siljander: Imperial College London, Email: j.siljander@imperial.ac.uk. Tripathy: Bank of England, Email: jagdish.tripathy@bankofengland.co.uk. Badarinza and Tripathy were visiting researchers at Imperial College London during the production of this draft. We thank Ed Burgess, Tim Bannister, Natalie Jakomis, Rob Murphy, Leanne Pienaar, Amit Tiwari, and Oscar Walet at Rightmove for data access and numerous useful conversations, and John Campbell, Stefano Della Vigna, Daniel Greenwald, Ben Lockwood, seminar participants at the London School of Economics Macro Workshop, the Imperial-LSE-UCL-IFS-CEPR Micro-Macro Household Finance Seminar, the London Behavioural Finance Workshop, Princeton University, Emory University, INSEAD, Swansea University, the 5th Joint BoC-ECB-NY Fed Conference, EDHEC, the Stanford Institute for Theoretical Economics (Psychology in Economics and Financial Regulation), the Imperial-Bank of England Household Finance and Housing Conference, the 2024 Nordic Summer Symposium in Macroeconomics, the 14th Helsinki Finance Summit, the 2024 BoF-CEPR conference, the CREI @30 Conference and Oxford University for comments. Any views expressed are solely those of the author(s) and so cannot and should not be taken to represent, or reported to represent, the views of the Bank of England, or members of the Monetary Policy Committee, Financial Policy Committee or Prudential Regulation Committee, or to state Bank of England policy.

1 Introduction

Housing market taxes contribute significantly to fiscal revenue around the world. An important policy question in this market—similar to other settings such as income, wealth, and carbon emissions—is the appropriate mix of taxes on the flow of transactions versus the stock of housing.[1] While stock-based taxes are generally seen as more efficient because they are less distortionary (Mirrlees et al., 2012), there is considerable debate on how aggregate housing market quantities and welfare are affected by alternative tax regimes (Best and Kleven, 2018; Eerola et al., 2021; Han et al., 2023; Coven et al., 2024; Cho et al., 2024). An important complication in this setting is the role of behavioral frictions. A growing body of evidence shows that agents in housing markets are persistently attached to historical nominal anchors and reluctant to realize nominal losses (Genesove and Mayer, 2001; Bracke and Tenreyro, 2021; Andersen et al., 2022). Such behavioral frictions can significantly alter classic public finance calculations;[2] understanding precisely how requires carefully modeling equilibrium relationships (Allcott et al., 2019; Farhi and Gabaix, 2020).

To study these questions, we build a micro-founded dynamic equilibrium model of the housing market, with reference-dependent agents and realistic financial constraints. Using granular administrative data on housing transactions, property listings, property search, and mortgage borrowing in the U.K. over the period 2010–2022, we structurally estimate the parameters of the model by targeting a set of micro-level moments that capture individual buyer and seller behavior. The estimated model is well able to explain patterns in more aggregated data on house prices and transaction volumes that are untargeted in estimation; we use the model to shed light on the impacts of transactions taxes and ongoing property taxes.

Households' behavioral frictions generate a novel source of nominal rigidity at the aggregate level. When house sellers make their decisions contingent on the gains and losses relative to the prices they originally paid for these houses, their behavior links nominal variables with real outcomes. The mechanism is similar to the way in which firm-level price and wage stickiness prevents aggregate quantities from reflecting changes in fundamental economic conditions. At the aggregate housing market level, nominal quantities adjust sluggishly, the health of the housing market becomes dependent on past states, and policy impacts can differ based on the timing and context of the intervention.

The model shows that reference dependence and loss aversion increase the distortionary effects associated with the (flow-based) transaction tax, introducing a source of short-term

[1] Revenue from housing market taxation accounts for 30% of local tax take in the U.S. (Urban-Brookings Tax Policy Center, 2024) and above 25% in the U.K. (Office for Budget Responsibility, 2024). Related literature includes Saez and Zucman (2019); Timilsina (2022); Bastani and Waldenström (2023).

[2] See, for example, Mullainathan et al. (2012); Chetty (2015); DellaVigna et al. (2017); Taubinsky and Rees-Jones (2018).

inefficiency for the (stock-based) ongoing property tax, which would have otherwise been non-distortionary in a neoclassical setting. The model allows reference points to endogenously change in the economy as agents trade and codify these nominal anchors (today's purchase price becomes tomorrow's anchor); this endogenous variation of reference points changes the extent of the inefficiency over time. In the short run, taxation creates a wedge between property valuations and the owners' historical nominal anchors; in the long run, housing turnover leads to a gradual updating of reference points, and the distortion disappears.

A corollary of this result is cross-regional variation in the impact of taxation. Depending on how strong the behavioral motive is in each region, different parts of the country can respond differently to the same tax change, and the trade-off between alternative fiscal regimes can look different depending on the location. Both in the model and the data, we find that a single statistic, the prevalence of "paper losses" in the stock of residential properties (henceforth the "loss share"), effectively explains cross-regional variation in a range of housing market outcomes. The loss share summarizes the distribution of nominal anchors in the population of homeowners, and serves as an aggregate statistic that aids policy impact calculations. Intuitively, when many owners are reluctant to realize nominal-loss-inducing sales, house price declines are accompanied by substantial declines in housing market volume. This finding is consistent with the well-known observation that housing market crashes are first visible in market liquidity, and then only gradually reflected in prices.

Our model features homeowners that are reference dependent and loss averse.[3] To isolate the effects of this empirically-grounded behavioral mechanism, we model agents as forward-looking, rational, and fully informed about aggregate quantities, shocks, and the distributions of reference points and mortgage balances in the population. Homeowners also face realistic mortgage down-payment constraints, which allows for a separate and distinct role for the effect of financial leverage on house selling decisions, first identified by Stein (1995). Homeowners receive idiosyncratic mobility (or productivity) shocks that motivate them to sell. They trade off these mobility payoffs optimally against the nominal gains and losses that they make from selling their houses at prices above or below a pre-determined reference point, and against penalties for falling below a pre-determined down-payment level of home equity.[4] They evaluate these trade-offs dynamically in an infinite horizon setup, optimally solving for whether or not to list in each period, and choosing a pricing strategy conditional on listing. In the event that

[3]Technically, agents realize utility à la Barberis and Xiong (2012) from nominal (log) gains and losses relative to their historical nominal reference point, in addition to the "standard" log utility that they derive from the final sale price.

[4]Outstanding mortgage amounts evolve according to a pre-specified amortization schedule. With heterogeneous holding periods, this generates rich heterogeneity in homeowners' mortgage balances, with a methodological resemblance to the quantitative overlapping generations models that have a long history in the public finance literature (Auerbach and Kotlikoff, 1987).

they sell, they return to the market as potential buyers in the next period, and take this into account when optimizing.[5]

Buyers receive idiosyncratic taste shocks when they are randomly matched with properties, and they also optimize dynamically, trading off the probability of a successful transaction today against waiting for more promising outcomes in the future. When buyers in the model purchase properties, they become homeowners/prospective sellers, and their purchase prices are encoded as their reference prices for future property sale decisions. The distribution of reference prices in the economy thus varies endogenously with the realized set of transactions. We solve for the stationary distribution of these reference prices as an equilibrium quantity, which means that the model endogenizes the prevalence of "paper losses" in the economy.

Consistent with the implications of Krusell and Smith (1998), Lucas (2003) and Ahn et al. (2018), in our model, the heterogeneity of individual state variables matters for aggregate equilibrium outcomes, because of agents' reference dependence, loss aversion, and occasionally binding mortgage constraints. More specifically, buyers' and sellers' nonlinear decision rules generate aggregate externalities through their impact on market tightness (which determines the rate at which buyers and sellers meet one another), and the probability of sale conditional on a meeting (which reflects the full distribution of seller list prices). In this setting, sellers that face the possibility of realizing nominal losses become "behaviorally locked-in," eschewing potentially valuable moving opportunities. A positive nominal change in property valuations generated by a higher rate of inflation can therefore lead homeowners to more readily accept moving opportunities, which supports the role of "location as an asset," (Bilal and Rossi-Hansberg, 2021) and speaks to the potentially positive role that inflation can play in a market with nominally-anchored agents.

When agents are reference-dependent, bargaining power shifts from the demand to the supply side, and equilibrium prices are higher and less sensitive to the prevailing tax regime. This is because behavioral sellers trade off any tax loss or benefit against the probability of realizing an additional nominal loss or gain on the sale of the property. As a consequence of the higher price and the lower tax elasticities associated with the role of behavioral frictions, counterfactual simulations suggest that, in order to remove the ongoing property tax, transaction taxes would need to rise by less in the estimated model compared to the frictionless version.[6] Finally, nominal anchoring links the shape of the Laffer curve with the prevailing loss share in a given location at any given point in time. We validate this insight, documenting that the degree of bunching of transactions prices around historical notches in the U.K. stamp

[5]In a downturn, sellers rationally anticipate the fact that selling their property at a low price might subsequently enable them to purchase another property at a similarly low price.

[6]See, for example,"Rent controls will not fix Britain's housing crisis", *Financial Times*, 27 May 2024, for a summary of the current debate on the reform of the council tax system in the U.K.

duty tax schedule depends on the size of the loss share. This reinforces the usefulness of the loss share as an important statistic to aid policy calculations on the likely impacts of tax policy changes on the housing market.

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-agent setup (Krusell and Smith, 1998; Ahn et al., 2018), and the impact of behavioral frictions on optimal policy (O'Donoghue and Rabin, 2006; Mullainathan et al., 2012; Chetty, 2015; DellaVigna et al., 2017; Taubinsky and Rees-Jones, 2018; Rees-Jones, 2018; Allcott et al., 2019). As in many public finance applications, some of our empirical work relies on a bunching estimator (Kleven, 2016; Allen et al., 2017; Rees-Jones, 2018; Anagol et al., 2022). Our work emphasizes 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). 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; Piazzesi et al., 2020), 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 sources that we employ to document both micro and aggregate patterns in the data. Section 3 introduces our dynamic search and matching model of the housing market. Section 4 discusses the calibration and structural estimation. Section 5 describes the ability of the model to fit untargeted aggregate moments. Section 6 considers the implications of the model for housing market tax policy, documents evidence in the data on historical tax policy responses, and outlines other implications of reference dependence for economic policy. Section 7 concludes.

2 Data

Our analysis uses five main data sets: i) address-level information on the U.K.'s residential property stock from the U.K. Ordnance Survey; ii) the universe of residential property transactions in England and Wales from HM Land Registry; iii) hedonic characteristics and listings information for virtually all properties listed for sale, and detailed information about online searches and initiated physical inspections of these properties from Rightmove.com; iv) additional hedonic characteristics on properties sourced from U.K. Energy Performance Certificates (EPCs); and v) loan-level data on the outstanding stock of all mortgage contracts in the U.K.

from the Bank of England.

2.1 Residential property stock and transactions

The U.K. residential property stock comprises 27.3 million postal residential addresses, recorded in the Royal Mail Postcode Address File, released by the Ordnance Survey. We use these address data in combination with house listings and sales data (described below) to compute the fraction of the housing stock that is turned over.

HM Land Registry tracks the universe of residential property transactions in England and Wales. These publicly available data include details on the address of the unit (including the property postcode), the date when the contractual sale agreement was signed, and the price recorded in the contract. In total, 28 million transactions were recorded between January 1995 and December 2022, corresponding to a turnover rate of the housing stock of around 1.8% for every 6 months. For comparison purposes, we also acquire publicly available U.S. data on residential property sales from Zillow. Using this source, we construct a panel of median prices and transaction volumes aggregated at the U.S. state level for the monthly frequency between January 2010 and December 2022.

2.2 Property listings and the hedonic model

We acquire listing information for individual properties from Rightmove.com, the largest online portal for house listings in the UK. These data include listings for sale by sellers and searches for these properties from potential buyers. The listings data track all listings on the platform: those resulting in a successful transaction as well as those that were withdrawn and archived. We merge these listings with the transactions registry. The merge rate is high—for example, 81% 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 sold 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, the building type (detached and terraced houses, vs. apartments), 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 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 use property-level address information to implement two different data merges: (i) we match listings to a preceding transaction, which allows us to find the initial purchase price for the current owner; and (ii) we match transactions with preceding listings to facilitate estimation of a hedonic pricing model using the hedonic characteristics in the Rightmove listings data.

For the hedonic model, we constrain to the set of properties that are transacted within 365 days of the first listing to avoid potential changes in hedonic characteristics from potentially "stale" listings information. We also augment the hedonic characteristics with information from energy performance certificates (EPCs), which record the floor area for properties for which this information is missing in the Rightmove data. Using the final data set of 7.1 million transactions, we estimate an adjusted-for-characteristics price for each property, predicting 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.[7]

2.3 Search and matching

The Rightmove data also record online search activity for all Rightmove.com listings observed between January 2019 and December 2022. We distinguish between two types of engagements between an online user and a property listing.[8] The first, which we denote as a "search visit," is an instance of the user clicking the "detail view" hyperlink on a property listing. This provides the full set of property characteristics to the user (e.g., the floor area) and 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,

[7]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.

[8]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 and those who search over more than 1,000 listings, as these are likely bots.

to organize a physical viewing of the property. When we compute market tightness, i.e., the number of buyers divided by the number of listings, we use the number of initiated physical meetings as our 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 Financial Conduct Authority's PSD007 data set. 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 eventually transacted listings, 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 zero 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 Rightmove listings and Bank of England mortgage 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. 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). We rely on a sub-sample of mortgages originating in the first half of 2015 to construct an implied amortization schedule. This sample comprises 70,000 observations with an average origination loan size of £157,500, an initial interest rate of 2.95%, and a monthly payment of £776. On average, mortgages originating in 2015H1 amortize 2.53p.p. of the loan balance every six months and are amortized by a cumulative 30.14p.p. by 2022H2.

2.5 "Paper losses" and home equity

We compute nominal "paper" gains and losses in our sample of property listings as the percent difference between the estimated hedonic value of the property at the time of listing, and the initial purchase price. This "potential gain" distribution for the full set of listings in the data suggests that approximately 25% of sellers would face nominal losses if they sold their properties at the estimated hedonic value. The share of owners with potential paper losses varies between 12.8% and 40.8% across local authorities of the U.K., a sizable fraction of the population. For properties financed with a mortgage, the "potential home equity" position of the seller is calculated as the difference between the hedonic value and the outstanding mortgage amount at the time of listing. In the U.K. mortgage market, interest costs start to increase for loan-to-value ratios above 70% (Liu, 2022). This implies that a seller with home equity below 30% will find it more costly to take a loan to finance a property of similar value to the one they are selling, and may have to consider downsizing. In the data, we estimate that a tiny fraction (1.2%) of all outstanding mortgage contracts across all time periods are underwater, and 23.7% have a home equity level below 30%. Low home equity introduces down-payment constraints for both seller strategy and final transaction outcomes (Stein, 1995). We incorporate these forces in our theoretical and empirical analyses.

2.6 Listing behavior and transaction outcomes

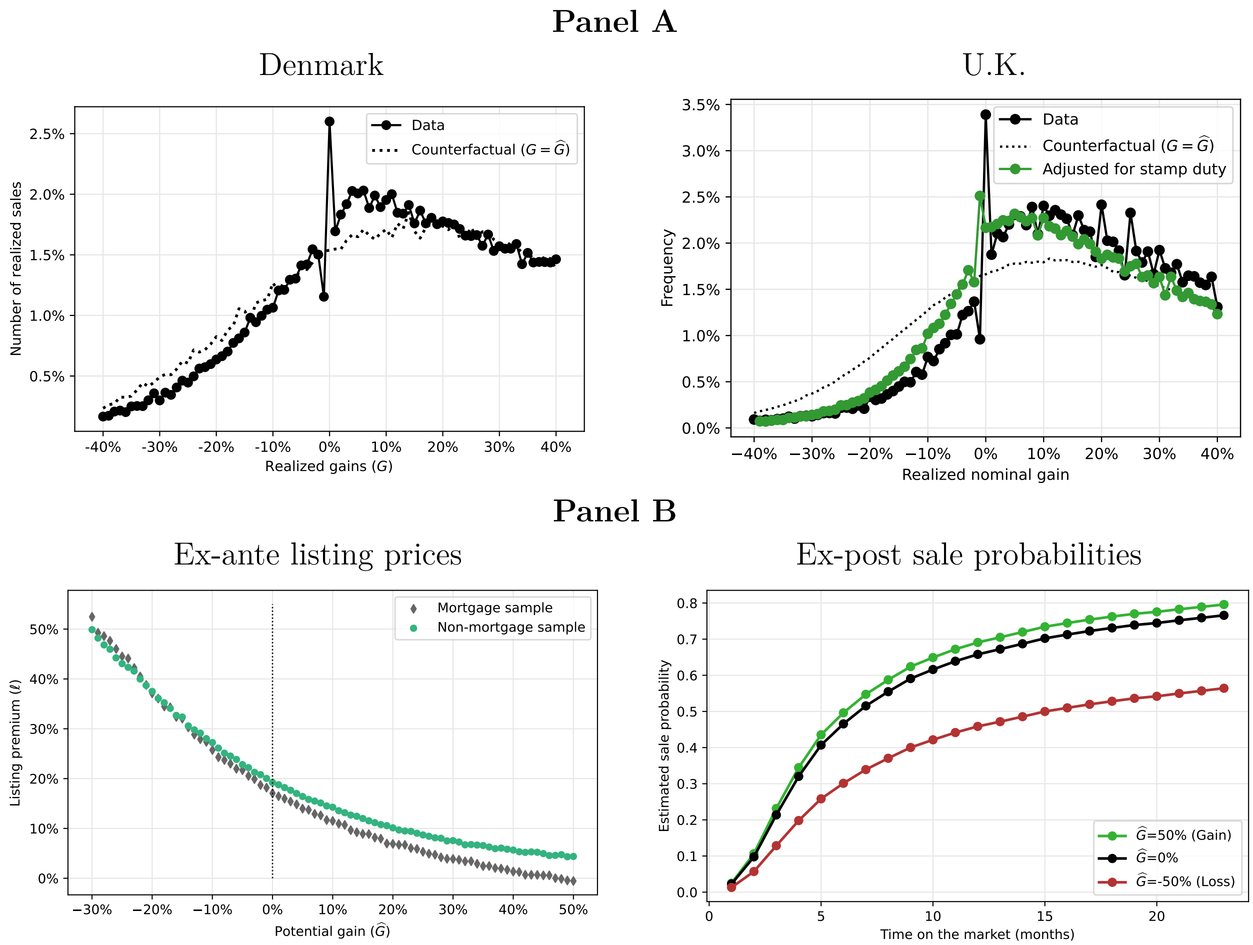
Andersen et al. (2022) use administrative data from Denmark and identify the nominal purchase price of a property as a quantitatively relevant reference point for sellers of residential properties. They test for reference-dependent preferences using a joint set of *ex-ante* and *ex-post* empirical moments that capture the behavior of sellers throughout the transaction process. They rationalize the empirical patterns using a model in which preferences exhibit reference dependence and loss aversion, with a change in slope (a "kink") at the reference point.

In Figure 1, we verify that such patterns are also evident in granular U.K. housing transactions data. Panel A shows the distributions of nominal gains on all housing transactions in Denmark and the U.K. These are computed as the simple difference between the sale transaction price and the original purchase value for each property. To extract a measure of "excess mass" from the distribution of realized transaction prices, we compare these distributions with the counterfactual frequency of nominal gains that would occur if properties were sold exactly at their estimated hedonic values. The two plots are very similar, with 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). The solid green line shows the distribution of differences between the sale transaction price and the sum of the original purchase value and the stamp duty initially paid by the buyer. No price bunching is observed at this adjusted reference point, which validates the role of the contractual purchase price as a nominal anchor.

To document *ex-ante* reference-dependent seller behavior, we plot average listing prices set by sellers (i.e., the step preceding bilateral negotiations and contractual outcomes) on the y-axis against the potential gain ($\widehat{G}$) on the x-axis (the potential gain is the percent difference

Figure 1
Reference dependence and loss aversion

Panel A 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), and compares it with the counterfactual distribution of nominal potential gains among the same set of properties. We use 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%). The left plot in Panel A is sourced from Andersen et al. (2022), the right plot is constructed based on transactions lodged with HM Land Registry. Panel B left plot shows 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 right plot reports estimated sale probabilities from a Cox proportional hazards model, controlling for holding period at the time of sale, and with separate coefficients in the nominal loss ($\widehat{G} < 0$) and the nominal gain ($\widehat{G} \geq 0$) domain.



between the hedonic valuation of the property and its initial purchase price). The left plot in Panel B of Figure 1 shows that the listing premium is negatively sloped with respect to 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 with higher magnitudes of the negative potential gain. The effect of losses exist over and above the effects of mortgage leverage. We report the mean listing premium in each potential gain percentage point bin for two different samples: a sample of listings for which a mortgage contract is outstanding at the time of listing ("Mortgage sample"), and second among listings where the mortgage has either been completely repaid or the seller's ownership is outright to begin with.

Table 1
Housing market transaction volume: "Paper gains" and home equity

This table reports results from the following specification:

$$\ln T^{\text{sale}}_{ikt} = \beta_0 + \beta_1 \widehat{G}_{ikt} + \beta_2 \widehat{H}_{ikt} + \beta_3 T^{\text{hold}}_{ikt} + \beta_4 1^{mortgage}_{ikt} + \mu_i + \delta_t + \varepsilon_{ikt}, \tag{2}$$

where $1^{mortgage}_{ikt}$ indicates whether the property i located in location k at time t has a mortgage outstanding. $\widehat{G}_{ikt}$ and $\widehat{H}_{ikt}$ are the potential gains and home equity levels, respectively. T^{sale}_{ikt} is the number of months between the initial listing and the time at which a sale contract is signed, and T^{hold} is the number of years between the initial purchase of the property and the time of the listing. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, based on standard errors clustered at the local authority level.

Potential "paper gain"	-0.197***		-0.182***	
	(0.002)		(0.004)	
× Loss domain				-0.430***
				(0.012)
× Gain domain				-0.081***
				(0.004)
Potential home equity		-0.062***	0.001	0.019***
		(0.002)	(0.006)	(0.006)
Ln Time since purchase	0.019***	0.010***	0.015***	0.016***
	(0.000)	(0.001)	(0.003)	(0.001)
Location fixed effects	Yes	Yes	Yes	Yes
Listing month fixed effects	Yes	Yes	Yes	Yes
No. of obs.	3,429,467	2,468,686	2,468,686	2,468,686
R^2	0.040	0.044	0.049	0.050

The right plot in Panel B of Figure 1 shows that these *ex-ante* strategies of sellers are linked with *ex-post* transaction outcomes beyond the realized price. For each property, we record the time between the initial listing and the time at which it is either sold or withdrawn from the platform. Since we can track properties in the transactions register, we can calculate the likelihood of whether a listing results in a successful sale after a particular time period, or whether the observation is censored, i.e., withdrawn without a sale. This data structure allows us to estimate a Cox proportional hazards model, which links the probability of sale with the nominal "paper gain" on a given property, controlling for the holding period at the time of sale, and allowing for separate coefficients in the nominal loss ($\widehat{G} < 0$) and gain ($\widehat{G} \geq 0$) domains. The results suggest that a seller with a 50% nominal return since purchase is twice as likely to sell the property within 6 months after listing as compared to a seller facing a 50% nominal loss. Consistent with the asymmetry visible in listing prices around the reference point (i.e., Panel B left plot), transaction volumes are also more affected by potential losses than gains. To further quantify the magnitude of this effect, Table 1 estimates the following specification:

$$\ln T_{ikt}^{\text{sale}} = \beta_0 + \beta_1 \widehat{G}_{ikt} + \beta_2 \widehat{H}_{ikt} + \beta_3 T_{ikt}^{\text{hold}} + \beta_4 1_{ikt}^{mortgage} + \mu_i + \delta_t + \varepsilon_{ikt}, \tag{3}$$

where $1_{ikt}^{mortgage}$ indicates whether the property i located in location k at time t has a mortgage outstanding, $\widehat{G}_{ikt}$ and $\widehat{H}_{ikt}$ are the potential gains and home equity levels, respectively, T_{ikt}^{sale} is the number of months between the initial listing and the time at which a sale contract is signed, and T^{hold} is the number of years between the initial purchase of the property and the time of the listing. We find that a one percentage point higher nominal loss is associated with a 0.197% longer time to sale. The estimated coefficient is quantitatively similar after controlling for the home equity position and the holding period. The extended wait times characteristic of sellers with nominal losses can therefore not be explained by potential confounds such as being in negative home equity, or averse to potential downsizing. Such sellers are "locked in" by behavioral anchoring to a nominal reference point, with the marginal effect of a nominal loss being more pronounced than the effect of a marginal gain. In the next section, we analyze whether and how these micro-level effects have material consequences for the aggregate levels of prices and volumes in the housing market.

3 The Model

We develop a dynamic heterogeneous agent search and matching model of the housing market where homeowners are reference dependent and loss-averse around a pre-determined anchor, and face realistic 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.

3.1 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 $q_t = N_B/N_{St}$. The probability that a seller meets a buyer is modelled using a constant returns to scale matching function $\chi(q_t)$, which we specify as $\chi(q_t) \equiv \bar{\chi} \cdot q_t^{\upsilon}$, for some constants $\bar{\chi} > 0$ and $\upsilon \in [0, 1]$. 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.[9]

3.2 Homeowners

Owning a home generates flow utility u. At the beginning of period t, each homeowner i draws a mobility shock $\theta_{it} \sim F_\theta(\cdot)$ with probability ρ. The mobility shock represents a newly available outside 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 (with probability ρ). If the homeowner chooses to list, they choose a log list price l_{it}.

With probability $\alpha_t(l_{it})$, the sale transaction completes successfully at price $p_{it} \equiv p(l_{it})$ and 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 $1 - \alpha_t(l_{it})$, the homeowner is unable to sell their property, and they draw another independent and identically distributed realization of the mobility shock in the next period.

We assume that the function $p(\cdot)$ transforming listing prices to transaction prices is deterministic and common knowledge. Therefore, the listing price l_{it} is isomorphic to a take-it-or-leave it offer at price $p(l_{it})$. In our empirical analysis, we estimate $p(\cdot)$ directly from the data.

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

[9] Thus a positive demand shock leads households to "move up the housing ladder", and individual decisions spill over to the broader housing market (Aiello et al., 2022).

Bellman equation:

$$
\begin{aligned}
V_t^h(r_i, m_{it}) = u - \tau^h + \mathbb{E}_\theta \max\{\max_{l_{it}} & \underbrace{\alpha_t(l_{it})[U(\cdot) + \theta_{it} + \beta\mathbb{E}_t[V_{t+1}^b]]}_{\text{Listing success}} \\
& + \underbrace{(1-\alpha_t(l_{it}))\beta\mathbb{E}_t[V_{t+1}^h(\cdot)]}_{\text{Listing failure}} - \phi, \underbrace{\mathbb{E}_t[\beta V_{t+1}^h(\cdot)]}_{\text{No listing}}\},
\end{aligned}
\tag{4}
$$

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

3.2.1 Seller utility

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

$$
U(p_{it}, r_i, m_i) = p_{it} + \underbrace{W(p_{it}, r_i)}_{\substack{\text{Reference}\\ \text{dependence}}} - \underbrace{\mu(\gamma - (p_{it} - m_i))_+^2}_{\substack{\text{Downsizing}\\ \text{penalty}}},
\tag{5}
$$

where:

$$
W(p_{it}, r_i) = \begin{cases} \eta(p_{it} - r_i), & \text{if } p_{it} \geq r_i, \\ \lambda\eta(p_{it} - r_i), & \text{if } p_{it} < r_i. \end{cases}
\tag{6}
$$

The function $W(\cdot)$ describes reference dependent ($\eta > 0$) and loss averse ($\lambda > 1$) preferences. We also include a convex downsizing penalty as previously mentioned, 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.

3.2.2 Homeowners' extensive margin decision

Conditional on drawing a θ shock and listing, the maximization problem for the list price l produces an optimal list price $l_t^*(r, m, \theta)$ and corresponding transaction 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:

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

This yields a threshold rule for listing:

$$\theta_{it} \geq \frac{\phi}{\alpha_t(l^*_{it})} - \left[U(p^*_{it}, r_i, m_{it}) + \beta\mathbb{E}_t[V^b_{t+1}] - \beta\mathbb{E}_t[V^h_{t+1}(r_i, m_{i,t+1})]\right] \equiv \theta^*_{it}(r_i, m_{it}), \tag{7}$$

where we have denoted $l^*_{it} \equiv l^*_t(r_i, m_{it}, \theta), p^*_{it} \equiv p^*_t(r_i, m_{it}, \theta^*_{it})$, and V^b_t is the buyer's value function at time t. Notice that the equality in (7) is a consistency condition for θ^*_{it}. Together with $p_{it} = p(l_{it})$ and the optimal price setting condition from the seller's optimization problem, these constitute three equations on three unknowns l^*_{it}, p^*_{it} and θ^*_{it} for each (r_i, m_{it}) pair.

3.3 Buyers

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

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

where V^b_t is the buyer's value function at time t, p_{it} is the log transaction price of the sale (associated with the log listing price l_{it} 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:

$$\varepsilon_{jt} \geq p_{it} + \tau^b + \beta\mathbb{E}_t[V^b_{t+1}] - \beta\mathbb{E}_t[V^h_{t+1}(p_{it}, m_{j,t+1})] \equiv \varepsilon^*_t(p_{it}). \tag{8}$$

Note that both match quality shocks are measured in units of log price. In particular, the model implicitly assumes log utility on transaction prices for buyers and sellers.

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

$$V^b_t = \underbrace{\beta\mathbb{E}_t[V^b_{t+1}]}_{\substack{\text{Value of remaining}\\ \text{as buyer}}} + \frac{\chi(q_t)}{q_t}\int_l \int_{\varepsilon^*_t(p(l))}^{\infty} \underbrace{\left[\varepsilon - \varepsilon^*_t(p(l))\right]}_{\text{Option value for high taste}} d\Phi_\varepsilon(\varepsilon)\, d\Omega_t(l). \tag{9}$$

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

After the purchase of a property 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 $(r_i, m_{i,t+1}) = (\ln R_i, \ln M_{i,t+1})$. 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. The online appendix provides empirical evidence consistent with this assumption.

3.4 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 $l_t^*(r, m_t, \theta_t)$. These optimal choices induce an endogenous listing price distribution, which we denote by $d\Omega_t(l) = \omega_t(l)\, dl$.

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

$$\alpha_t(l) = \underbrace{\chi(q_t)}_{\substack{\text{Probability that}\\ \text{seller meets a buyer}}} \times \underbrace{[1 - F_\varepsilon(\varepsilon_t^*(p(l)))]}_{\substack{\text{Probability of acceptance}\\ \text{conditional on a meeting}}} . \tag{10}$$

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:[10]

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

where we denote by $\omega(r), \alpha(r)$ the listing density and probability of transaction, respectively, for listing price l which leads to the transaction at price $r(l)$, should the buyer accept the offer.

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

[10] To simplify notation, we replace the listing price l with the associated sales price $p(l)$, which becomes the buyer's reference price $r = p(l)$ upon the transaction. That is, each listing price is associated with a deterministic transaction price $p(l)$ upon a transaction and the demand function and listing distribution can also be considered w.r.t. these transaction prices.

by:

$$f_{t+1}(r, m_{t+1}) = \text{Existing homeowners not selling} + \text{New homeowners}$$

$$= \underbrace{f_t(r, m_t)}_{\text{Existing homeowners}} \times \underbrace{\left[1 - \int_{\theta_t^*(r,m_t)}^{\infty} \alpha_t(l_t^*(r, m_t, \theta))\, d\Phi_\theta(\theta)\right]}_{\text{Non-sellers and failed sellers}} \tag{11}$$

$$+ \underbrace{N_{St}\omega_t(r)\alpha(r) f_m(m_{t+1})}_{\text{New homeowners}},$$

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

$$N_{St} = \rho \int_{r,m} \int_{\theta^*(r,m)}^{\infty} f_\theta(\theta)\, d\theta\, dF_t(r, m), \tag{12}$$

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

3.5 Equilibrium

We define the equilibrium concept as follows.

Definition. An equilibrium consists of:

- Seller and buyer value functions $V_t^h(r, m), V_t^b$ defined through the Bellman equations (4) and (9), respectively;
- Buyer policy function $\varepsilon_t^*(p)$ satisfying (8);
- Seller price setting policy $l_t^*(r, m, \theta)$, which solves the seller's price setting problem, and extensive margin policy function $\theta_t^*(r, m)$, which solves (7);
- Aggregate transaction probability $\alpha_t(l)$ satisfying (10);
- Distribution of reference prices and mortgage balances $F_t(r, m)$, whose law of motion satisfies (11);
- Distribution of listing prices $\Omega_t(l)$, which arises endogenously from the sellers' extensive and intensive margin decisions; and
- Market tightness q_t satisfying (12).

In our analyses, we concentrate on studying a stationary equilibrium with $F(\cdot,\cdot) \equiv F_t(\cdot,\cdot) = F_{t+1}(\cdot,\cdot), V^b \equiv V_t^b, V^h(\cdot,\cdot) \equiv V_t^h(\cdot,\cdot)$.

4 Model estimation

We exploit the granularity of our data to estimate a number of key model parameters, building on the growing micro literature on the effects of reference dependence and loss aversion in the housing market. Our estimation targets three sets of micro-level moments that are well-known in the existing literature (Andersen et al., 2022; Guren, 2018; Genesove and Mayer, 2001) and documented in Figure 2: (i) listing premium hockey stick: sellers who face nominal losses substantially mark up their listing prices over the hedonic value of the property, consistent with preferences that are reference-dependent and loss-averse; (ii) home equity hockey stick: financially constrained sellers similarly mark up their listing prices in an attempt to avoid costly downsizing; and (iii) concave demand: the probability of a transaction going through decreases in the listing price, but is bounded above for low or negative listing premia. We use these micro patterns in the U.K. data as targets in our estimation exercise, which we describe in detail below. We then evaluate the ability of the resulting calibrated model to explain a set of untargeted macro moments.

4.1 Externally calibrated parameters

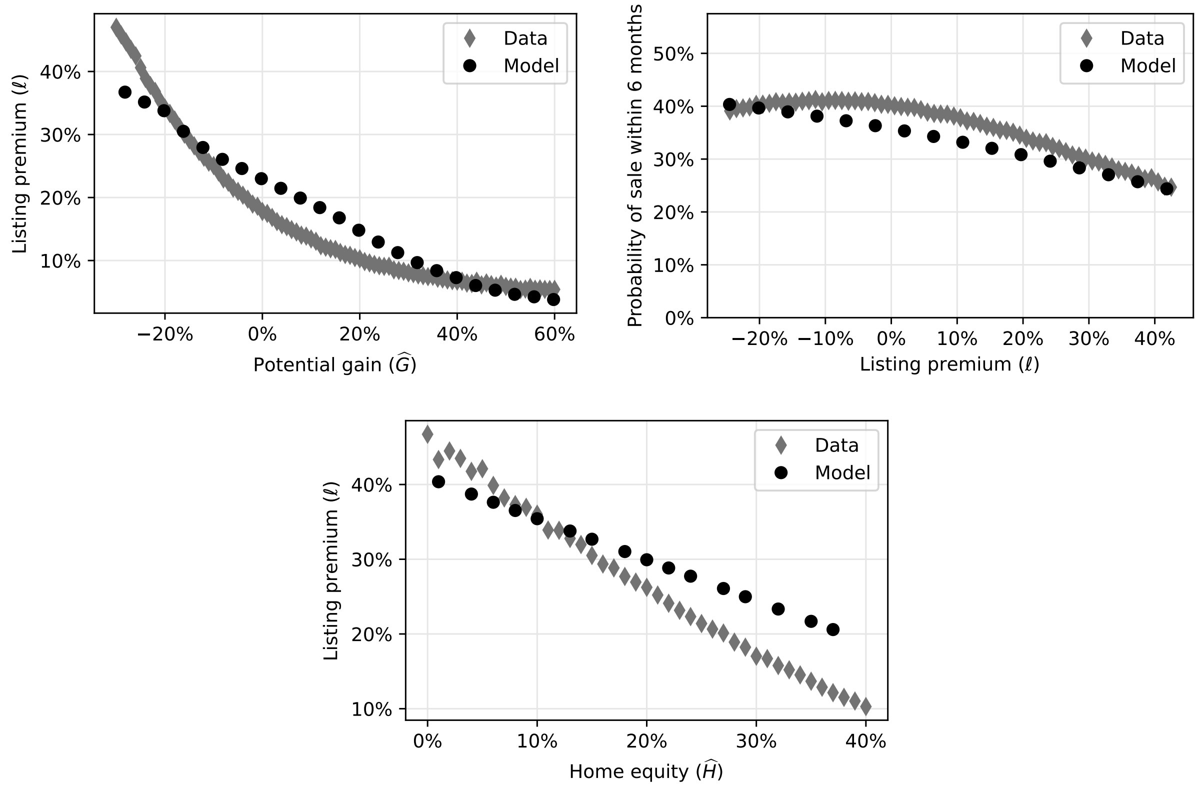
We solve the model numerically, using value function iteration to solve for a deterministic steady state. We define a time period in the model to correspond to 6 months in the data, and set the time discount factor equal to $\beta = 0.99$ (i.e., we assume an annualized real discount rate of 2%). For a convenient interpretation of aggregate quantities, we normalize the housing stock to $N_H = 1$ and the average log price level to 1. This means that all volumes in the model are relative to the housing stock, and all prices are relative to the price of a representative property. The top part of Table 2 lists the parameter values that we calibrate independently from the structural estimation. The bottom part of the table shows parameters that reflect the institutional and policy environment in the U.K.

We calibrate the distribution of mortgage draws $F_M([0, R])$ non-parametrically using Bank of England data on initial loan-to-value (LTV) ratios, for a 30-point grid running from 42.8% LTV to 95% LTV. The mortgage amortization rate is set equal to $\delta_m = 1.8\%$, corresponding to observed amortization patterns in the data, for a six-month horizon.

For the calibration of the aggregate matching function, we use observed listings and search behavior between 2018 and 2022. We set the elasticity to be equal to $\upsilon = 0.571$, following Badarinza et al. (2024) who use the same data to estimate the housing market matching func-

Figure 2
“Hockey stick” pattern and concave demand: Model vs. data

The left hand side graph reports the listing premium (difference between listing price and hedonic value) as a function of potential gains (difference between hedonic value and purchase price) in the data as well as for the full and frictionless model versions. The right hand side graph reports the transaction probability within six months of listing in the data and for both model versions. The bottom graph reports the listing premium as a function of potential home equity.



tion. We use the number of residential addresses in the Ordnance Survey address data as a proxy for the stock of residential properties and calibrate the listing probability at 5.6% to match the 1.8% semi-annual turnover rate for the housing stock, given a semi-annual transaction probability conditional on listing equal to 32.5% in the data. In addition to being a target in structural estimation, the average listing probability and the steady-state level of market tightness imply a steady-state value of demand (i.e., the number of potential buyers relative to the housing stock) equal to $N_B = 0.181 = 0.056 \times 3.229$.

To calculate the transactions tax rate (i.e., the buyer stamp duty in the U.K. context), we consider all housing transactions lodged with the Land Registry during the time period covered by our data (2010–2022). We compute the stamp duty rate that applies to each transaction, given the prevailing tax regime at the time at which it takes place. The representative transactions tax rate that we use in the calibration ($\tau^b = 0.012$) is given by the average of all stamp duty rates paid over the sample period. For the case of ongoing property taxes (i.e., council tax in the U.K. context), the situation is complicated by the fact that the taxable base is not the current market value of the property. Depending on the location, the reference price band that applies to each property can refer to market valuations as of 1991, 2003, or the year of construction. As we do not have access to price band data at the property level for each local council, we exploit information about the composition of aggregate government revenue, which suggests that council taxes account for 2.2 times as much tax income relative to stamp duty. This ratio allows us to back out the average rate of council tax. We set $\tau^h = 0.0027$, which gives the utility cost out of consumption. To interpret this as a property tax, we follow the procedure described in section 6.1, setting the exogenous rental yield at $y_o = 2.75\%$ and the housing consumption share at $\nu_o = 18.6\%$.[11]

Finally, we calibrate the bargaining function $p(\cdot)$ which translates listing prices to final transactions prices as a linear function of the listing premium, and estimate the parameters by regressing the binned realized premium on the binned listing premium. We obtain an intercept of $\beta_0 = -0.016$ and slope of $\beta_1 = 0.904$.

Table 2
External calibration

The table reports the model parameters and their sources for externally calibrated parameters as well as for the baseline policy parameters considered in our counterfactual exercises.

Parameter		Value	Target/Source
Externally calibrated parameters			
Time discount	β	0.990	Semi-annual calibration
Housing Stock	N_H	1.000	Normalization
Matching function elasticity	υ	0.571	Listings and search data
Number of buyers	N_B	0.181	Market tightness
Rental yield	y_o	0.028	Annual 5.5% rental yield
Housing consumption share	ν_o	0.186	Office for National Statistics
Bargaining intercept	β_o	-0.016	Realized vs. listing premium
Bargaining slope	β_1	0.904	Realized vs. listing premium
Mortgage amortization	δ_m	0.018	Bank of England mortgage data
Policy parameters			
Down payment constraint threshold	γ	0.300	Mortgage interest rate schedule
Stamp duty	τ^b	0.012	Average rate of stamp duty
Council tax	τ^h	0.003	Share of tax revenue

[11] Note that in the homeowner's problem, the role of τ^h is not separately identified from the utility component u. In structural estimation, we estimate the net housing utility $u - \tau^h$ and calibrate the tax rate τ^h ex-post to match the targeted level of government revenues.

4.2 Structural estimation

We specify the distribution $F_\theta(\cdot)$ of seller shocks as generalized extreme value with parameters μ_θ (location), σ_θ (shape), and ξ_θ (scale), and the buyer shock distribution $F_\varepsilon(\cdot)$ as normal with mean zero and standard deviation σ_ε. These and other remaining structural parameters are estimated by minimizing a quadratic loss function, where the model-implied moments $\mathbf{M_m}(\mathbf{x})$ are calculated numerically from the equilibrium solution of model for any given set of parameters $\mathbf{x}$. The corresponding empirical target moments are denoted by $\mathbf{M_d}$:

$$\widehat{\mathbf{x}} = \arg\min_{\mathbf{x}} \left(\mathbf{M_m}(\mathbf{x}) - \mathbf{M_d}\right)' \mathbf{W} \left(\mathbf{M_m}(\mathbf{x}) - \mathbf{M_d}\right).$$

We start with a restricted version of the model where $\eta = \mu = 0$, and estimate eight structural parameters, targeting seven empirical moments: the normalized average price level equal to 1, the average listing premium of 15.3%, the demand schedule (probability of a successful sale) for listing premiums of 0%, 20%, and 30%, and an average per-period listing probability of 5.6%. The weighting matrix $\mathbf{W}$ is chosen to normalize all empirical target moments to 1. In Panel A of Table 3, we compare the estimated parameters with an unrestricted version of the model, where we allow for reference dependence, loss aversion and financial constraints, which we pin down through the two additional behavioral parameters $\eta > 0$ and $\lambda > 1$ and through the downpayment penalty parameter $\mu > 0$. The additional moments used in this estimation are the listing premium at nominal potential gains of $\widehat{G} = -20\%$ and $\widehat{G} = 40\%$, and the listing premium at home equity levels of $\widehat{H} = 0\%$ and $\widehat{H} = 40\%$. The estimated coefficients have economically plausible magnitudes which are broadly similar between the restricted and unrestricted versions of the model. We find the estimated magnitude of reference dependence to be similar ($\eta = 0.464$), and the strength of loss aversion higher ($\lambda = 3.289$) than the value of 2.5 estimated by Andersen et al. (2022), but consistent with the larger magnitude of excess bunching observed in Figure 1 for the case of the U.K.

4.3 Model fit at the micro level

Figure 2 shows the model fit for the unconditional listing premium profiles along the potential gain and home equity dimensions, as well as for the probabilities of transactions associated with different levels of listing premiums. Panel B of Table 3 quantitatively compares the model-implied moments with their counterparts in the data for both versions of the structural estimation. The restricted model provides a tight fit to the seven targeted moments. The unrestricted model can also match all of these moments relatively well, although the fit for the transactions probabilities is slightly worse than that of the restricted model. On the other hand, the restricted model cannot explain the listing premium profile for different levels of

Table 3
Structural estimation

The table reports the estimated parameters and moments targeted in the estimation procedure. The mean listing premium is calculated from the sample, where potential gains are restricted between -20% and 40%. The listing probability target is adjusted to match the true half-yearly turnover rate of 1.8%, assuming 31.9% transaction probability within six months of first listing in the merged Rightmove-Land Registry database.

Panel A
Estimated parameters

Parameter		Model version	
		Restricted	Unrestricted
Flow utility	u	0.020	0.072
Demand level	$\bar{\chi}$	0.218	0.240
Taste shock (st. dev.)	σ_ε	0.316	1.291
Probability of θ draw	ρ	0.069	0.064
Mobility shock (location)	μ_θ	0.544	-1.827
Mobility shock (shape)	σ_θ	2.198	9.370
Mobility shock (scale)	ξ_θ	0.111	0.981
Listing cost	ϕ	0.01%	0.004%
Reference dependence	η	-	0.464
Loss aversion	λ	-	3.289
Down-payment penalty	μ	-	5.784

Panel B
Targeted moments

Moment	Data	Model version	
		Restricted	Unrestricted
Price (normalization)	1.000	0.989	0.998
Listing probability	0.056	0.056	0.050
Matching probability	0.413	0.428	0.502
Demand at $\ell = 0\%$	0.401	0.390	0.358
Demand at $\ell = 20\%$	0.339	0.334	0.308
Demand at $\ell = 30\%$	0.296	0.294	0.279
Listing premium (mean)	0.153	0.153	0.190
Listing premium at $\widehat{G} = -20\%$	0.342	0.153	0.338
Listing premium at $\widehat{G} = 40\%$	0.067	0.153	0.060
Listing premium at $\widehat{H} = 0\%$	0.467	0.153	0.418
Listing premium at $\widehat{H} = 40\%$	0.103	0.153	0.190

potential gains or home equity, whereas the unrestricted model provides quantitatively correct behavior for all the four "hockey stick" moments.

4.4 Model validation: Loss share as an aggregate statistic

Let $s^*_{it} = s^*(r_i, m_{it}, \theta_{it})$ denote the binary indicator describing the optimal extensive margin decision for a homeowner i. The model-implied transaction volume is now given by:

$$\text{Transaction Volume} = \int_{r_i, m_{it}} \int_{-\infty}^{\infty} s^*(r_i, m_{it}, \theta_{it}) \alpha(l^*_{it}(r_i, m_{it}, \theta_{it}))\, d\Phi_\theta(\theta_{it})\, dF(r_i, m_{it}). \tag{13}$$

Denote by $\bar{\ell}^*_{jt} \equiv p(\bar{l}^*_{jt}) - \mathbb{E}_t[V^h_{t+1}(r_j, m_{j,t+1})]$ the listing premium as observed by the seller. Using second order approximation for the demand function as $\alpha(\ell) = \alpha_o - \alpha_1 \ell - \alpha_2 \ell^2$, and using a two-bin Riemann sum approximation for the outer integral yields

$$\begin{aligned} \text{Transaction Probability} &= \frac{\text{Transaction Volume}}{\text{Listing Volume}} \\ &\approx \alpha_o - \alpha_1 \Big[\text{Loss share} \times \bar{\ell}^*_{\text{loss}} + \big(1 - \text{Loss share}\big) \times \bar{\ell}^*_{\text{gain}} \Big] \\ &\quad - \alpha_2 \Big[\text{Loss share} \times (\bar{\ell}^*_{\text{loss}})^2 + \big(1 - \text{Loss share}\big) \times (\bar{\ell}^*_{\text{gain}})^2 \Big], \end{aligned} \tag{14}$$

where $\bar{\ell}^*_{\text{loss}}$ and $\bar{\ell}^*_{\text{gain}}$ are the conditional average listing premia for homeowners facing losses and gains, respectively. In particular, this shows that conditional on sellers' listing premium and buyers' demand profiles, the loss share is a simple structurally informed statistic for predicting the transaction probability. To evaluate the performance of this approximation in the data, we consider the role of the loss share in the price–volume relation. The first column of Table 4 reports a price–volume comovement coefficient of 4.20, but once we control for the loss share in the third column, the coefficient on the price growth rate drops to half its previous magnitude. More importantly, the explanatory power as measured by regression R^2 is much higher for loss shares than for price growth when each variable is considered independently. We also include an additional bin with 20% threshold for potential gains, but the increase in R^2 from doing so is marginal, as can be seen in the fourth column. According to equation (14), we would expect listing premiums to be another major driver of transaction volumes. We test for this in the fifth column of Table 4. Indeed, the coefficient on listing premium is statistically significant. However, when including the loss share bins in columns (6) and (7) of the table, the coefficient on the listing premium (both on average and conditional on losses) lose their statistical significance and the model's explanatory power is only marginally improved by adding these additional variables. When interacting the loss share measure with the listing premium in column (8), as predicted by equation (14), the interaction terms are not statistically significant, and the explanatory power does not notably differ from the case of only including the loss share/paper gains.

5 Untargeted aggregate moments

Does nominal anchoring manifest in aggregate prices and quantities in the housing market? We investigate the relationship between prices and transaction volumes at the ITL2 regional level in the U.K. (and at the equivalent state-level in U.S. data) at the monthly frequency between January 2010 and December 2022.

We first 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 in each month and location.[12] 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 demean volumes and prices using their location-specific means to clean out any persistent differentials between locations. Panel A of Figure 3 shows a robust positive price-volume comovement in both markets. This unconditional comovement at a location-month level is material: an 8% decrease in prices is associated with a 20% decrease in transaction volumes in the U.S., and 30% in the U.K.

We next calculate the share of sellers facing nominal losses in each month in each ITL2 region of the U.K. Panel B of Figure 3 conditions the price-volume comovement on this loss share, comparing region-months where the share of nominal losses lies in the top quartile of the full-sample distribution ("High" in the plot's legend), with those where the share of nominal losses lies in the bottom quartile ("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 that the positive relationship between prices and volumes is far 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. Importantly, we find that this effect is driven by the post-listing behavior of individual sellers, as there seems to be no strong link between the evolution of prices and the number of new listings that arrive on the market.

[12] To construct the price indices at ITL2 level, we replace the LAD-year and region-month fixed effects with ITL2-month fixed effects in the hedonic model.

Table 4

Transaction volumes: Explanatory power of alternative model specifications

The table reports the results for a monthly panel regression of log transaction volume on contemporaneous price growth rates across ITL2 regions with regional controls for average listing premium, loss share, and their interaction for new listings measured at monthly frequency. Transaction volumes are deseasonalized by regressing the raw log volumes on quarter fixed effects and taking the residuals. Regional price growth rates are similarly deseasonalized year-on-year growth rates observed in a time fixed-effect of a hedonic model controlling for observable characteristics in realized transactions. Standard errors are clustered on ITL2 level.

	Dependent variable: Transaction volume							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price Growth	4.20***		2.16***		2.52***	2.19***	1.95***	
	(0.553)		(0.432)		(0.465)	(0.444)	(0.406)	
Loss Share		-2.58***	-1.73***	-2.77***		-1.56***	-1.85***	-3.52***
		(0.086)	(0.103)	(0.111)		(0.155)	(0.161)	(0.789)
Share of gains in [0%, 20%]				3.28***			2.63***	2.99***
				(0.483)			(0.398)	(0.487)
Listing premium (mean)					-3.62***	-0.863	-0.645	-2.44***
					(0.277)	(0.467)	(0.366)	(0.477)
Cond. listing premium (loss domain)					1.04***	-0.218	-0.193	-0.232
					(0.188)	(0.233)	(0.201)	(0.580)
Cond. listing premium squared								0.328
								(0.601)
Loss share × Cond. listing premium (loss domain)								5.76
								(3.79)
Loss share × Cond. listing premium squared (loss domain)								-2.49
								(3.19)
ITL2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,040	5,459	5,040	5,459	5,040	5,040	5,040	5,459
R^2	0.291	0.373	0.424	0.462	0.394	0.434	0.501	0.478

To acquire more granular evidence, we next analyze prices and volumes across regions. In an initial validation exercise, Plot a) of Figure 4 shows an (ex-post) measure of excess bunching mass in realized transactions for each ITL2 region of the U.K. (on the y-axis) against the (ex-ante) share of sellers who face potential nominal losses in each of these regions. The figure shows that the excess bunching mass in ex-post realized transactions to the right of the original nominal purchase price reference point is tightly linked to the ex-ante size of the population of sellers facing nominal losses. This reinforces our interpretation that reference dependence is a major driver of bunching in realized transaction prices and highlights that the share of sellers facing nominal losses is a useful regionally-varying measure of the strength of the behavioral motive.

Plot b) of Figure 4 estimates the price–volume comovement separately for each location, using the following specification: $\ln V_{i,t} = \gamma_i + \beta_{i,P} \Delta \ln P_{i,t} + \varepsilon_{i,t}$, where $V_{i,t}$ is the number of transactions recorded in ITL2 region i and month t, and $P_{i,t}$ is the corresponding price level. We plot the estimated location-specific coefficients $\beta_{i,P}$ against the location-specific share of properties that face nominal losses. The plot shows a positive association, with a univariate $R^2 = 0.44$. The elasticity of volumes with respect to price declines is more pronounced in regions where a large number of prospective house sellers face nominal losses, consistent with the presence of a lock-in mechanism driven by behavioral frictions. The online appendix shows that this relationship is of similar magnitude when re-estimated in a sample of properties for which both the buyer and the seller do not have any mortgage contract outstanding. Plots c) and d) of Figure 4 consider the role of extensive (whether or not properties are listed) and intensive margins (whether or not properties sell once they are listed) in explaining the price–volume relationship across region. The figure shows that across time and regions, the conversion rate of listings to sales comoves far more strongly with price changes, and is responsible for the cross-regional variation in comovement between total housing volumes and price changes.

Put differently, the price-volume comovement mainly comes from faster turnover of already listed properties when price growth increases; in contrast, listing volumes hardly comove with price growth. This important feature of the data is one that we revisit when discussing the predictions of the model.

Finally, plots e) and f) of Figure 4 report the time-series volatility (i.e. standard deviation) of volumes and price growth rates across regions, plotted against the regional share of potential nominal losses. In regions where the potential loss share is high, the time series volatility of volumes is substantially higher, and the volatility of prices is slightly lower. This finding aligns with broad intuition about the behavioral nominal rigidity–in areas where many agents are reluctant to realize nominal losses when housing values decline, volumes collapse and absorb shocks that would otherwise be manifest in price volatility, and vice versa when housing values rise.

Figure 3

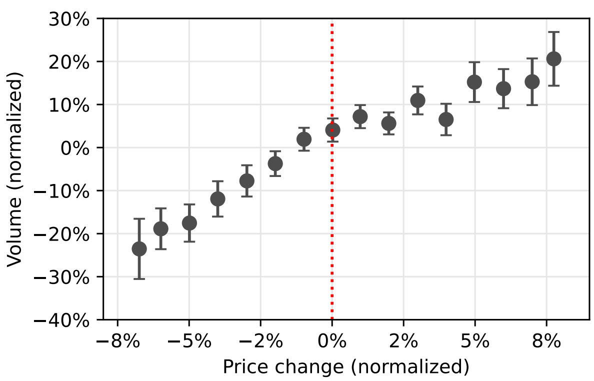
Comovement of prices and volumes

Panel A 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 monthly 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. Panel B reports the correlation between year-over-year changes in housing prices and the volume of listings (i) and realized transactions (ii). We distinguish between periods and regions for which the share of sellers that face the possibility of a loss is below/above the respective bottom/top quartile ("Low/High loss share"). Error bars indicate 95% confidence intervals for bin-specific means.

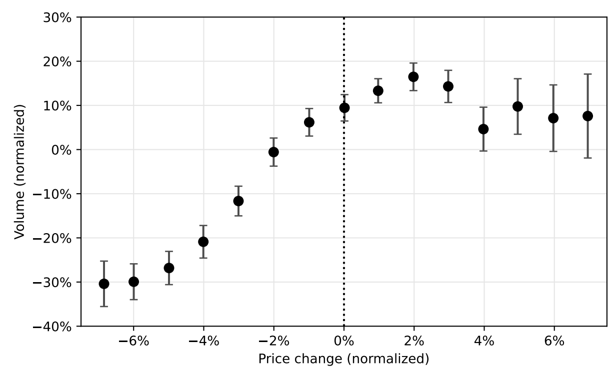
Panel A

Aggregate effects

a) U.S. (Zillow)



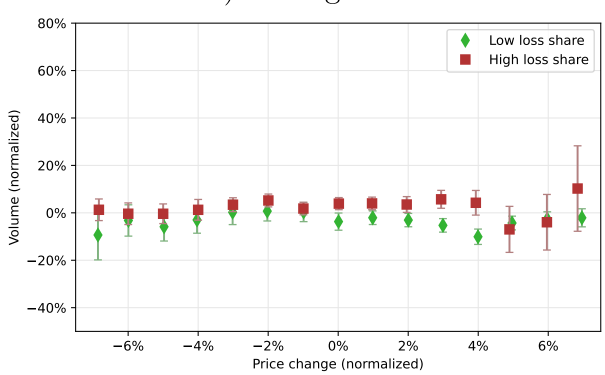
b) U.K. (Land Registry)



Panel B

The role of the loss share

c) Listing volumes



d) Transaction volumes

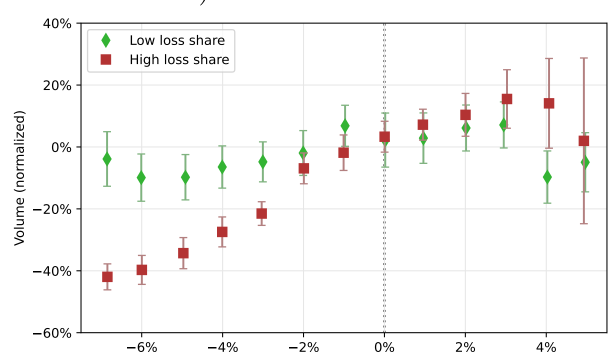
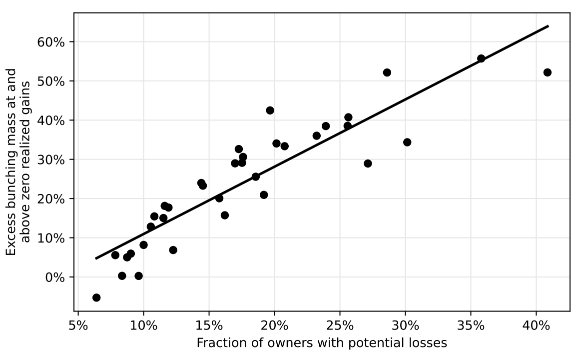


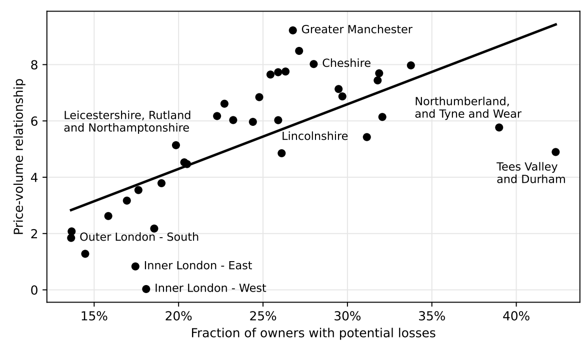
Figure 4
Cross-regional variation in the price-volume relationship

In figures below, the horizontal axis indicates the average "loss share" for UK ITL2 regions between between January 2010 and December 2022, i.e., the fraction of owners that list a property for sale for which the estimated hedonic value is below the initial purchase price . Sub-figure (a) reports the total relative excess mass for nominal realized gains between 0% and 20% for each ITL2 region separately against its average "loss share". Sub-figure (b) plots coefficients from regressions of the realized monthly transaction volume on the year-on-year price change in each ITL2 region during the period. Sub-figures (c) and (d) report corresponding region-specific regression coefficients where the dependent variable are, respectively, the listing volume and the ratio between the transaction volume and the listing volume, i.e., the transaction probability. Sub-figures (e) and (f) report region-specific volatilities of transaction volumes and price growth rates, respectively, measured as the standard deviation of their monthly value during this period.

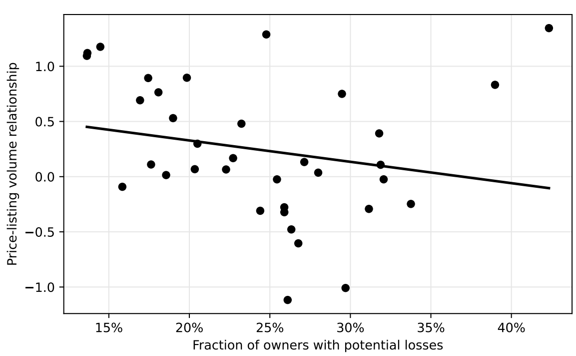
a) Magnitude of price bunching



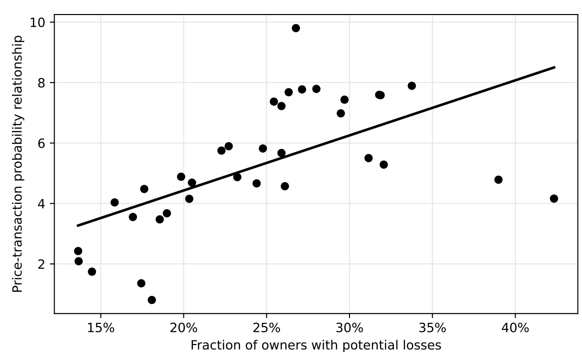
b) Price-volume relationship



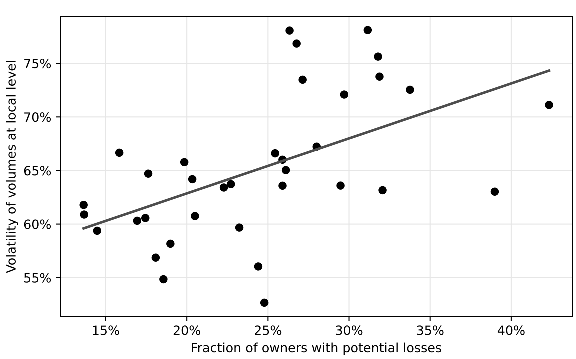
c) Listing volumes



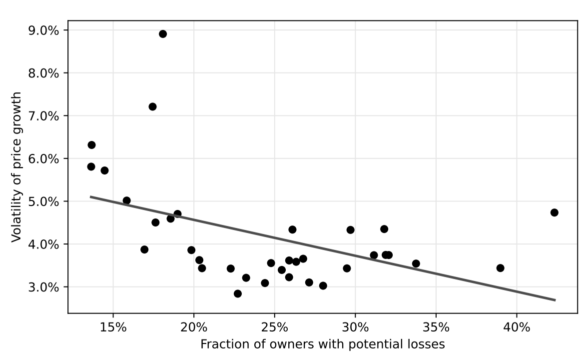
d) Transaction probability



e) Volatility of transaction volumes



f) Volatility of transaction prices

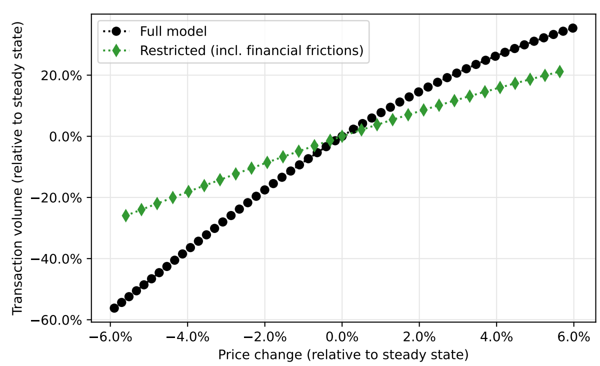


To test the model's ability to explain these data patterns, we consider the model responses to a demand shock and compare the model-implied elasticities with those observed in the data.[13] We do this analysis in partial equilibrium, assuming that none of the other model quantities is changed. In particular, since we only shift the buyers' policy function, sellers' behavior and market tightness remain unchanged. We calculate the price-volume elasticity as the percentage change in volumes divided by the change in the average log price in response to demand shocks.

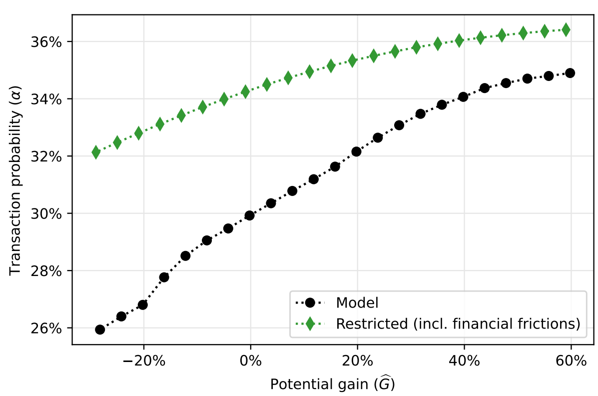
Figure 5
Untargeted aggregate moments

The figure simulates partial-equilibrium responses to a demand shock from the estimated version of the model. The quantitative magnitudes of the elasticities are only partially comparable to similar data objects in Figure 3, because the partial equilibrium price shock is different from the sequence of shocks faced by the full economy.

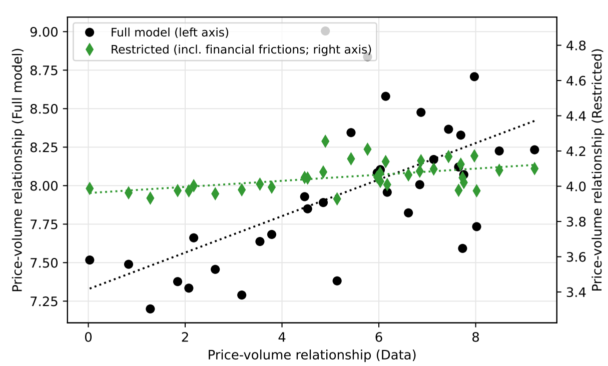
a) Transaction volumes



b) Transaction probabilities



c) Price-volume relationship



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

[13] We simulate demand shocks by shifting the transaction tax (stamp duty) in the model. Transaction taxes are equivalent to demand shocks that shift the mean of the match quality shock (ε) distribution. A positive one percentage point shock in the stamp duty rate increases the buyers' threshold value ε^* for accepting a sales offer by 0.01 in partial equilibrium.

gain after a price increase makes the seller list for a lower price, in an attempt to attract more buyers and ensure that this gain will be realized. This creates a negative relationship between the level of the potential gain that the seller stands to make and the listing premium that they set. This leads all sellers to be less "aggressive," i.e., to list with lower listing premia, prioritizing lower times on the market. These lower listing premia lead to an increased buyer likelihood of accepting sellers' offers, which in turn leads to more transactions. This mechanism generates an observed positive correlation between aggregate prices and realized transaction volumes, consistent with the results reported in Figure 3. We replicate the positive price-volume correlation and the positive link between potential gains and the transaction probability through the lens of the model in plots a) and b) of Figure 5.

We then test the model's ability to explain the cross-regional variation in price-volume elasticities observed in the data by considering the partial equilibrium responses for different subpopulations of the endogenous aggregate distribution of agents. More precisely, for each region in the data, we identify the observed joint distribution of reference prices and mortgage amounts with specific subpopulations in the model. For each subpopulation we obtain the (partial equilibrium demand-shock) implied price-volume elasticity, by feeding in the regional joint distribution of reference prices and mortgage amounts from the data. Plot c) reports region-by-region estimates of the price-volume relationships in the data against their model-implied counterparts across ITL2 regions of the U.K. The model qualitatively captures the cross-regional patterns.[14]

We also compare the model results with a restricted version of the model considering only the financial channel, setting $\eta = 0$. As expected, the volume elasticities reported in plots a) and b) of Figure 5 are smaller in the model without the behavioral channel. Furthermore, as implied by plot c) of the figure, without the behavioral mechanism the model cannot reproduce the strong link between price-volume correlation and loss shares documented in the data.

6 Housing market tax policy

6.1 Government revenue

While we do not explicitly model the government sector, we note that the presence of both transactions taxes and ongoing property taxes in the model facilitates our later work on understanding how fiscal policy related to housing is affected by the presence of behavioral frictions. In our setup, we assume that the government collects taxes from both the transactions tax and ongoing property taxes. The transaction tax is paid as a proportion of the contractual price.

[14]We slightly over-estimate the lowest price-volume comovements observed in the data—this may because our exercise omits general equilibrium forces, which we would typically expect to dampen the elasticities.

Therefore, the total transaction tax revenue is given by:

$$\text{Revenue from transaction tax} = \underbrace{[\exp(\tau^b) - 1]}_{\text{Stamp duty rate}} \times \underbrace{N_{St} \int \alpha_t(l) \exp(p(l)) \, d\Omega_t(l)}_{\text{Total value of sales}} . \tag{15}$$

The ongoing property tax is modeled as a consumption tax τ^h paid from the flow utility produced by the property. To interpret this in units of the house price, we must first convert the flow utility into monetary units. To do so, we note that in our model, the flow value of owning a home consists of two components: (i) the housing utility flow, the value of which is equal to the (potentially imputed) rental value of the property, and (ii) unmodeled non-durable consumption, the flow utility of which is normalized to 0, but which needs to be accounted for to properly calculate tax revenues.

We calibrate/set the steady-state rental yield y_o as well as the housing consumption share ν_o outside the model. The total value of consumption is then given by:

$$\text{Value of consumption} = \frac{\text{Rental value}}{\nu_o} = \frac{y_o \times \text{House value}}{\nu_o}. \tag{16}$$

Consequently, for the ongoing property tax revenue, we obtain:

$$\begin{aligned} \text{Revenue from ongoing property tax} &= \text{Tax rate} \times \text{Value of consumption} \\ &= \underbrace{[1 - \exp(-\tau^h)]}_{\text{Tax rate}} \times \frac{y_o}{\nu_o} \times \text{House value}. \end{aligned} \tag{17}$$

We consider two alternative possible assessment models of “house value” relevant in this context. The first model considers a constant assessed house value as an exogenously calibrated number, which does not respond to counterfactual changes in the tax rates or other model inputs. This corresponds to the current institutional setting in the U.K., where the “council tax” for each property is paid as a fixed sterling amount set by the local authority. When considering the house value as exogenous, changes in the tax rate τ^h mechanically affect the tax payments measured in pounds, similar to a classic “land tax” with no possible margins of adjustment that the homeowners could leverage to avoid the tax.

The second version considers the house value as an endogenous equilibrium object:

$$\text{House value} = \frac{\int \alpha_t(p) \exp(p) \, d\Omega_t(p)}{\int \alpha_t(p) \, d\Omega_t(p)}. \tag{18}$$

In this case, the property tax revenue is proportional to the endogenous property value, where the constant of proportionality is determined by the tax rate τ^h.[15]

6.2 Steady state quantities and welfare

Table 5 contrasts average steady state values of aggregate quantities for two alternative calibrations of the model. The "restricted version" shuts down behavioral and financial frictions, while the "unrestricted version" allows for these frictions. With behavioral and financial frictions, listing volumes are lower and price levels are significantly higher. This results from two competing forces. On the one hand, behavioral and financially constrained sellers list at higher prices than non-behavioral and financially unconstrained agents. These higher list prices translate to higher transaction prices, pushing the average transaction price upwards. Sellers are less inclined to list properties for sale; and when they do list, they tend to demand higher asking prices, consistent with the role of frictions as a source of nominal rigidity. On the other hand, behavioral and financially constrained agents do not act on all profitable moving opportunities (i.e. high θ shocks) due to their unwillingness to realize a nominal loss on their property. In line with the idea of *rational behavioralism*, the buyers foresee this preference ex-ante, when they first purchase the property, and thus do not value their houses as highly as non-behavioral or financially unconstrained agents. This puts downward pressure on house prices, but the effect is second-order, i.e., it affects current decisions through the expectation of future valuation changes. As expected, in our calibration, the first force dominates, and transaction prices in the unrestricted model are higher than in the non-behavioral restricted model.

However, in steady state, transaction volumes are unaffected by the presence of the frictions. A way to understand this seemingly puzzling observation is as follows: In the unrestricted version of the model, sellers with positive nominal "paper gains" have an incentive to decrease listing prices, to ensure that the transaction goes through. As these low past prices become low future reference points, this pushes up the entire (endogenous) distribution of "paper" gains. The opposite effect holds for sellers with "paper losses", who now have a more aggressive listing strategy, but these transactions are also less likely to get realized, so their impact on the potential gain distribution is relatively more muted. In the unrestricted version of the model, the "paper loss" share is therefore lower, and transactions are disproportionally more

[15] This formulation of the assessment value introduces Laffer curve effects, where the increasing tax rate may lower the property value fast enough to generate decreasing tax revenues as the function of the tax rate—i.e., a peaking Laffer curve. In this case, homeowners suffer a higher utility cost even if their tax payment decreases. This feature matches reality in that the tax payment is not the only utility cost associated with higher tax rates. Indeed, in practice, some homeowners may postpone home improvements and other renovations—lowering house quality—to avoid higher tax payments associated with higher-valued property. While we do not model this margin explicitly, we note that such (unmodeled) adjustments are implicitly embedded in our second assessment model, where the utility cost associated with τ^h is linear, but tax payments respond non-linearly to changes in τ^h.

likely to be realized in the gain domain. This is an important conclusion, because it means that the listing strategy of reference dependent and financially constrained sellers in a world with endogenously determined reference prices effectively offsets the distortionary role of behavioral frictions, and minimizes their long-term impact on the volume of transactions.

The table also shows that while steady-state volumes are broadly the same across the two models, this does not mean that the expected household surplus is unaffected by the presence of frictions. First, the lock-in effect associated with behavioral and financial frictions decreases the expected value of mobility. Second, frictions decrease the total supply of listings, shifting the bargaining power in favor of sellers who are patient enough to "fish" for higher prices (this is seen in the row entitled "listing premium", and limiting the efficient allocation of housing – this reduces buyer surplus. Finally, reference dependent sellers feel the burden of high reference prices because they incur utility declines from selling properties at nominal losses. Taken together, these factors result in an overall lower expected household surplus in steady state.

On the fiscal side, government tax take from transaction taxes increases with behavioral frictions, as average price levels are higher and transaction volumes remain virtually unchanged. The effect of frictions on ongoing property tax revenue depends on how property values are assessed for tax purposes. If ongoing property tax assessments are fixed and independent of current market prices, revenue is unaffected by frictions. If assessment values are linked to market prices, frictions create higher tax take, similar to the case of transaction taxes. In the next section, we explore these effects in more detail.

6.3 Behavioral frictions and housing market responses to taxes

6.3.1 Short-run tax elasticities

Figure 6 plots model-implied partial equilibrium responses of prices and volumes to a change in the levels of taxes, conditional on the share of "paper losses" in the stock of properties. To implement this analysis, we reduce the value of the tax rate by one percentage point and consider the partial equilibrium responses, holding all other model quantities constant. We implement the analysis for different subpopulations of the stationary equilibrium, matching each subpopulation with the empirical joint distribution of reference prices and mortgage amounts for each ITL2 region in England and Wales (analogous to Figure 5). The vertical axis shows the model-implied percentage change in prices and volumes associated with a 1p.p change in the tax; the horizontal axis shows the loss share of the particular subpopulation for which the policy change is evaluated.

An increase in the level of the transaction tax unambiguously decreases both prices and transaction volumes. As this tax is levied on the buyer, the effects of a fiscal tightening are similar to a demand shock, and both prices and transaction volumes decrease. But the

Table 5
Model-implied aggregate quantities

The table reports average steady state values of aggregate quantities, implied by our estimated model. We distinguish between a restricted version, where we set $\eta = \mu = 0$, and an unrestricted one, where we use estimated values for all structural parameters.

	Restricted version	Unrestricted version
Average price	0.7071	2.7545
Listing volume	0.0565	0.0496
Transaction volume	0.0150	0.0150
Loss domain	0.0054	0.0051
Gain domain	0.0096	0.0099
"Paper loss" share	0.3585	0.3412
Household surplus		
Buyer surplus	0.0224	0.0200
Seller surplus	0.0569	0.0577
Decomposition:		
Listing premium	-0.0141	-0.0103
Mobility	0.0710	0.0699
Gains/Losses	-	-0.0017
Financial penalty	-	-0.0001
Total surplus	0.0793	0.0777
Government revenue		
Transaction tax	0.0001	0.0005
Ongoing property tax		
Alternative specifications:		
Constant assessment value	0.0012	0.0012
Endogenous assessment value	0.0003	0.0012

buyers' lower willingness-to-pay is less likely to be accommodated in an environment in which reference dependent sellers avoid realizing nominal losses. A higher "paper" loss share is therefore associated with a more muted response of prices and a stronger response of volumes. This is a key result of our paper, because it quantifies the unequal impact of tax policy across regions, depending on the valuation of the local housing stock. Panel A shows that in regions around London, where only 15% of homeowners face a "paper" loss, a 1p.p. increase of the transaction tax would be associated with a decline of 0.10% in prices and 0.75% in volumes; in Northern regions, where up to 50% of homeowners are in the loss domain, the price effect is slightly more muted, and the volume response increases to 0.85%.

Figure 6

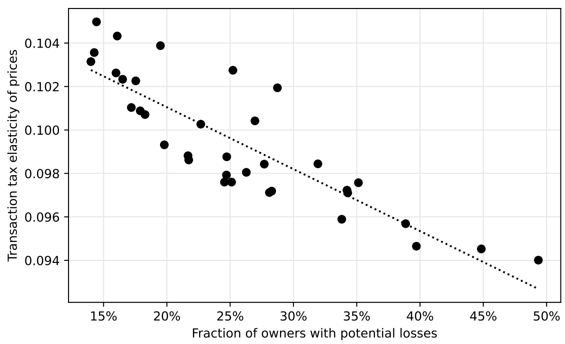
Model-implied short-term tax elasticities: Cross-sectional variation

The figure reports the model-implied short-run response in transaction volumes to changes in transactions and ongoing property taxes. We reduce the values of the parameters τ^b and τ^h by 1 percentage point and consider the one-period ahead partial equilibrium response of average realized transaction prices and total realized number of transactions.

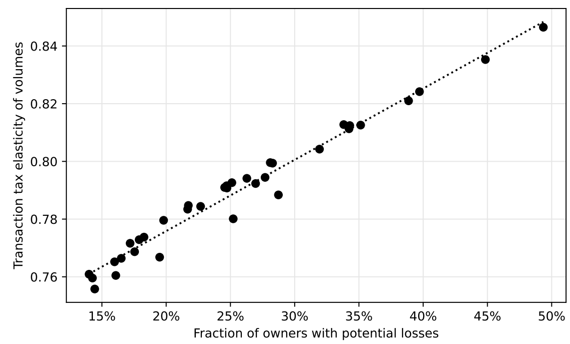
Panel A

Transaction tax

a) Average prices



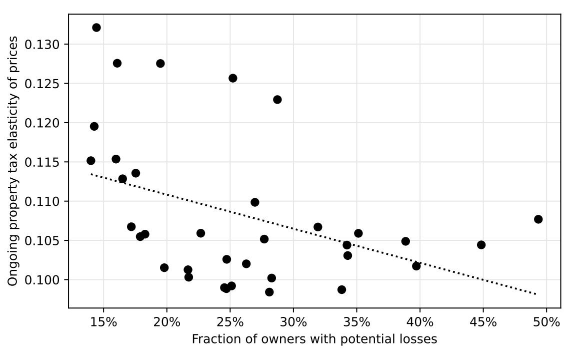
b) Transaction volumes



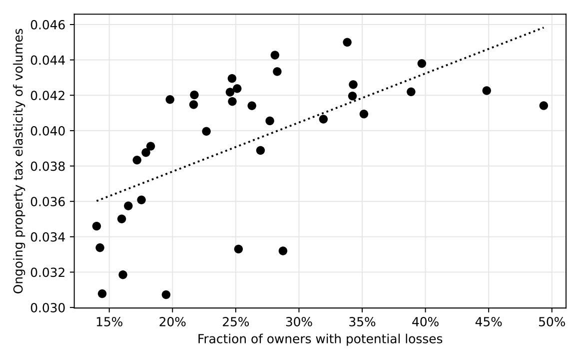
Panel B

Ongoing property tax

c) Average prices



d) Transaction volumes



Do ongoing property taxes have similar distortionary effects in the short term? Yes. In an environment with behavioral and financial frictions, the decrease in property valuations associated with a higher property tax leads some sellers to perceive a nominal loss position, which they seek to avoid by deferring transactions into the future. This is very different from a standard frictionless setting, where an increase in ongoing property taxes is simply capitalized into lower nominal valuations by both buyers and sellers, without an associated volume response. The core difference here is that while valuations adjust immediately to the tax, the distribution of reference points moves only very sluggishly, as only a low fraction of of the housing stock trades every period. In this case, changes in ongoing property tax are short-run distortionary, different from the classic result that ongoing property/land taxes only affect prices without material economic consequences (Mirrlees et al., 2012). Taken together, our results reinforce the interpretation of the loss share as an important statistic to predict housing market responses to tax changes. But before revisiting these effects in the data, we evaluate the impact of changes in the fiscal regime on steady-state aggregate quantities.

6.3.2 Long-run tax elasticities

Figure 7 reports the results of a comparative statics analysis across steady-state values of aggregate quantities in the model, associated with different levels of the tax rates. Panel A shows that the long-run impact of the transaction tax is similar to the short-run response, with prices and volumes decreasing predictably. The same mechanisms that we discussed above generate both a more muted price response and a stronger volume response in the presence of behavioral and financial frictions.

For the case of ongoing property taxes, the pattern of long-term impacts is subtly different. Panel B suggests two main differences relative to the short-run effects reported in Figure 6. First, higher ongoing property taxes reduce property valuations symmetrically for both buyers and sellers, and there is no distortion of real quantities, similar to the model without behavioral and financial frictions. This is because reference points adjust in steady state to reflect the changes in aggregate valuations. This restores the homeowners' nominal gain/loss position, and allows the aggregate volume of transactions to return to its initial level.

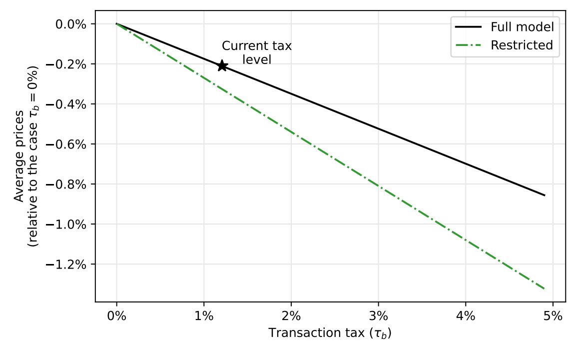
Second, in the long-run, the elasticity of the price response to the ongoing property tax is an order of magnitude higher than the response to a similar change in the transaction tax. To understand this difference quantitatively, we note that the turnover rate in the U.K. is equal to 3.6% per year, and therefore the one-off cost of the expected next move is heavily discounted by the representative buyer. While an increase in the ongoing property tax reduces the flow utility generated by the property for *every period* in the future, the transaction tax must be paid only once, in the event of a sale. Additionally, the price sensitivity to the transaction tax depends on the buyers' bargaining power; it decreases when the buyer-seller ratio is high, such as, e.g., in an environment with high perceived loss shares, when owners refuse to list properties for sale. Comparing our results with the literature, we find an average short-term elasticity of 0.1 for prices and 0.8 for volumes. These values lie between the high magnitudes of 2–5 for prices and 10 for volumes identified using "tax holiday" periods (Best and Kleven, 2018; Eerola et al., 2021), and magnitudes close to zero, which emphasize reversal effects (Mian and Sufi, 2012).

Figure 7
Long-run tax elasticities across model versions

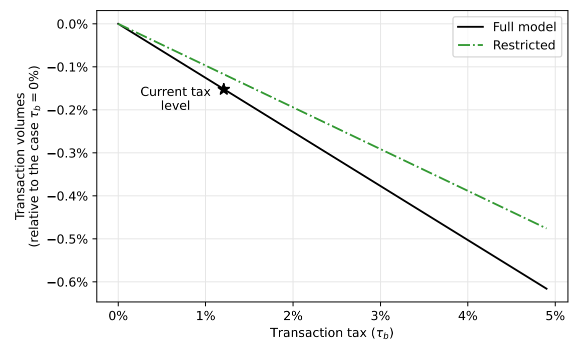
The figure reports the model-implied steady state response in transaction volumes to changes in transactions and ongoing property taxes. We distinguish between a restricted version, where we set $\eta = \mu = 0$, and an unrestricted one, where we use estimated values for all structural parameters.

Panel A
Transaction taxes

a) Average prices

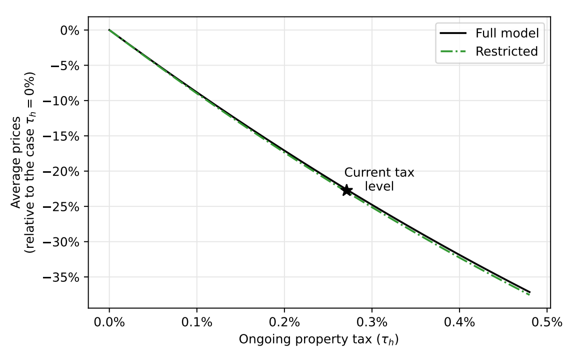


b) Transaction volumes

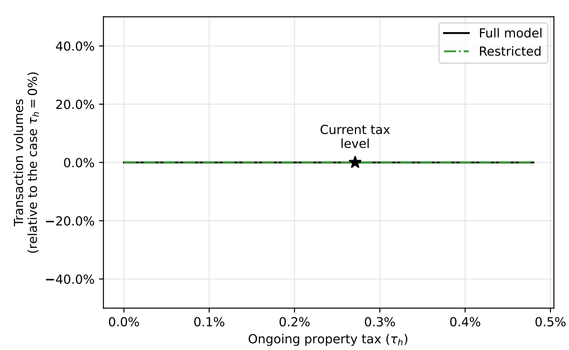


Panel B
Ongoing property taxes

c) Average prices



d) Transaction volumes



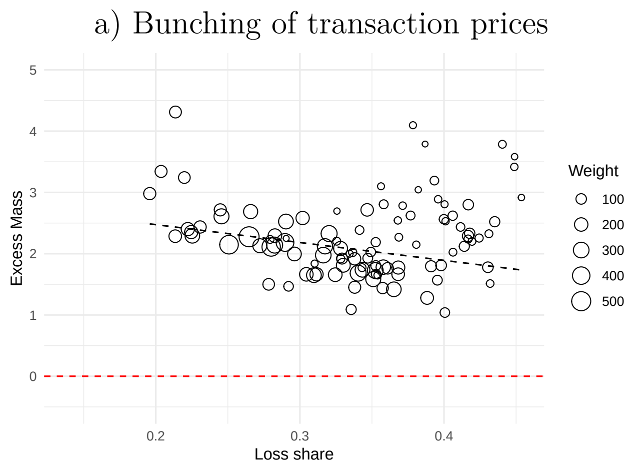
6.4 Empirical validation using transaction tax notches

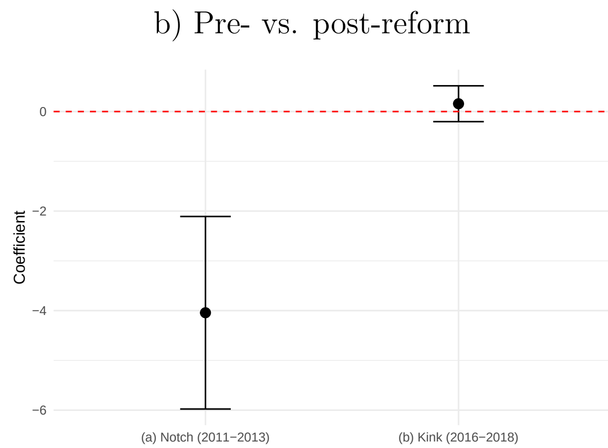
Before December 2014, the U.K. stamp duty rate schedule featured "notches" with transactions taxes discretely increasing at specific threshold price levels. This created strong incentives for buyers to seek transactions prices exactly at or below these threshold points to avoid paying a higher rate on the *entire* purchase value of the property, generating visible "bunching" in observed realized price distributions. This system was replaced in December 2014 with a schedule that replaced the discrete increase in the tax rate at the threshold (a "notch") with a continuous increase in the schedule (a "kink"). This reduced the incentive of buyers to bargain for prices that bunch at particular levels, as the marginal fiscal cost of a transaction price above each threshold is only slightly higher at a kink.

Figure 8

Cross-regional variation in the effect of reference dependence on bunching

Panel A plots the excess bunching mass for transaction prices in the interval (£245,000, £250,000] against the loss share at the level of ITL2 regions. The figure on the right corresponds to observations in periods with a tax schedule notch; figure on the left corresponds to a tax schedule kink. The dark dotted line shows a linear fit between bunching mass and loss shares weighted by the number of expected transactions for the price band (the weights are shown by the relative size of the circles in both sub-figures). Panel B reports regressions coefficients obtained by regressing excess bunching mass on the loss shares at the ITL2 level for (i) observations during periods when the tax schedule had a notch (2011-2013) at the price £250,000 vs. a kink (2014-2016) and (ii) annual data.





Theoretically, how does seller-side reference dependence influence these outcomes? As discussed above, a seller that faces the possibility of losses when selling at a "notch" threshold transactions price is less likely to accommodate the buyer's incentive to decrease the price up to the threshold, which should result in an overall lower magnitude of observed bunching in the distribution at the relevant tax threshold.

We validate this mechanism in the data by studying transaction bunching at stamp duty notches. The stamp duty tax rate discretely increases at transaction price thresholds that include £125,000, £250,000 and £500,000. In our validation analysis, we focus on bunching at the £250,000 threshold, which is close to the median house price in the U.K.

We estimate excess bunching mass relative to a counterfactual measure of mass at the price threshold. The counterfactual mass is the number of transactions that would occur at each price point if every house were to trade at its hedonic price. Thus, our measure of excess bunching mass is the difference between the number of realized transactions at the tax notch price threshold and the counterfactual mass at the same price point.

First, we find a negative association between the magnitude of excess bunching mass at the £250,000 price threshold and loss shares across UK ITL2 regions. In plot a) of Figure 8, the

y-axis shows the annual excess bunching mass observed at this threshold for each UK ITL2 region for the years 2011, 2012, and 2013 against the x-axis, which is the "paper loss share" prevailing in each of these UK ITL2 regions for each year. These loss shares are computed as the proportion of all listed properties in each ITL2 region that are estimated by the hedonic model to trade at a nominal loss relative to their original purchase prices. We lag the loss shares to avoid any mechanical correlation, computing these shares in the 6-months preceding the period in which we compute the bunching mass. The figure shows a negative association, as we confirm using the weighted fit line as well as using a simple regression whose coefficients we report in plot b) of the same figure. Overall, a higher proportion of potentially loss-making listings is associated with lower excess bunching mass, consistent with sellers' reluctance to lower prices even marginally to accommodate the higher stamp duty for buyers.

Second, we find that that both the excess bunching mass, and consequently the negative association of the excess bunching mass with loss shares across the ITL2 regions is weaker after the notched tax schedule was modified to a kink following the December 2014 tax reforms. Plot b) of Figure 8 shows this by comparing the (significantly negative) coefficients of a regression of the regional excess bunching mass against loss shares in the 2011-2013 period featuring the notch in the tax schedule, versus a much weaker and statistically insignificant effect in 2016-2018, when this notch was replaced with a kink in the tax schedule.

6.5 The Laffer curve and household surplus

To quantify the long-run welfare implications of the behavioral motive, we follow Saez (2001), Saez and Stantcheva (2016) and Anagol et al. (2023). We denote by g the marginal social value of an extra pound sterling of tax revenues, and calculate total welfare as the sum between household surplus and the social value of tax revenue:

$$\text{Total welfare} = \text{Household surplus} + g \times \text{Tax revenue}. \tag{19}$$

For the case of the transaction tax, a higher rate increases government tax take proportionally, as a function of the average transaction price. However, both average prices and transaction volumes decrease with the tax rate, generating a Laffer curve. On the other side, household surplus is affected as well: transaction taxes distort moving decisions, meaning that changes in mobility affect the degree to which buyers and sellers can capture the surplus from transactions. The sum of government revenue and surplus could therefore increase in the tax rate if price and volume elasticities are low, or decrease if elasticities are high enough for the surplus effect to dominate.

In plot a) of Figure 9, we show the relationship between total welfare and the level of the transaction tax, implied by our estimated version of the model, for two values of the marginal value of public funds equal to $g = 1$ and $g = 2.5$.[16] In both the frictionless version and the full model, the welfare function does not peak for realistic values of the tax rate, consistent with results on consumption taxes (Trabandt and Uhlig, 2011). Put differently, when we increase the level of the transactions tax within a reasonable range, neither the price nor the volume response are large enough to decrease consumer surplus enough to offset the increase in government revenues. Behavioral and financial frictions magnify these effects: If the government has a high social marginal value for additional tax revenues (g), it benefits from the presence of behavioral agents who drive up the transaction prices; at the same time, behavioral frictions lower price elasticities to taxes, further dampening the Laffer curve effect.

The case of ongoing property tax is again slightly different: as it is levied on the entire stock of properties, total government revenue from this source strictly depends on the average assessed property value at any given point in time. In the version of the model where assessed values are constant, as is currently the case in the U.K., the government revenue curve is proportional to the tax rate, and the total welfare function is therefore trivially equal to the tax take plus a constant surplus term. However, more interestingly, if assessed values are linked to the set of realized transactions through a hedonic-type valuation model, and assuming that rental values capitalize the future tax effect, a Laffer curve emerges, where increasing the tax rate has decreasing marginal benefits. The role of behavioral frictions in this context is to increase the overall tax take and to make it less sensitive to the tax. The intuition is that with behavioral and financial frictions, the market is less likely to allow prices to decrease, and the government has much more room for action. Plot b) of Figure 9 quantifies this effect numerically in our estimated version of the model: the Laffer curve is shifted to the right when compared with the restricted non-behavioral model.[17]

In steady state, households in our model strictly prefer the non-distortionary ongoing property tax—it does not affect their expected surplus. However, the government faces a trade-off between transaction taxes and ongoing property taxes from the perspective of total welfare, since transitions between different tax systems are potentially distortionary. In plots c) and d) of Figure 9, we illustrate this trade-off across steady states by plotting the indifference curve between the two types of taxes, corresponding to the welfare level that obtains for the current level of taxation ($\tau_h = 0.27\%$ and $\tau_b = 1.21\%$). This plot answers the question: keeping the

[16] In the literature, there is no consensus on the calibration of social welfare functions; we illustrate the quantitative implications of our model using a marginal value of public funds up to 2.5, consistent with Hendren and Sprung-Keyser (2020).

[17] An increase in the property tax rate will generate lock-in during the transition between the steady states. Decreases in nominal prices that arise due to increases in taxes will, *ceteris paribus*, increase the share of households facing nominal losses and therefore affect their behavior as potential sellers. While the government gains revenue from the higher collection of property taxes in the behavioral model, it may lose revenue from other sources (such as, e.g., the labor market), because of reduced income and mobility of behavioral agents.

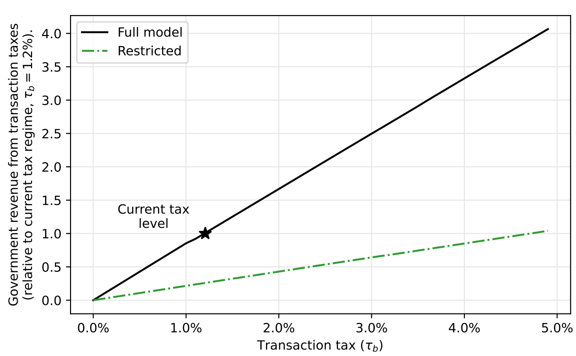
Figure 9
Welfare effect of behavioral frictions

Panel A reports the variation of tax take implied by the model, for different levels of the transaction tax and ongoing property tax. We distinguish between a frictionless version ($\eta = \mu = 0$) and the full model ($\eta > 0, \lambda > 1, \mu > 0$). For the calculation of government revenue from ongoing property taxes, in plot b) we use the assessment value endogenously determined by the average transaction price. In panel B, we report the combinations of transaction taxes and ongoing property taxes for which total welfare is equal to the one in the baseline estimated version of the model, for value of the parameters $g = 1$ and $g = 2.5$. We separately consider the case where the assessment value is constant (corresponding to the current fiscal regime of the U.K.), and the one where it is endogenously determined in steady state.

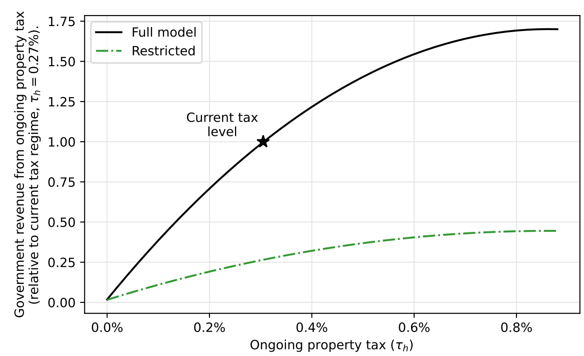
Panel A

Total welfare calculation

a) Transaction tax



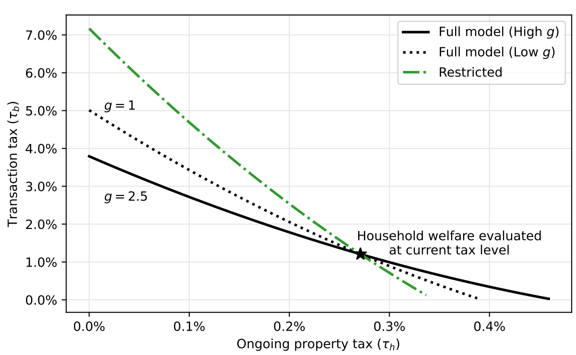
b) Ongoing property tax



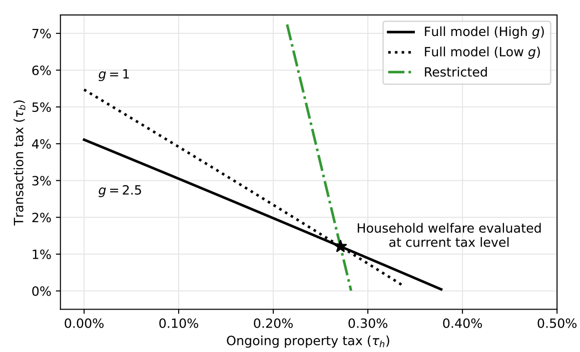
Panel B

Fiscal policy trade-off

c) Endogenous assessment



d) Constant assessment



current level of total welfare constant, what flexibility does the government have to adjust either of the two types of taxes? We find that behavioral frictions increase the use of transaction taxes—for example, in order to remove the ongoing property tax, transaction taxes would need to rise to a level of 3.8% in the behavioral model compared to 7.3% in the frictionless version. The effect carries through qualitatively irrespective of the assessment method, because in the behavioral model transaction taxes are relatively more effective; prices are higher and home owners are less sensitive to a higher level of the tax.

7 Conclusions

Careful experiments in a wide variety of economic settings and across a wide range of countries show that agents are reference dependent and loss averse. Such non-standard preferences generate observable behavioral biases in field settings with real stakes—including marathon running, job search, income tax filings, and financial investments (Ingersoll and Jin, 2013; Kleven, 2016; Allen et al., 2017; DellaVigna et al., 2017; Rees-Jones, 2018). Do these individual biases have a material impact on economic outcomes at the aggregate level? We explore this question in the systemically important residential real estate market. This is also an important market for individual households, as housing is generally the largest asset on the household balance sheet.

We embed loss-averse and reference-dependent sellers into a dynamic equilibrium model of the housing market with search and matching frictions, featuring rich heterogeneity, aggregate shocks, and realistic financial constraints. We structurally estimate the model to fit a wide set of micro data moments. The model delivers predictions about aggregate housing market fluctuations (untargeted in structural estimation), which we verify in the data. This exercise confirms the importance of accounting for behavioral frictions to better understand aggregate outcomes in this important market.

More specifically, we find that the distributions of historically determined nominal reference prices in different regions of the U.K. are tightly empirically linked with the dynamics of aggregate quantities and prices in the housing market. We find that: (i) prices and transaction volumes co-move positively; (ii) the comovement is asymmetric, and more pronounced in locations or times when a high share of houses face "paper losses"; (iii) the fraction of households facing such paper losses is a simple but very important statistic to predict aggregate effects, computed as the share of houses in any given regional market that would realize a nominal loss if it were sold at hedonic value; and (iv) the volatility of housing transaction volumes is substantially more pronounced in regions with high levels of paper losses.

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. Finally, we validate the importance of these insights by evaluating the appropriate design of housing taxation policies in market populated by behavioral agents. We show that fiscal policy trade-offs in this market alter in the presence of behavioral frictions, and present empirical evidence consistent with this observation. This demonstrates more broadly that behavioral frictions should be taken into account when considering a range of policy interventions targeted at the housing market; we look forward to future work along these lines.

Online Appendix

The online appendix provides an overview of the composition and filtering of our data, it describes the mortgage binning procedure and the determination of loan-to-value ratios and interest rates and the corresponding estimated amortization schedule in the U.K. mortgage market, repeats the cross-sectional analysis in a sample of properties for which both the buyer and the seller do not have any mortgage contract outstanding, illustrates additional dimensions of cross-regional variation in the data, describes the evolution of the U.K. transactions tax schedule through time, provides details about the numerical solution of the model, and lists additional steps to understand the derivation of analytical results and quantitative results mentioned in the main body of the paper.

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. 4, 5

Aiello, Darren, Jason D. Kotter, and Gregor Schubert, "When Money Moves In: The Consequences of Housing Wealth," Technical Report, Brigham Young University, Working Paper 2022. 13

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. 2, 5

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. 5, 42

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. 5

Anagol, Santosh, Benjamin B Lockwood, Allan Davids, and Tarun Ramadorai, "Diffuse Bunching with Frictions: Theory and Estimation," Technical Report, Working Paper 2022. 5, 9

_, Vimal Balasubramaniam, Tarun Ramadorai, and Antoine Uettwiller, "A bad bunch: Asset value under-reporting in the Mumbai real estate market," *Available at SSRN 4055401*, 2023. 39

Andersen, Steffen, Cristian Badarinza, Lu Liu, Julie Marx, and Tarun Ramadorai, "Reference dependence in the housing market," *American Economic Review*, 2022, *112*, 3398–3440. 2, 9, 10, 14, 18, 21

Anenberg, Elliot and Daniel Ringo, "The propagation of demand shocks through housing markets," *American Economic Journal: Macroeconomics*, 2022, *14* (3), 481–507. 5

_ and Patrick Bayer, "Endogenous Sources Of Volatility In Housing Markets: The Joint Buyer–Seller Problem," *International Economic Review*, 2020, *61* (3), 1195–1228. 5

Auerbach, Alan J and Laurence J Kotlikoff, "Dynamic fiscal policy," *(No Title)*, 1987. 3

Badarinza, Cristian, Vimal Balasubramaniam, and Tarun Ramadorai, "In Search of the Matching Function in the Housing Market," Technical Report, Working Paper 2024. 18

Bailey, Martin J, Richard F Muth, and Hugh O Nourse, "A regression method for real estate price index construction," *Journal of the American Statistical Association*, 1963, *58* (304), 933–942. 17

Barberis, Nicholas and Wei Xiong, "Realization utility," *Journal of Financial Economics*, 2012, *104* (2), 251–271. 3

Bastani, Spencer and Daniel Waldenström, "Taxing the wealthy: the choice between wealth and capital income taxation," *Oxford Review of Economic Policy*, 2023, *39* (3), 604–616. 2

Best, Michael Carlos and Henrik Jacobsen Kleven, "Housing market responses to transaction taxes: Evidence from notches and stimulus in the UK," *The Review of Economic Studies*, 2018, *85* (1), 157–193. 2, 36

Bilal, Adrien and Esteban Rossi-Hansberg, "Location as an Asset," *Econometrica*, 2021, *89* (5), 2459–2495. 4

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

Burdett, Kenneth and Kenneth L Judd, "Equilibrium price dispersion," *Econometrica: Journal of the Econometric Society*, 1983, pp. 955–969. 5

Chetty, Raj, "Behavioral economics and public policy: A pragmatic perspective," *American Economic Review*, 2015, *105* (5), 1–33. 2, 5

Cho, Yunho, Shuyun May Li, and Lawrence Uren, "Stamping out stamp duty: Housing mismatch and welfare," *Quantitative Economics*, 2024, *15* (2), 381–426. 2

Coven, Joshua, Sebastian Golder, Arpit Gupta, and Abdoulaye Ndiaye, "Property Taxes and Housing Allocation Under Financial Constraints," Technical Report, CESifo 2024. 2

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. 2, 5, 42

Diamond, Peter A, *A search-equilibrium approach to the micro foundations of macroeconomics*, Vol. 1982, MIT press, 1984. 5

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. 5

Eerola, Essi, Oskari Harjunen, Teemu Lyytikäinen, and Tuukka Saarimaa, "Revisiting the effects of housing transfer taxes," *Journal of Urban Economics*, 2021, *124*, 103367. 2, 36

Farhi, Emmanuel and Xavier Gabaix, "Optimal taxation with behavioral agents," *American Economic Review*, 2020, *110* (1), 298–336. 2

Fisher, Jack, Alessandro Gavazza, Lu Liu, Tarun Ramadorai, and Jagdish Tripathy, "Refinancing cross-subsidies in the mortgage market," Technical Report, Working Paper 2023. 5

Fonseca, Julia and Lu Liu, "Mortgage Lock-In, Mobility, and Labor Reallocation," Technical Report, Working Paper 2023. 5

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. 2, 18, 17

Grindaker, Morten, Artashes Karapetyan, Espen Moen, and Plamen Nenov, "Transaction Sequence Decisions and Housing Market Volatility: Evidence from Norway," Technical Report 2021. 5

Guren, Adam M, "House price momentum and strategic complementarity," *Journal of Political Economy*, 2018, *126* (3), 1172–1218. 5, 18

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. 5

_, Rachel Ngai, and Kevin Sheedy, "To Own or To Rent? The Effects of Transaction Taxes on Housing Markets," 2023. 2

Hendren, Nathaniel and Ben Sprung-Keyser, "A unified welfare analysis of government policies," *The Quarterly Journal of Economics*, 2020, *135* (3), 1209–1318. 40

Huckfeldt, Christopher, "Understanding the scarring effect of recessions," *American Economic Review*, 2022, *112* (4), 1273–1310. 5

Ingersoll, Jonathan E and Lawrence J Jin, "Realization utility with reference-dependent preferences," *The Review of Financial Studies*, 2013, *26* (3), 723–767. 42

Kleven, Henrik Jacobsen, "Bunching," *Annual Review of Economics*, 2016, *8*, 435–464. 5, 42

Krainer, John, "A theory of liquidity in residential real estate markets," *Journal of Urban Economics*, 2001, *49* (1), 32–53. 5

Krusell, Per and Anthony A Smith Jr, "Income and wealth heterogeneity in the macroeconomy," *Journal of Political Economy*, 1998, *106* (5), 867–896. 4, 5

Liu, Lu, "The demand for long-term mortgage contracts and the role of collateral," Technical Report, Working Paper 2022. 9, 3

Lucas, Robert E Jr., "Macroeconomic priorities," *American economic review*, 2003, *93* (1), 1–14. 4

Merlo, Antonio and Francois Ortalo-Magne, "Bargaining over residential real estate: evidence from England," *Journal of Urban Economics*, 2004, *56* (2), 192–216. 5

Mian, Atif and Amir Sufi, "The effects of fiscal stimulus: Evidence from the 2009 cash for clunkers program," *The Quarterly journal of economics*, 2012, *127* (3), 1107–1142. 36

Mirrlees, James, Stuart Adam, Tim Besley, Richard Blundell, Stephen Bond, Robert Chote, Malcolm Gammie, Paul Johnson, Gareth Myles, and James Poterba, "The Mirrlees review: A proposal for systematic tax reform," *National Tax Journal*, 2012, *65* (3), 655–683. 2, 36

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. 5

Mullainathan, Sendhil, Joshua Schwartzstein, and William J Congdon, "A reduced-form approach to behavioral public finance," *Annu. Rev. Econ.*, 2012, *4* (1), 511–540. 2, 5

Ngai, L Rachel and Silvana Tenreyro, "Hot and cold seasons in the housing market," *American Economic Review*, 2014, *104* (12), 3991–4026. 5, 17

O'Donoghue, Ted and Matthew Rabin, "Optimal sin taxes," *Journal of Public Economics*, 2006, *90* (10-11), 1825–1849. 5

Office for Budget Responsibility, "Council Tax," 2024. 2

Piazzesi, Monika, Martin Schneider, and Johannes Stroebel, "Segmented housing search," *American Economic Review*, 2020, *110* (3), 720–59. 5

Rees-Jones, Alex, "Quantifying loss-averse tax manipulation," *The Review of Economic Studies*, 2018, *85* (2), 1251–1278. 5, 42

Saez, Emmanuel, "Using elasticities to derive optimal income tax rates," *The Review of Economic Studies*, 2001, *68* (1), 205–229. 39

_ **and Gabriel Zucman**, "Progressive wealth taxation," *Brookings Papers on Economic Activity*, 2019, *2019* (2), 437–533. 2

_ **and Stefanie Stantcheva**, "Generalized social marginal welfare weights for optimal tax theory," *American Economic Review*, 2016, *106* (01), 24–45. 39

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. 3, 5, 9, 14

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. 2, 5

Timilsina, Govinda R, "Carbon taxes," *Journal of Economic Literature*, 2022, *60* (4), 1456–1502. 2

Trabandt, Mathias and Harald Uhlig, "The Laffer curve revisited," *Journal of Monetary Economics*, 2011, *58* (4), 305–327. 40

Urban-Brookings Tax Policy Center, "The Tax Policy Briefing Book," 2024. 2

Wheaton, William C, "Vacancy, search, and prices in a housing market matching model," *Journal of Political Economy*, 1990, *98* (6), 1270–1292. 5

Behavioral Lock-In: Housing Market Taxation with Reference Dependent Agents

Online Appendix

Cristian Badarinza, Tarun Ramadorai,
Juhana Siljander, Jagdish Tripathy

March 20, 2025

A Appendix

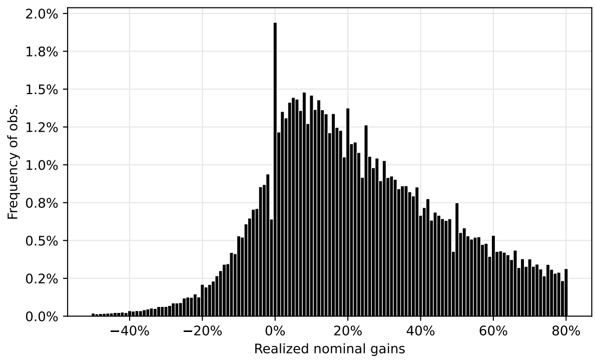
Contents

A.1 Additional tables and figures

Figure A.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).

(i) Distribution of transaction prices



(ii) Excess mass

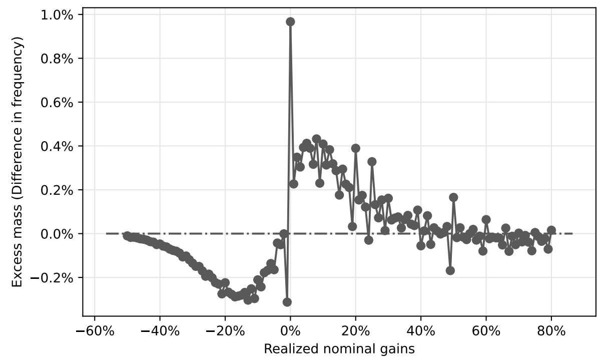


Figure A.2

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.

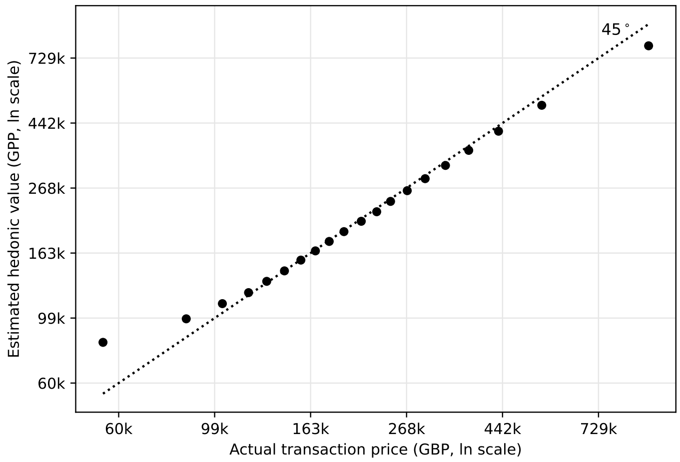


Figure A.3

Cross-regional variation in the price-volume relationship: Non-mortgage sample

The figure 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 analysis uses transaction volumes and price growth (using repeat sales price indices) calculated in the sub-sample of Land Registry transactions which are associated with a mortgage contract. The loss share measure is based on the listings during 2010-2022.

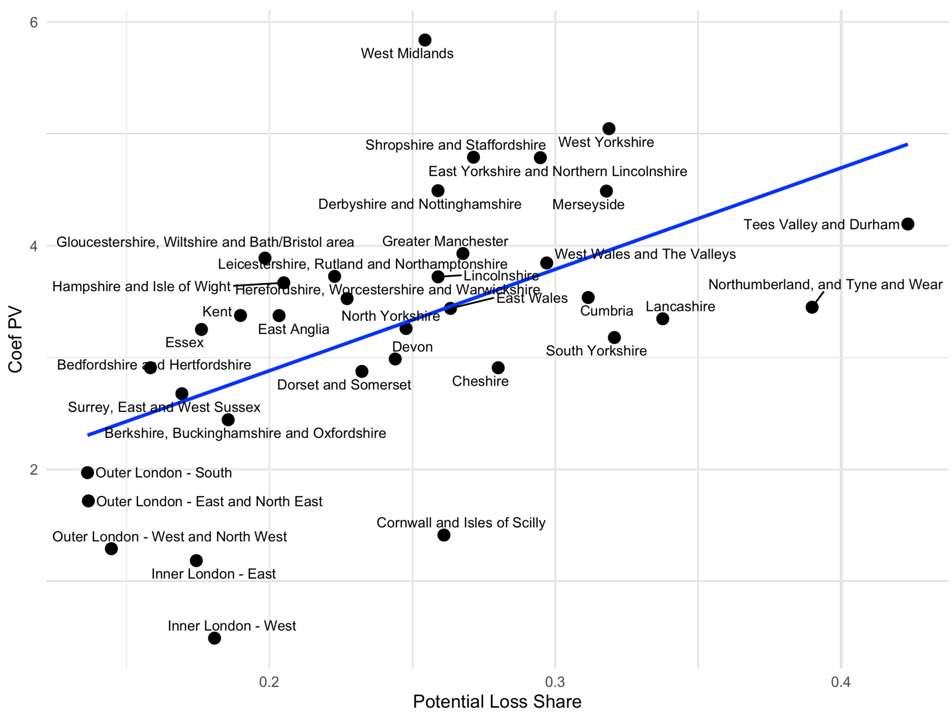


Figure A.4

Loss share as a sufficient statistic

The figure plots cumulative R-square statistics from a regressions of the realized transaction volume on the year-on-year price change and loss share in each ITL2 region, for the period between January 2010 and December 2022, corresponding to table 4. In addition to the loss share, we further discretize the nominal gain distribution in multiple bins (indicated on the horizontal axis), and add to the regression the share of nominal gains in each bin in each ITL2 region and each period.

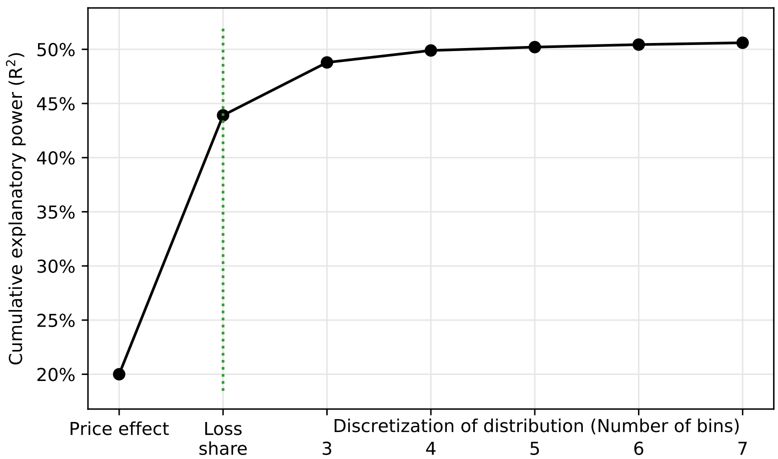


Figure A.5

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.

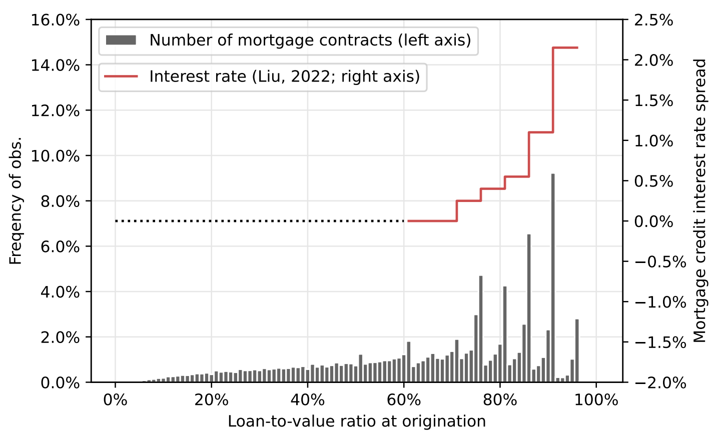


Figure A.6
Amortization and repayment of mortgage loans

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.

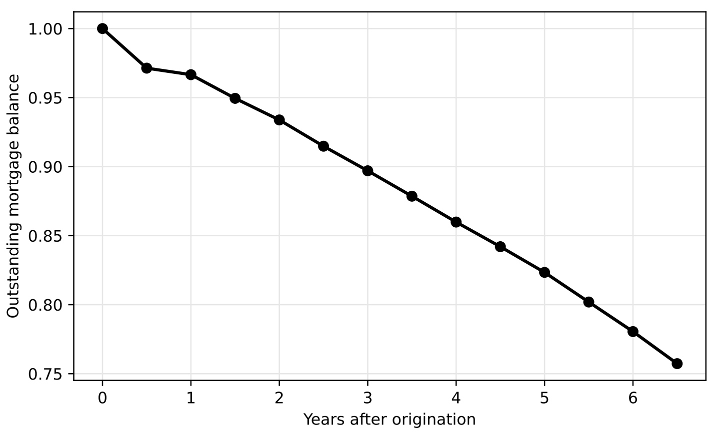
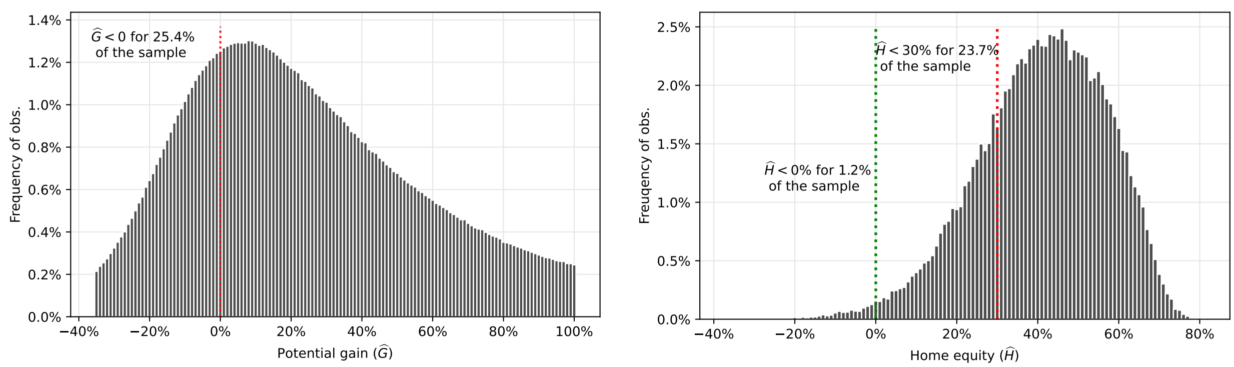


Figure A.7
“Paper losses” and home equity

The figure reports histograms for potential home equity, i.e., the percent differences between hedonic property values and outstanding mortgage amounts. The data cover the period between 2015 and 2022, and are recorded in half-yearly snapshots as part of the PSD007 data set of the Financial Conduct Authority.

Panel A
Full-sample distributions



Panel B
Cross-regional heterogeneity

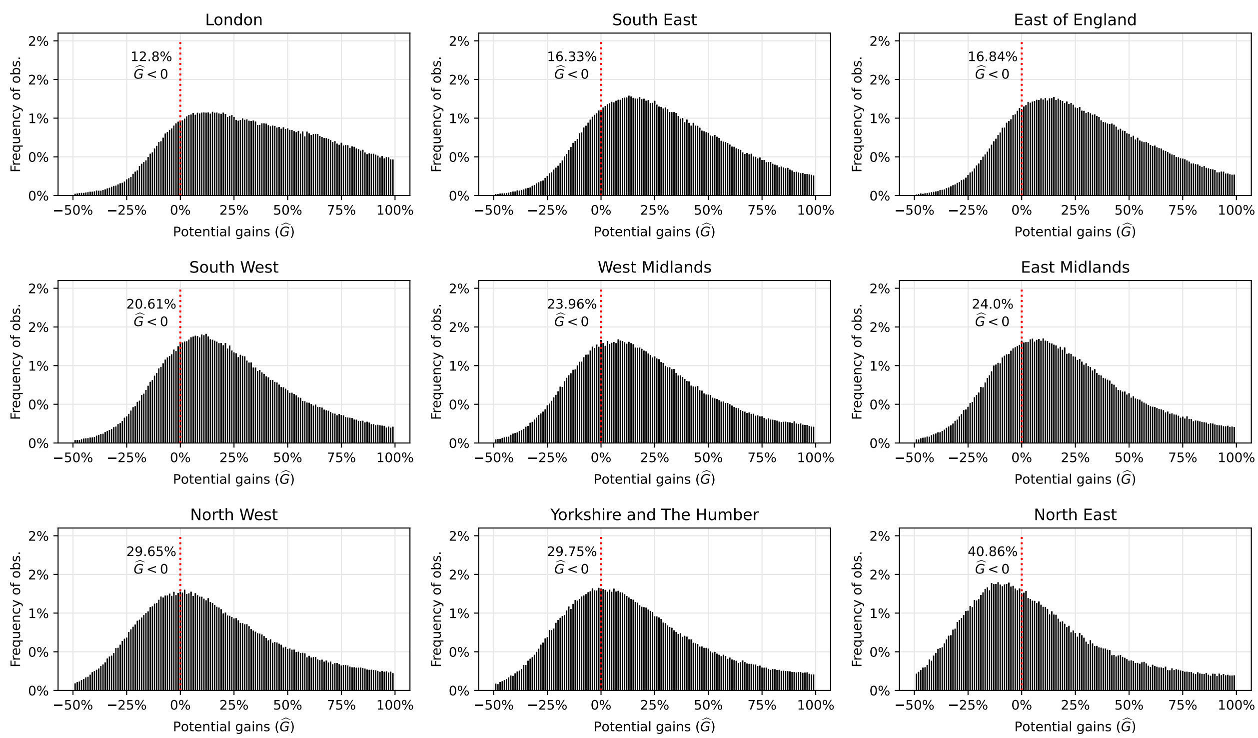
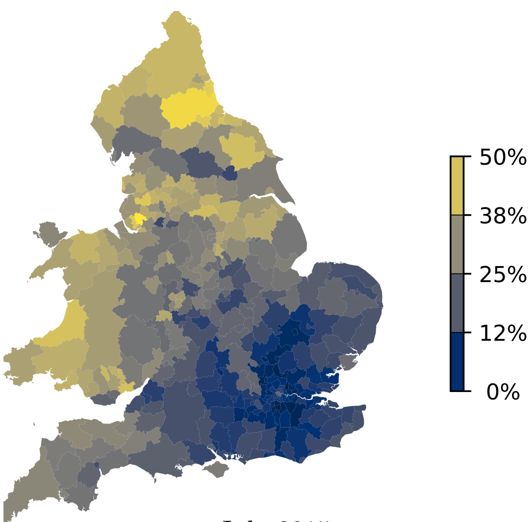
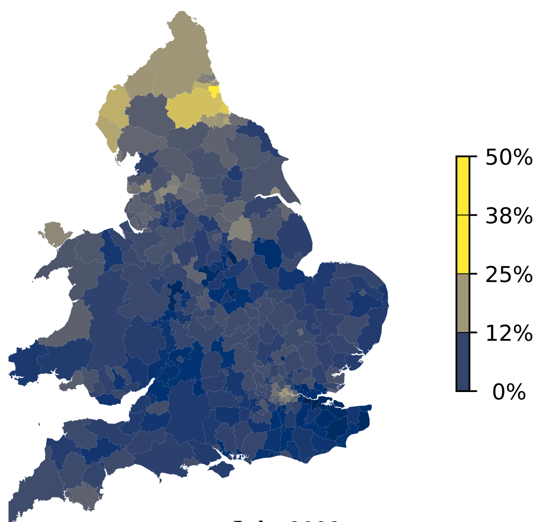


Figure A.8
Variation of "paper loss" share across locations and time

The figure reports average shares of nominal losses in listings for properties for sale outstanding during a given month, indicated below each map, and a local authority district.



July 2015



July 2022

Figure A.9
Regional variation in bunching of transaction prices

The figure 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), computed for nine different ITL1 regions of the U.K.

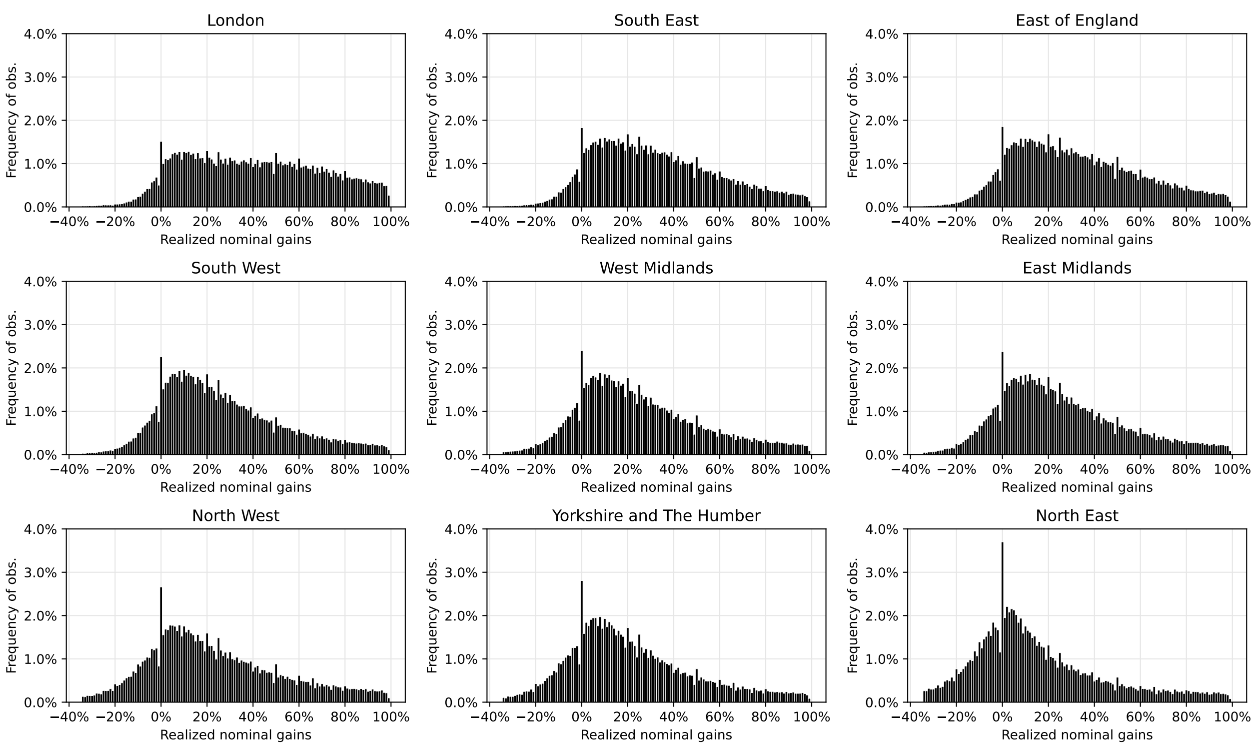


Figure A.10
“Hockey stick” pattern across regions

The figure reports 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. The frequency distribution of potential gains is shown in gray shading. The numbers reported in the left upper corner of each plot indicate the share of home-owners in each ITL2 region for the nominal potential gain has a value below zero.

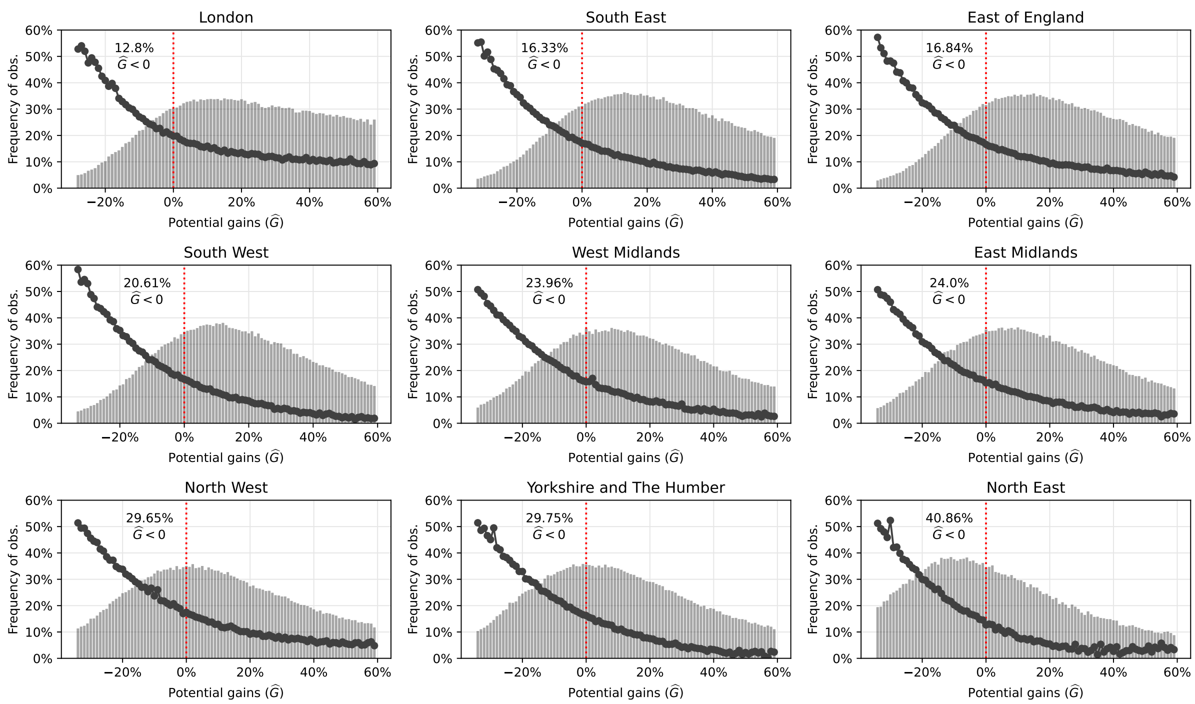
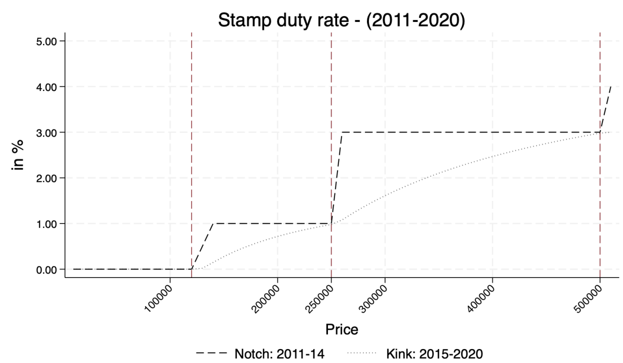


Figure A.11
Transaction tax schedule and bunching

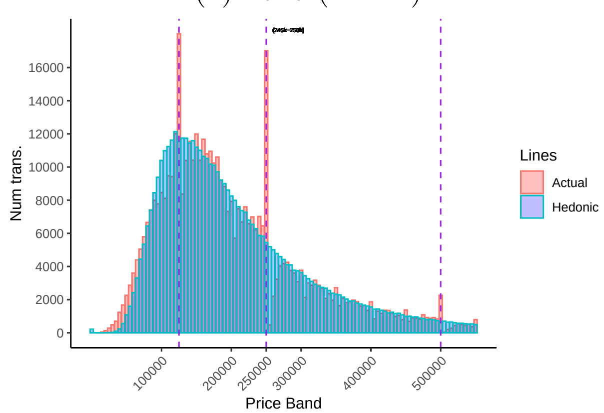
Panel A plots the average stamp duty rate paid for different levels of housing transaction prices in the UK during 2011-2014 (notch schedule) and 2015-2020 (kink schedule). The average rate paid changes at threshold prices indicated by the dashed vertical red line. Panel B shows histograms of all transactions in 2013 (under notch tax schedule) and 2016 (under kink tax schedule) by the hedonic price and the transaction mass. The difference in the mass by transaction and hedonic price for any given price band gives the bunching mass for the price level.

Panel A
Transaction tax rates for different prices (2011-2020)



Panel B
Histograms of transaction and hedonic prices in 2013 (notch schedule) and 2016 (kink schedule)

(a) 2013 (Notch)



(b) 2016 (Kink)

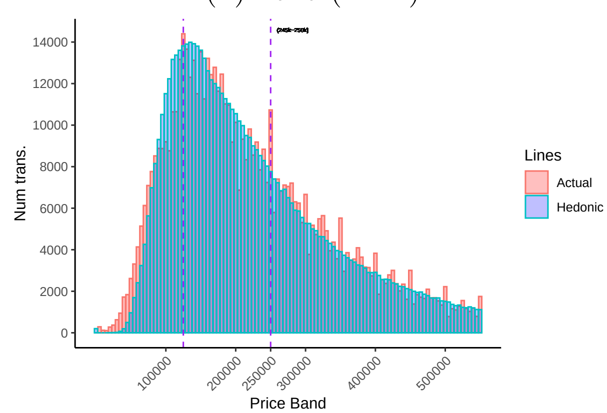
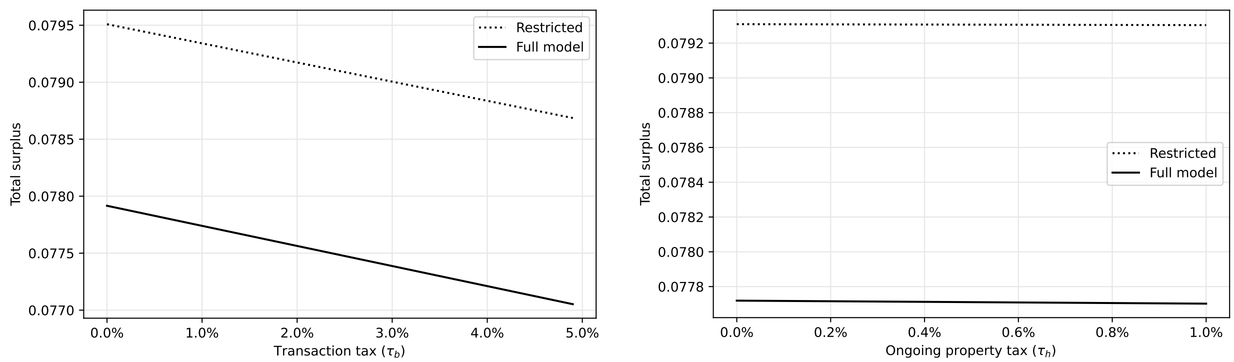


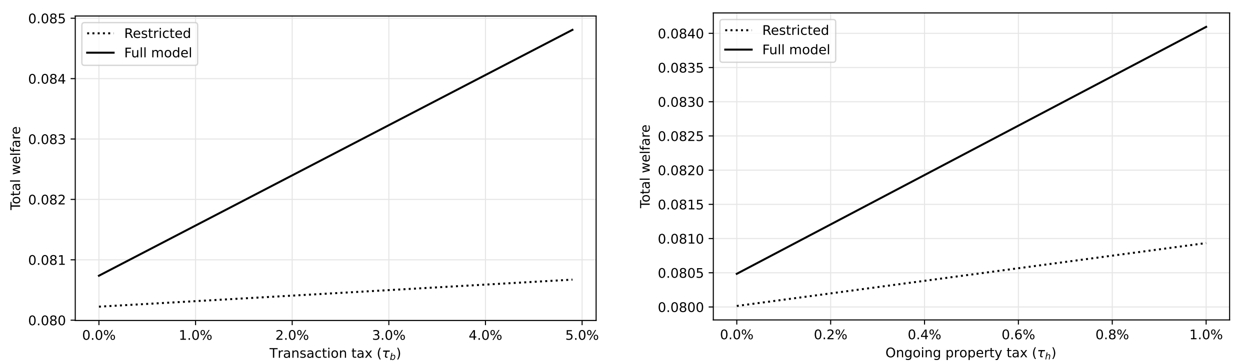
Figure A.12
Welfare implications of behavioral frictions

The figure reports the variation of surplus and total welfare implied by the model, for different levels of the transaction tax and ongoing property tax, and for a value of the parameter $g = 2.5$. We distinguish between a frictionless version ($\eta = \mu = 0$) and the full model ($\eta > 0, \lambda > 1, \mu > 0$).

Panel A
Total surplus



Panel B
Total welfare (Endogenous assessment)



Panel C
Total welfare (Constant assessment)

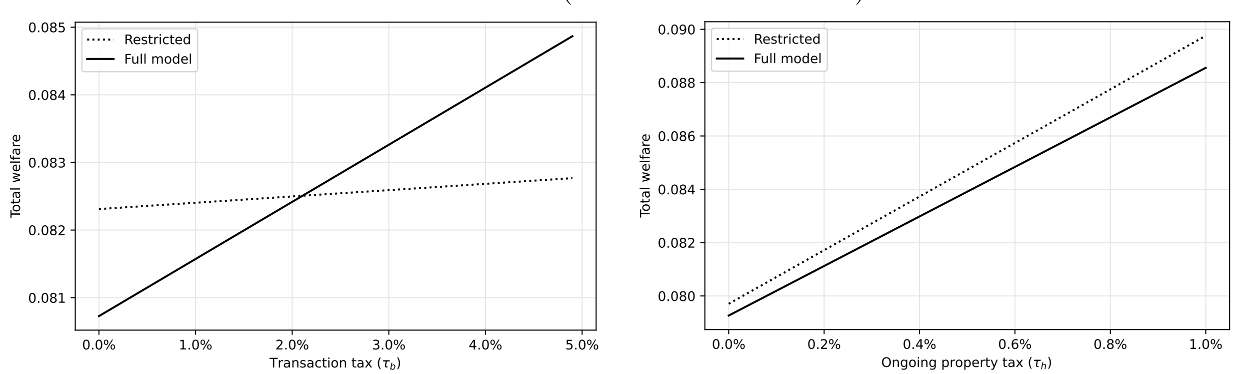


Table A.1
Summary statistics on mortgages originated in 2015

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

Table A.2
Transactions and listings data: sample description and cleaning

The table reports the data cleaning process for two different samples used in the paper. The left column begins with the Rightmove listings data, and for each listing, looks for the last transaction on the property in the Land Registry transactions data. The merged data is used to estimate the potential gain associated with each property. The right column begins with the Land Registry transaction data and looks for the listing associated with the transaction in the Rightmove data. The merged data is used to run the hedonic model, using the hedonic characteristics from the Rightmove data and the transaction prices from the transactions data.

Rightmove listings data		HM Land Registry Price Paid data	
All unique listings	**21,014,152**	**All transactions**	**28,011,482**
		Transactions before 2010	-16,227,465
Ambiguous addresses	-3,359,879	Ambiguous addresses	-1,057,402
Not in England or Wales	-650,724		
Total	17,003,549		10,726,615
Development prop.	371,498		
Non-development prop.	16,632,051		
Listings/transactions match			
Unmatched to a preceding transaction	-6,661,410	Unmatched to a preceding listing	-3,107,906
Development prop.	-228,687		
Non-development prop.	-6,432,723		
	10,342,139		7,618,709
Development prop.	142,811		
Non-development prop.	10,199,328		
Hedonic sample			
Auction properties	-105,495		-106,544
Transaction within 30 days of first listing	-70,748		
Incomplete hedonic characteristics	-1,102,478		-372,321
Final listings data	**9,063,418**	**Hedonic model data**	**7,139,844**

Table A.3
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

Table A.4
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.5
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 (£)	215,347	237,519	70,000	110,500	168,000	250,000	385,000
Hedonic price (£)	304,211	255,556	109,818	155,925	237,993	369,659	555,383
$\hat{G}$	0.17	0.26	-0.15	0.00	0.16	0.33	0.49
$\hat{H}$	0.41	0.26	0.11	0.26	0.41	0.58	0.74
$\hat{H}$ (Binned)	0.41	0.18	0.19	0.31	0.43	0.54	0.62

Table A.6
Price-volume correlation: intensive vs. extensive margins

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

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

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.7
Robustness check: Restricted sample

This table reports the results for a monthly regression of log transaction volume on contemporaneous price growth rates and loss shares at the level of ITL2 regions and months. The analysis uses transaction volumes repeat sales price indices and loss shares computed in the sub-sample of Land Registry transactions for which neither the buyer nor the seller are associated with a mortgage contract. The loss share measure is calculated monthly for properties which have at least one transaction in the data preceding each respective month. The data cover the period between 2010–2022. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, based on standard errors clustered at the level of ITL2 regions.

	Log Transaction Volumes (Non-mortgage)		
Price growth (Non-mortgage)	4.252***		0.8470***
	(0.3299)		(0.1144)
Loss share (Non-mortgage)		-1.372***	-1.393***
		(0.0388)	(0.0377)
Fixed effects (ITL2)	Yes	Yes	Yes
No. of obs.	7,105	7,489	7,105
R^2	0.196	0.230	0.442

Table A.8
Understanding tax trade-off calculations

This table reports the coefficients from a linear approximation of the welfare function for different model versions. Specifically, assuming that:

$$W(\tau_b, \tau_h) = \nu_0 + \nu_b \tau_b + \nu_h \tau_h,$$

and the values of taxes in the data are $\overline{\tau}_b$ and $\overline{\tau}_h$, respectively, we have the following implicit function that characterizes the tax trade-off at the current level of total welfare:

$$\tau_h = \frac{W(\overline{\tau}_b, \overline{\tau}_h) - \nu_0 - \nu_b \tau_b}{\nu_h} = \overline{\tau}_h - \frac{\nu_b}{\nu_h}\left(\tau_b - \overline{\tau}_b\right).$$

	Endogenous assessment		Constant assessment	
	Restricted	Full model	Restricted	Full model
Intercept (ν_0)	0.080	0.079	0.080	0.078
Transaction tax (ν_b)	0.009	0.084	0.009	0.083
Ongoing property tax (ν_h)	0.180	0.708	0.999	0.900
Ratio ν_b/ν_h	0.052	0.119	0.009	0.092

A.2 Other regression evidence

It is well-known that housing market liquidity is lower when house prices fall and higher when prices rise (Genesove and Mayer, 2001; Ngai and Tenreyro, 2014). We also estimate a standard geometric repeat sales model (Bailey, Muth and Nourse, 1963) on repeated transactions of properties since 1995 using the universe of housing transactions reported by the Land Registry. In each month, we assign each property in the data to either the gain or loss domain depending on whether the repeat sales price index has increased or decreased since the last transaction on the property. This allows us to build a monthly aggregate loss share measure on the *whole stock of properties*. The estimation is implemented from 2005 onwards to allow for a 10-year build-up of transactions in the data from which the loss share is calculated. We replicate this analysis in the U.S. housing market using price and volume indices from Zillow, starting in 2008, and collecting a representative sample of purchase dates collating all the versions of the Survey of Consumer Finances since 2000. For each month, and for each purchase date preceding that month in any SCF wave, we assign the purchase to loss or gain domain, depending on whether the state-level Zillow price index has decreased or increased since purchase. Consistently in U.S. and U.K. data, we find that the loss share measure explains a large part (up to 70%) of the observed price–volume elasticity. Building on these results, our framework provides a conceptually novel approach to interpret the dynamics of transaction volumes in the housing market, replacing a mechanism that relies on price changes to one that emphasizes the distribution of nominal reference points in the population.

A.3 Notes on the construction of the mortgage data

Column 1 of Table A.4 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 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 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 where 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.

Table A.5 shows that the binned versions of the home equity variables have the same mean but a lower standard deviation than their non-binned counterparts.

We use the mortgage balances tracked over multiple snapshots to calculate an amortization schedule. Since mortgage borrowers in the U.K. may close their accounts when moving houses or refinancing, we restrict this sample to contracts with a non-zero balance in each half-yearly snapshot between 2015H2 and 2022H2. Thus, we condition on the particular postcode–date of birth combination being present in all subsequent snapshots, with a non-zero balance on the associated mortgage. In 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.4 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

$$\ln(L_t) = \gamma_L + \beta_L P_{\Delta,t} + \varepsilon_{t,V}, \tag{20}$$

$$\ln(V_t/L_t) = \gamma_{VL} + \beta_{VL} P_{\Delta,t} + \varepsilon_{t,VL}, . \tag{21}$$

The results for these price-volume regressions are shown in Table A.6. 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.5 Loss share as sufficient statistic: Analytical derivations

Consider a partition of the (r, m) domain into J bins, each with mass N_j of homeowners. Denoting by $\bar{s}^*_{jt}$ and $\bar{l}^*_{jt}$, the binned means of $s^*_{it}(\theta)$ and $l^*_{it}(\theta)$, respectively for each $\theta \in (-\infty, \infty)$, we can now approximate the right-hand side of the above formula using the corresponding

Lebesgue sum as

$$\text{Transaction Volume} \approx \sum_{j=1}^{J} N_j \int_{-\infty}^{\infty} \bar{s}^*_{jt}(\theta)\alpha(\bar{l}^*_{jt}(\theta))\, d\Phi_\theta(\theta).$$

Let $\bar{\theta}^*_{jt}$ denote the binned mean of the threshold θ for listing in bin j. Using the second order approximation for $\alpha(\cdot)$, we obtain

$$\begin{aligned}
\text{Transaction Volume} \approx \alpha_o \sum_{j=1}^{J} N_j \int_{-\infty}^{\infty} \bar{s}^*_{jt}(\theta)\, d\Phi_\theta(\theta) \\
- \alpha_1 \sum_{j=1}^{J} N_j \int_{-\infty}^{\infty} \bar{s}^*_{jt}(\theta)\bar{\ell}^*_{jt}(\theta)\, d\Phi_\theta(\theta) \\
- \alpha_2 \sum_{j=1}^{J} N_j \int_{-\infty}^{\infty} \bar{s}^*_{jt}(\theta)\big(\bar{\ell}^*_{jt}(\theta)\big)^2\, d\Phi_\theta(\theta) \\
\approx \alpha_o N_{St} - \sum_{j=1}^{J} N_{Sjt}\big[\alpha_1 \bar{\ell}^*_{jt} + \alpha_2 \big(\widehat{\ell}^*_{jt}\big)^2\big],
\end{aligned} \tag{22}$$

where we have denoted the number of listings in bin j by

$$N_{Sjt} \equiv [1-\Phi(\bar{\theta}^*_{jt})]N_j = N_j \int_{-\infty}^{\infty} \bar{s}^*_{jt}(\theta)\, d\Phi_\theta(\theta), \quad \text{and} \quad N_{St} = \sum_{j=1}^{J} N_{Sjt},$$

and the binned listing premium conditional on listing by

$$\bar{\ell}^*_{jt} \equiv \frac{1}{1-\Phi(\bar{\theta}^*_{jt})} \int_{\bar{\theta}^*_{jt}}^{\infty} \bar{\ell}^*_{jt}(\theta)\, d\Phi_\theta(\theta)$$

and

$$\widehat{\ell}^*_{jt} \equiv \left[\frac{1}{1-\Phi(\bar{\theta}^*_{jt})} \int_{\bar{\theta}^*_{jt}}^{\infty} \bar{\ell}^*_{jt}(\theta)^2\, d\Phi_\theta(\theta)\right]^{1/2}.$$

Equation (22) can now be used to approximate the model-implied transaction volumes with high precision as the number of bins $J \to \infty$. In particular, equation (14) now follows from considering a partition with $J = 2$, with only two bins $\{r_i > \bar{p}\}$ and $\{r_i \leq \bar{p}\}$, where $\bar{p}$ denotes the average (log) transaction price, and approximating the conditional L^2-norm above by the L^1-norm. In practice, in our empirical tests of this approximation we consider interaction terms of loss share and listing premium with second order terms for the listing premium.

A.6 Household surplus

To quantify the effect of tax policy on household welfare, we decompose the expected lifetime utility of homeownership. At the time of purchase, buyers hope to be able to benefit from a high match quality (ε); their expected surplus is given by:

$$N_B \frac{\chi(q_t)}{q_t} \int_l \int_{\varepsilon_t^*(p(l))}^{\infty} \left[\varepsilon - \varepsilon^*\right] d\Phi_\varepsilon(\varepsilon)\, d\Omega_t(l).$$

On the other side, at the time of listing and sale, sellers primarily hope to be able to successfully realize the payoff from moving (θ); their expected surplus from mobility is given by:

$$\int_{r,m} \mathbb{E}_\theta[s^*(r,m,\theta) \cdot \alpha(p^*)\theta]\, dF(r,m),$$

where $s^*(r,m,\theta)$ is the optimal binary extensive margin listing decision for (r,m,θ) given the original homeowner problem.

In addition, sellers also realize a surplus from their chosen listing premium over the outside option, given by:

$$\int_{r,m} \mathbb{E}_\theta[s^*(r,m,\theta) \cdot \alpha(p^*)(\log p - \beta V^h + \beta V^b)]\, dF(r,m),$$

a loss/gain surplus from the behavioral component of utility equal to:

$$\int_{r,m} \mathbb{E}_\theta[s^*(r,m,\theta) \cdot \alpha(p^*)(\eta(p^* - r)_+ - \eta\lambda(p^* - r)_-)]\, dF(r,m),$$

and they face an expected utility loss from potential future binding credit constraints equal to:

$$\int_{r,m} \mathbb{E}_\theta[s^*(r,m,\theta) \cdot \alpha(p^*)\mu(p^* - m - \gamma)^2]\, dF(r,m).$$

A.7 Numerical solution

The model is solved by value function iteration on a two-dimensional grid of reference prices and mortgages. The implementation is otherwise standard, but for the mortgage grid we provide the following additional details.

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 $w_1^m, \dots w_{n_m}^m$ at issuance. The mortgage grid runs from 42.8% LTV to 95% LTV (relative to original purchase price). Note that the financial down-payment constraint cannot bind even for positive mortgage amounts, if the home equity at the particular transaction price exceeds $\gamma = 30\%$.

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 (11) 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 $l = 1$, and where k denotes the kth step of the value function iteration and $p^{k,*}$ sellers' optimal price setting function in the kth step.

A.8 Computation of comparative statics

To assess the model's ability to fit untargeted moments, we solve for the calibrated model steady state and the associated general equilibrium policy functions for all agents. The steady-state policy functions inform us about the agents' optimal responses to idiosyncratic shocks which do not affect the aggregate economy. Aggregating over these responses for a particular subpopulation of agents gives us the aggregate partial equilibrium response when the general equilibrium quantities (market tightness, listing price distribution) are kept constant. This differs from having a partial equilibrium model, in that the agents still have a highly sophisticated understanding of the general equilibrium to the extent that it affects their steady-state policy functions. The simple assumption here is that these agents confuse an aggregate shock with an idiosyncratic shock and that they do not account for the shocks' effects on the behavior of other market participants.

A.9 Model calibration

For the model estimation, we need to establish the proper target objects in the data, which include both transactions data and listings data. In the model, most of the objects are defined in terms of post-bargaining prices p that would actually occur conditional on sale. These correspond to some pre-bargaining listing prices l via $p = p(l)$. This formulation encounters the problem that in the data the natural mapping between listing prices and the conditional transaction prices is determined with respect to the *listing premium* relative to the hedonic value of the property, but in the model, where all the properties are identical, we can define the listing premium only ex-post after solving for the endogenous average transaction price.

Conceptually, this is a non-issue, since all the agents form rational expectations of prices. Nevertheless, we wish to avoid this for computational reasons. Instead, we solve the issue by reformulating the homeowner problem equivalently as a maximization over conditional transaction prices p rather than l. This is possible as long as the function $p(l)$ is bijective with inverse $l(p)$, which we assume.

$$\begin{aligned} V_t^h(r_i, m_{it}) = u_t - \tau^h + \mathbb{E}_\theta \max\{\max_{p_{it}} & \underbrace{\alpha_t(l(p_{it}))[U(\cdot) + \theta_{it} + \beta\mathbb{E}_t[V_{t+1}^b]]}_{\text{Listing success}} \\ & + \underbrace{(1 - \alpha_t(l(p_{it})))\beta\mathbb{E}_t[V_{t+1}^h(\cdot)]}_{\text{Listing failure}} - \phi, \underbrace{\mathbb{E}_t[\beta V_{t+1}^h(\cdot)]}_{\text{No listing}}\}. \end{aligned} \tag{24}$$

The benefit of doing so is twofold. First, the seller's problem now only depends on the conditional transaction prices and not on the listing prices, which in the data should be interpreted as listing premia over hedonic values. Second, we may now define a modified demand function $\tilde{\alpha}(\cdot)$ as

$$\widetilde{\alpha}(p) = \alpha(l(p)) = \chi(q) \cdot [1 - F(\varepsilon^*(p))].$$

This depends on the conditional transaction price p instead of the listing price l, indeed confirming that listing prices do not enter the seller's problem. Moreover, for the estimation, we can now adjust the demand function in the data by the function $l(\cdot)$ to match the data objects with those arising from the model.

More precisely, defining the listing premium as $\ell = l - \widehat{p}$, where $\widehat{p}$ is the hedonic value of the property, corresponding to the average transaction price in the model, both functions $\alpha(\ell)$ and $\ell(p - \widehat{p})$ are observable in the data. Therefore, for each price p, we can produce $\widetilde{\alpha}(p - \widehat{p})$ in the data, which can then be targeted in the model estimation. In practice, we assume a linear form for the listing premium as function of the realized premium by estimating

$$\ell_{it} = \beta_o + \beta_1(p_{it} - \widehat{p}) + \varepsilon_{it},$$

and set the targets in terms of data by scaling the model implied moments correspondingly. For any given model-implied value of α_{it} associated with some post-bargaining listing price p_{it}, we match that against a listing premium ℓ_{it} using the above empirical model and target α_{it}

from the model against $\alpha(\ell_{it})$ in the data.

Note that each estimation step solves for the model for some parameter values, and after solving the model for any such set of parameters, we may produce $p - \widehat{p}$ also from the model for targeting the shape of $\widetilde{\alpha}$ to match that of the data.

Secondly, we also need to adjust the sellers' price setting rule. In the data, we observe the listing premium as a function of the potential gain $\ell(\widehat{p} - r)$. On the other hand, for each triplet (r, m, θ) the model gives an optimal post-bargaining price $p^*(r, m, \theta)$ set by the seller, which can be mapped to some listing premium $\ell(p^*)$ using the above empirical model. In the estimation, we then target the shape of $\ell(p^*(\widehat{p}-r))$ to match $\ell(\widehat{p}-r)$ in the data. In particular, we will average over the values of m and θ when producing the model implied price setting rule $p^*(\widehat{p} - r)$. Assuming that $\ell(\cdot)$ is linear, this averaging does not bias the estimation procedure.

Finally, when working with the conditional post-bargaining transaction prices p rather than the listing prices, we should note that the listing price distribution $\widetilde{\Omega}(p) = \Omega(l(p))$ is also modified via the change of variables. In the estimation procedure, we target moments of the listing price distribution, so we have to account for this change of variables:

$$\widetilde{\omega}(p)\,dp = \omega(l)\frac{dl}{l'(p)}.$$

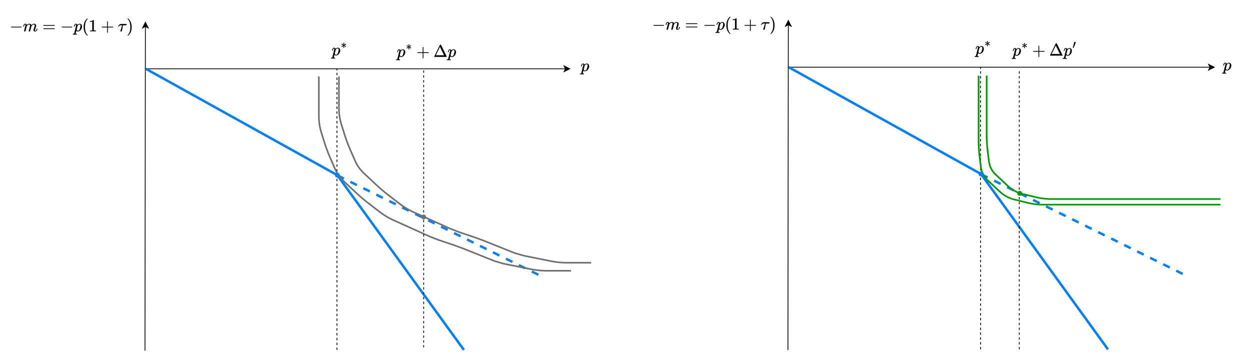
Assuming the estimated linear structure above, this implies that $\mu(\ell) = \beta_0 + \beta_1(\mu(p) - \widehat{p})$ and $\sigma(\ell) = \beta_1\sigma(p - \widehat{p})$, which are the transformations that will be used for the model implied moments in our moment matching exercise.

A.10 Theoretical intuition: Bunching at tax threshold levels

To understand the quantification of bunching effects at tax kinks and notches, define $m = p(1+\tau)$ as the total cash outflow of the household, for a property valued at price p and a tax rate τ. shows that buyers in the interval $[p^*, p^* + \Delta p]$ bunch at p^*.

With a steeper indifference curve, the bunching mass decreases. In this context, the only decision variable of the buyer in relation to a particular property/seller is the timing of the purchase. In the labor market, the worker adjusts the number of hours to determine final income. Their trade-off is driven by the individual consumption-leisure choice. Here, the situation is similar: The buyer can choose to either buy immediately for a high price, or buy later for a lower one, if the seller is not able to sell the property in the meantime. In the labor market, a bunching worker works less; here, a bunching buyer waits longer, or threatens to do so. The magnitude of the trade-off is determined by the seller's urgency, i.e., the degree to which they are likely to decrease the price as time goes by. Note that, in contrast to a worker, a buyer also has the option to walk away from the current property, and search harder in the market. Reference dependence affects the sellers' willingness to negotiate, i.e., a seller in the loss domain is less likely to decrease the price as the time-on-the-market decreases. As the buyer's indifference curve is steeper, this leads to a lower magnitude of bunching.

Figure A.13
Illustration of bunching at tax kink points



A.11 Housing taxation in the U.K.

Housing consumption in the UK is subject to two taxes: a stamp duty paid by the owner at the time of buying the property, and a property tax paid monthly to the local government by the occupant (owner-occupier or renter). Below we provide an overview of the stamp duty in the UK.

Stamp duty transaction tax is imposed on all housing transactions in the UK, and paid by the buyer. There was a substantial change in December 2014 in the way stamp duty was calculated on the transaction price. As shown in panel (A) of Figure A.11, the average stamp duty paid was a notched schedule of the transaction price, with the tax paid jumping at discrete thresholds such as £125,000 and £250,000. Since Dec 2015, the average tax rate follows a more gradual profile, with kinks at the same thresholds and subsequent tax reform focusing on the slope of the tax rate between the thresholds.

Panel (B) of Figure A.11 shows a large effect of the tax reform on bunching of transaction prices at the tax thresholds. We describe excess bunching mass at a price band (of size £5000) as the difference in the actual mass (based on transaction price) vs the expected mass (based on hedonic price) for the price band in a given period. The two figures in panel (B) show that the switch in the stamp duty from a notched to a kink schedule has a marked impact on bunching at the £250,000 price threshold.