In Search of the Matching Function in the Housing Market

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Abstract

The aggregate matching function is at the core of structural search and matching models, but its microfoundations remain elusive. We use granular and comprehensive data from the U.K. housing market to identify individual behavior at different stages of the matching process. In the sales segment of the market, a Cobb-Douglas functional form with constant returns to scale finds broad support, with an estimated demand elasticity between 0.2–0.3. In the rental segment, additional congestion effects occur at the level of bilateral bargaining, which leads to weakly decreasing returns to scale. Motivated by a stylized model of cross-market search, we document a novel source of cross-segment dependence; an increase in rental market tightness has a positive and economically significant impact on the sales transaction probability. We validate these findings by studying search and matching during the 2022 U.K. "mini-budget" natural experiment.

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1 Introduction

Search and matching models have become the workhorse characterization of equilibria in a broad range of markets which feature decentralized trading.[1] The widespread adoption of these models is supported by a large and increasing body of evidence confirming their empirical relevance. While this is reassuring, a deeper understanding of search and matching models requires detailed data to tease apart multiple frictions that can arise in interactions between counterparties. In particular, in many field settings we are still far from understanding the search process, how and where congestion effects originate,[2] how bilateral meetings between counterparties convert into final matches, when and how prices adjust to facilitate matches, and how different segments of the market (rental, leasing, and purchase, for example) relate to and depend on each other.

In this paper, we revisit these questions in one of the largest and most important household markets, namely residential real estate. We employ comprehensive granular data that track online search, physical meetings, listing prices, price revisions, and final transaction outcomes in sales and rental markets covering over three-quarters of all housing transactions in the U.K. market to shed light on the inner workings of the matching process. Our primary data set uses information from Rightmove.com, the largest online property listings platform in the U.K., and covers the period between January 2019 and December 2022, a period which also features several natural experiments which we harness to more precisely identify search and matching frictions.

Our analysis addresses five questions. First, we discriminate between alternative formulations of the aggregate matching function. In the literature, three different specifications are used inter-changeably in different market settings. These are an exponential form (Diaz and Jerez, 2013); Cobb-Douglas (Petrongolo and Pissarides, 2001); and constant-elasticity-of-substitution (Den Haan et al., 2000). We find that in the sales segment of the housing market, a standard Cobb-Douglas specification with constant returns to scale and an estimated demand elasticity in the range of 0.2 to 0.3 fits the data well, consistent with recent estimates for the labor market (Lange and Papageorgiou, 2020). In the rental segment, we find significant deviations from a Cobb-Douglas formulation, and evidence for decreasing returns to scale. These are, to our knowledge, the first direct empirical

[1] A distinguishing feature of these markets is that equilibrium does not happen solely through the adjustment of prices, but also–and sometimes, primarily–through variation in transaction volumes. Excess demand can persist, for example, in the form of unemployment in the labor market, and excess supply in the form of vacancy in real estate, both first-order policy concerns.

[2] We use the term "congestion effects," following convention in the literature, to describe a situation in which adding counterparties to one or other side of the market reduces the likelihood of market clearing.

estimates of returns to scale in the housing market, serving as a foundation for both the choice of matching function and values of calibrated parameters in structural models.[3]

Second, we quantify the contribution of different frictions to the overall magnitude of congestion effects in both rental and purchase segments of the housing market. We build a micro-founded model in the tradition of Shimer (2005) and Stevens (2007), which embeds preference segmentation, endogenous search and offer processing rates for both buyers and sellers, queuing when multiple offers arrive for the same property, and idiosyncratic variation in match quality. When we map the model to the data, we find in the purchase segment of the market that congestion effects arise in roughly equal proportions from two sources: (i) variation in the rate at which buyers view properties, and (ii) variation in match quality (frictions impeding successful matches could include, for example, buyers' tastes for hedonic characteristics that only become visible during a physical inspection, or sellers' adamance over prices). An important corollary is that technology has only limited potential to alleviate search and matching frictions given the offline/physical nature of congestion. In the rental market, the same two forces are prevalent, with an additional, important role for changes in the rate at which landlords process offers as the rental market becomes tighter.

Third, we find a strong role for both price setting and price adjustment in market clearing. In tight markets, both sellers and landlords are less likely to adjust prices post-listing, and when they do make adjustments, they are smaller in magnitude. Conversely, when market conditions are looser, we find that price adjustments are both more frequent, and larger when they happen. Thus, sluggish price adjustment in tight markets also contributes to observed congestion effects. This confirms the important role of seller behavior highlighted in Andersen et al. (2022) and Badarinza et al. (2024) and has implications for the appropriate design and calibration of structural models of the housing market.

Fourth, our results reveal that accounting for individual behaviour at different stages of the matching process (e.g., online search and physical inspections) as well as the stock-flow composition of outstanding listings significantly increases the explanatory power for final transactions volumes. This speaks for the importance of factors beyond the standard Cobb-Douglas matching model in describing equilibrium.

Fifth, in a stylized model of cross-search, we formalize spillover effects between rental and sales segments of the market, seeking to capture situations such as when an increase in rental market tightness can have a positive impact on the sales transaction probability,

[3]Online appendix Table A.1 provides an overview of current empirical evidence and results from structural estimation approaches in the literature, alongside a mapping of what we can and cannot take away individually and collectively from these exercises.

driven, for example, by buy-to-rent investors for whom a "hot" rental market promises a higher expected yield. As predicted by the model, we find a strong empirical link between matching patterns in the rental and sales segments of the market. This novel evidence suggests that such cross-segment spillovers are a potentially important addition to the search and matching mechanism, over and above the standard set of assumptions.

Finally, we validate these results using exogenous variation, checking whether our estimated elasticities and congestion effects can be used to predict short-run rental and sales market responses to unexpected shocks. We do so by studying a natural experiment in the U.K. in September 2022. At this time, Prime Minister Liz Truss's administration announced a surprise "mini-budget" with large unfunded fiscal giveaways which immediately stoked a strong U.K. gilt market reaction, and dramatically increased U.K. mortgage borrowing costs in a matter of days. As a plausibly exogenous shock to potential mortgage borrowers' financial capacity, and therefore their housing demand, studying this event allows us to trace how an unanticipated shift in the demand curve for housing purchases directly affects the sales market and indirectly (through cross-elasticities) affects the rental market.

To aid identification for this part of the analysis, we harness cross-local-market variation in the intensity of the housing demand shock. We use the fraction of homes owned with a mortgage across all U.K. local authority districts documented in the 2011 census as a proxy for the differential exposure of U.K. households to mortgage constraints. This generates an event study difference-in-difference specification, which compares regions with relatively high or low exposure to mortgage constraints before and after the mini-budget shock on 23 September 2022.

This research design reveals that market tightness, search activity, and meetings per listing in the sale segment all decrease, especially in regions with high exposure to mortgage constraints. The point estimates from this analysis are consistent with the elasticities obtained in the baseline reduced-form approach, with the exception of final transactions volumes, which we find respond somewhat more sluggishly to the demand shock.[4]

Our paper contributes to the large and growing literature on search and matching models, initially implemented in the labor market (Diamond, 1984; Hagedorn and Manovskii, 2008; Petrosky-Nadeau et al., 2018; Huckfeldt, 2022), and used in the real estate market (Head et al., 2014; Guren, 2018; Guren and McQuade, 2020), as well as the market for consumer goods (Burdett and Judd, 1983; Allen et al., 2019) among others. More specifically, our exploration of returns to scale in the matching technology in housing

[4]We caveat this finding, as the period under study coincides with the end of our available sample period, and the statistical power is affected particularly for volumes.

markets builds upon Diamond (1982), Duranton and Puga (2004), Head et al. (2014), Cheremukhin and Restrepo-Echavarria (2022), and Bernstein et al. (2021), and the empirical results in Petrongolo and Pissarides (2001), Rogerson et al. (2005), and Chade et al. (2017).

Our results underline the importance of price listing strategy, in the tradition of Wright et al. (2021), as well as the endogenous variation of individual search effort, as in Borowczyk-Martins et al. (2011), Kohlbrecher et al. (2016), Lange and Papageorgiou (2020), Kroft et al. (2013), Marinescu and Skandalis (2021), and DellaVigna et al. (2022).

Relative to the real estate literature, we extend the work of Genesove and Han (2012), Ngai and Tenreyro (2014) and Anenberg and Bayer (2020), using granular data that unpacks the matching function. Our analysis of stock-flow patterns and the Beveridge Curve in the housing market is consistent with recent results by Gabrovski and Ortego-Marti (2019) and Gilbukh (2023), and overall, our evidence suggests limitations to the use of market tightness as a sufficient statistic.

In terms of considering interactions between the sales and rental segments of the market, the paper is closest to Halket and di Custoza (2015), Ioannides and Zabel (2017), Greenwald and Guren (2021) and Han et al. (2022). In these frameworks, trading is subject to frictions (which either arise for "classic" search reasons, or because of segmented preferences), and the empirical work primarily inspects data on the listing and transaction behaviour of sellers and landlords, i.e., the supply side of the market. In contrast, we observe decisions of agents on both supply and demand sides of the market, as well as the intermediary steps (online search, physical meetings, and price adjustments) that eventually lead to a transaction.

The remainder of the paper is organized as follows. Section 2 describes the economic framework. Section 3 introduces the housing sales and rental market listings and search data, and reports a set of novel stylized facts. Section 4 estimates a baseline version of the matching function, quantifies elasticities and returns to scale at three different stages of the search process, documents pricing effects, and proposes an extended version of the matching function that accounts for cross-market effects. Section 6 uses natural experimental evidence to pin down elasticities, and Section 7 concludes.

2 Search and matching framework

The drivers of demand and supply have extensively been studied in economic settings with search frictions such as unemployment and vacancy in labor markets, potential home buyers looking for a property purchase, tenants for a rental agreement, and consumers

shopping across product varieties. While micro-foundations, preferences and constraints are generally validated empirically against observed actual decisions, closing the model typically requires a notion of equilibrium—a set of assumptions about the conditions under which markets clear. To date, there is limited observational evidence available about how matching equilibrium is determined. This is an important shortcoming because even small changes in assumptions can have dramatic consequences on transmission mechanisms and steady state outcomes.[5] In this section, we first introduce a general theoretical framework that nests popular specifications in the literature, then discuss the nature of frictions and congestion effects, the emergence of returns to scale, and the role of price determination.

2.1 Preliminaries

Consider a local economy i in period t, defined by S_{it} assets available for trade on the supply side and D_{it} actively searching counterparties on the demand side. S_{it} and D_{it} can be understood as the outstanding stocks of potential trading partners in any given market setting.[6] In an otherwise frictionless world, but where prices are not allowed to vary endogenously, the equilibrium market clearing condition implies a transaction volume V_{it} given by:

$$V_{it} = \min\{D_{it}, S_{it}\}. \tag{1}$$

This rationing equilibrium is far from rare in practice. For instance, minimum wage requirements, quantity purchase restrictions in consumer markets, or rent control are all examples when quantity rationing supersedes endogenous price determination.

When prices can adjust freely, they decrease to eliminate unmet demand, and increase to eliminate excess supply. In this world, market clearing would leave no demand or supply on the table, i.e., the excess mass is zero in equilibrium:

$$V_{it} = D_{it} = S_{it}. \tag{2}$$

A market with search and matching frictions lies in-between these two limiting extreme equilibria. Although transaction outcomes directly reflect fundamental (demand and supply) conditions, search and matching frictions prevent the market from clearing with no

[5] In particular, different assumptions about congestion effects and returns to scale can lead to multiple equilibria, local agglomeration effects, inequality (Diamond, 1982; Duranton and Puga, 2004; Bernstein et al., 2021), and significant variation in the response to shocks (Head et al., 2014; Cheremukhin and Restrepo-Echavarria, 2022).

[6] In our empirical application, we choose a U.K. local authority district to define a local market. This definition is similar to a neighborhood in the U.S. setting; e.g., there are 33 local authority districts in London.

excess mass. The ultimately realized number of transactions V_{it} depends on the rate at which counterparties are able to converge on successful contractual outcomes, denoted by a generic *matching function* $\mathcal{M}$:

$$V_{it} = \mathcal{M}(D_{it}, S_{it}). \tag{3}$$

Our goal is to capture the decisions of counterparties in exactly the sequence in which they arise in most field settings – and particularly in the case of the residential real estate market, which is the field setting in this paper. Guided by the structure of our data (described in more detail in the next section), the following table introduces the notation that we use to quantify search and matching activity at each stage of this process:

	Variables in the model			Measurement in the data
Aggregate conditions:	S_{it}	=	Supply	Outstanding number of listings
	D_{it}	=	Demand	Number of active searchers
	M_{it}	=	Meetings	Requests for direct contact with the agency/owner
	V_{it}	=	Transactions	Number of confirmed bilateral agreements

First, buyers or prospective tenants gather information about the available supply. In our data, we observe the online activity of searchers who open a particular listing's dedicated "detail view" page—possibly several times by the same searcher over multiple time periods. Starting from this first layer of information obtained online, individuals then initiate meetings (M) with potential counterparties, which we observe as requests for direct contact with the managing agency or the owner of the property. For a sub-set of meetings, the process of bilateral negotiation eventually results in a contractual agreement (V), and an archiving of the listing, which we also observe in the data.

In most of the past literature, the meeting and transaction stage are treated separately, with a particular search technology determining the rate at which direct contacts take place. However, in most cases it is assumed that transactions either cannot fail after a meeting takes place, or if they do, the failure rate is fully determined by buyers' acquisition of new information through direct inspection of the property (i.e., buyers draw a "taste shock"). In the next section, we compare alternative functional forms for the search technology, discuss their micro-foundations, and explore whether transaction outcomes are jointly determined by buyer and seller decisions.

2.2 Sources of congestion and functional forms

Queuing

The fundamental friction embedded in all models of search and matching stems from an imperfect coordination problem. If they had perfect information about everyone else's preferences and behaviour, buyers and sellers could simply decide to match according to algorithms that are incentive-compatible and Pareto efficient (Roth, 1982). However, the reality of many real-life economic settings is that agents on both sides of the market have imperfect information about each other and about the good being traded; in equilibrium, some sellers face more demand than they can meet, while others face less.

The congestion externality that arises due to the coordination problem is formally captured by the well-known urn-ball model, where each agent on the demand side (in our case, a potential buyer) generates a number κ of bilateral meetings with randomly chosen units of supply (in our case, properties listed for sale.) Under the assumption that each property can only be matched with one buyer, some meetings are unsuccessful, while at the same time some listings remain vacant. The functional forms that characterize this equilibrium are then given by:

$$M_{it} = \kappa D_{it}, \text{ and } V_{it} = S_{it}(1 - e^{-\frac{M_{it}}{S_{it}}}). \tag{4}$$

for the number of meetings and final transactions, respectively.

Preference segmentation and non-synchronous arrival rates

The urn-ball model assumes that the number of potential buyers that are interested in any given listing arises randomly. Alternatively, a large literature emphasizes the fact that individual preferences are segmented, in the sense that only a particular type of buyer will be interested in a particular unit of supply. Under the assumption of independent arrival rates for demand and supply in any given segment and frictionless matching within the segment, Shimer (2005) shows that the resulting aggregate matching function is indistinguishable from a Cobb-Douglas form with constant returns to scale:

$$M_{it} = \mu D_{it}^{\alpha} S_{it}^{1-\alpha}, \text{ and } V_{it} = M_{it}. \tag{5}$$

Equation (5) is very frequently used in the literature to characterize patterns of direct contact between buyers and sellers, especially in the housing market.

Search costs

An alternative source of congestion can arise due to the costly nature of search. Assuming that buyers initiate meeting requests with a Poisson rate α in each period, and sellers have a limited capacity/willingness to process applications (i.e., they may not respond immediately to the buyers' requests), the matching function takes the following form:

$$M_{it} = \mu \left(\alpha D_{it}^{-\rho} + (1-\alpha) S_{it}^{-\rho} \right)^{-1/\rho} \text{ and } V_{it} = \pi M_{it}, \tag{6}$$

where both buyers and sellers vary their search effort endogenously in anticipation of overall conditions. We allow for a probability π that any direct contact between counterparties will lead to a realized transaction, depending on the realization of the buyer's "taste shock" when they inspect a property. Interestingly, under the assumption $\rho = 0$, equation (6) reduces to a Cobb-Douglas form. More specifically, the Cobb-Douglas form is consistent with both preference segmentation and costly search, under the assumption that the search cost varies linearly with search intensity (Stevens, 2007).

Match quality

Most search and matching models of the housing market assume that the buyer faces a costly state verification problem, where each property has certain features that are only observed upon careful inspection (Weitzman, 1979). Upon meeting a seller, if the realization of the buyer's "taste shock" with regards to the particular property passes a certain threshold, the transaction goes through. The equilibrium price results from a division of the surplus through Nash bargaining, which results in realized volumes being an affine transformation of meetings, as captured above by the parameter π above.

However, this formulation does not leave room for the negotiation process to result in deal failure. An alternative formulation, where bargaining is sequential (Backus et al., 2020) allows both the buyer and the seller to play an active role, and to adapt their strategy depending on prevailing market conditions:

$$V_{it} = \pi(D_{it}, S_{it}) M_{it}. \tag{7}$$

In this formulation, sequential bargaining can result in additional congestion, as better outside options increase the continuation value of search and make a failed transaction less costly for agents on both sides of the market.

2.3 Calibration of structural parameters

Beyond identifying the structural form of the matching function, distinguishing between meetings between counterparties and finally traded volumes is also important. Recent structural models with search and matching frictions (Diaz and Jerez, 2013; Head et al., 2014; Anenberg and Bayer, 2020; Guren and McQuade, 2020; Kotova and Zhang, 2020) consider the two stages of the search process separately, with the Cobb-Douglas function applying at the initial matching stage, i.e., reflecting the technology through which potential buyers and sellers meet. In a second stage, volumes arise endogenously through a process that usually involves an additional bilateral bargaining mechanism.

The first empirical challenge that arises in the calibration of these models is that the demand elasticity estimated using data on final transactions volumes cannot be directly used as the demand elasticity associated with physical meetings, unless we are prepared to make the very strict assumption that aggregate demand and supply conditions in the market do not affect bargaining behaviour. And even when elasticities are estimated at the meeting stage, as in Genesove and Han (2012), the equally strong assumption needs to be made that final matches and meetings arise with similar technology.

While the notion of what constitutes an initial contact is straightforward in theory (it refers to a first touch-point of demand and supply, with individual preferences and "taste shocks" determining which available units will be pursued further), the definition remains elusive empirically. We address this by distinguishing a *direct* contact request (M) that a buyer makes to view a property from a *virtual* signal of interest (i.e., repeated online visits by searchers to the same listing) that carries a very low marginal cost and serves as an information gathering effort. Elasticities estimated separately for these two left hand side variables help paint a clearer picture of demand elasticities at both stages of the search process, and serve as an additional guide for the calibration of structural models.

2.4 Returns to scale

Returns to scale result from the fundamental economic tension between congestion and complementarity. When a large supply induces potential buyers to search more, and at the same time, a larger number of searchers induce sellers to readily accept offers, returns to scale can be increasing; when a wider set of available listings creates an information overload and more buyer interest leads sellers to wait and watch rather than commit to a deal quickly, returns to scale can be decreasing.

Past research usually assumed a simple version of the matching function in equation (3), which imposes a convenient Cobb-Douglas specification with constant returns to

scale. This allows the aggregate state space to be reduced to just two variables: the *transaction probability* $v_{it} = V_{it}/S_{it}$ (i.e., the likelihood that a representative listing results in a successful transaction), and the *market tightness* $\theta_{it} = D_{it}/S_{it}$ (i.e., the ratio between the numbers of available counterparties on either side of the market). This leads to the following convenient representation of the model:

$$\underbrace{v_{it}}_{\substack{\text{Transaction} \\ \text{probability}}} = \underbrace{\mu}_{\substack{\text{Matching} \\ \text{technology}}} \cdot \underbrace{\theta_{it}^{\alpha}}_{\substack{\text{Market} \\ \text{tightness}}} . \tag{8}$$

A log-linear version of equation (8) permits empirical estimation of the parameters μ and α of the matching function, in part the driving force behind the Cobb-Douglas formulation. In this setting, the constant returns to scale assumption is a particularly taxing one. This assumption implies that the negative externality that searchers impose on each other is precisely offset by the same magnitude by the externality arising from increasing supply. Markets have either relatively greater potential to be congested on the demand-side or the supply-side, but not both.

However, this assumption does not need to always hold. In many search and matching models of financial markets, returns to scale are assumed to be increasing (Vayanos and Wang, 2007; Weill, 2020), as larger and more liquid markets can potentially alleviate search and matching frictions.

2.5 Price determination

Finally, the matching function equations give an important but incomplete picture of the role of bilateral negotiations in determining final outcomes. The remaining ingredient is the role of price adjustment that affects the likelihood of a successful transaction.

The central mechanism across a large literature on price-setting in competitive markets appears broadly consistent: Prices increase when a large number of buyers compete for the same asset (i.e., in a situation of market tightness), and they decrease when a large number of assets compete for the same buyer (i.e., in a situation of market thinness).[7] But in a setting with search and matching frictions, sellers/landlords optimally choose their pricing and price adjustment strategy to reflect their desire to sell/rent (Andersen et al., 2022), as well as responding to prevailing market conditions. Seller/landlord behaviour has the potential to alleviate congestion if the response to a higher number of interested buyers is

[7]See, for example, Merlo and Ortalo-Magne (2004) and Han and Strange (2015) analyze price determination in the market for residential real estate, and Backus et al. (2020) discuss the role of sequential bargaining for transaction outcomes.

an increased willingness to negotiate, thus leading to quicker convergence of transactions. Conversely, seller behaviour can magnify congestion if the response to buyer interest is a speculative delay of negotiation, with the expectation of more favorable offers in the future.

Taken together, the patterns of pricing and subsequent adjustment and the elasticities estimated across stages of the search process allow for mapping search and matching equilibrium conditions onto the data, both in terms of volumes and prices. We now turn to specifying a model which nests buyer and seller behavior in a single micro-founded framework.

2.6 A comprehensive framework

Consider the local market setting i in period t, with a total number of outstanding listings equal to S_{it}, and a total number of searchers (i.e., outstanding demand) equal to D_{it}. As above, we consider both of these quantities as pre-determined from the perspective of the matching mechanism, and only model buyers and seller strategies conditional on having entered the market.[8]

Consistent with the mechanism introduced by Shimer (2005), we assume that each location i is composed of $j \in \{1, ..., J\}$ segments, and that segment-specific supply S_{ijt} and demand D_{ijt} are independently Poisson distributed at any given point in time. Similar to Piazzesi et al. (2020), such segmentation plausibly arrives at the level of micro-locations within a neighborhood, for example because families only consider particular locations that are in the catchment area of a particular school; or by property type, if single persons are exclusively interested in studio apartments.

The independently Poisson distributed arrival rates at the segment level can be justified by assuming that (i) a constant set of owners $\overline{S}_{ij}$ (re-)lists their property for sale with a probability χ_S in each period, which results in S_{kjt} outstanding listings, and (ii) a set of non-owners (i.e., potential buyers) $\overline{D}_{ij}$ (continue to) manifest their interest to buy with a probability χ_D. Aggregating at the local level, we have:

$$S_{it} = \sum_{j=1}^{J} S_{ijt}, \text{ and } D_{it} = \sum_{j=1}^{J} D_{ijt}. \tag{9}$$

The parameters χ_S and χ_D embed all information about in- and out-flows from the stock of

[8] In our empirical section, we quantify and discuss the variation and potential co-movement of in-flows of listings and searchers, but the endogenous variation of arrival rates extends beyond the current scope of the paper.

supply and demand in each location, and the state of the system can be fully characterized by three quantities: total local supply S_{it}, total local demand D_{it}, and the number of segments J. Segment-specific supply is then given by $S_{ijt} \sim \text{Poisson}(S_{it}/J)$, and segment-specific demand is $D_{ijt} \sim \text{Poisson}(D_{it}/J)$.

On the demand side of the market, we assume that potential buyers strictly consider the available set of listed properties within their segment. Consistent with Stevens (2007), buyers have a probability ϕ_D of requesting a direct meeting with a seller, in each period. The total number of meetings initiated in location i and period t is denoted by:

$$M_{it} = \sum_{j=1}^{J} M_{ijt}. \tag{10}$$

On the supply side of the market, sellers process meeting requests at rate ϕ_S, i.e., they place the potential buyer in a waiting queue, and have a probability ϕ_S in each period to invite them for a property inspection and an eventual price negotiation. A seller is therefore either in a *waiting* state, in which case they are open to accept potential buyer's requests, or in a *busy* state, when they reject the buyer's request for a meeting.

If a meeting request finds the seller in a *busy* state, the buyer continues to issue requests in the next period. If the seller decides to process the meeting request, a matching quality shock gets realized, which captures the joint buyer-seller surplus from the bilateral negotiation. If the realized surplus ε, drawn from a uniform distribution between 0 and 1, is above the value of an outside option which we denote by $\bar{\varepsilon}$, the meeting results in a successful transaction. If the negotiation fails, both the buyer and the seller continue searching. The total number of realized transactions in location k and period t is denoted by:

$$V_{it} = \sum_{j=1}^{J} V_{ijt}. \tag{11}$$

Overall, this framework parsimoniously nests the micro-founded sources of search and matching frictions that have been emphasized in previous research. This includes the segmentation of preferences, whereby a particular buyer is only interested in a particular type of property/listing, the mismatch in arrival rates between demand and supply across these segments, the coordination failure whereby buyers "step on each others' feet", as meeting request can only be accommodated sequentially, costly search, as buyers are only able to consider a sub-set of the outstanding stock, seller-side strategy, as they "take their time" to attract, evaluate and accept buyer offers, and variation in matching quality, which means that direct contact and physical inspections reveal additional (previously

unobserved) information that may lead a negotiation to fail. The table below summarizes the relationship between our framework and a selected set of previous literature, according to the functional form that each setting implies for the aggregate matching function.

	Exponential (Peters, 1991)	Cobb-Douglas (Shimer, 2005)	CES (Stevens, 2007)	Our framework
Segmentation	✗	✓	✗	✓
Mismatch of arrival rates	✗	✓	✗	✓
Search costs	✗	✗	✓	✓
Queuing	✓	✗	✓	✓
Match quality	✓	✗	✓	✓
Seller processing rate	✗	✗	✓	✓

Having outlined this broad framework, we turn to empirically investigating how supply, demand, market tightness and listing prices affect individual decisions and aggregate outcomes within and across regions of the U.K. housing market.

3 Data

3.1 Properties listed for sale and rent

Our main data set is provided by Rightmove.com, the largest online real estate listing platform in the U.K.. The first part of the data contain information about 9.4 million listings, for properties located across 356 local authority districts (out of a total of 374 in the U.K.[9]). We track all listings outstanding between January 2019 and December 2022 from the time they first appeared on the website until they were archived, if the archive date falls before December 2022. Each listing contains information on the address of the property unit that is being sold or rented out. When first posted online, the listing is flagged as available in our data set. Subsequent adjustments of the asking price, property characteristics, or the availability status, are then recorded until the archive date.

The change in the availability status captures the time at which a verbal non-binding agreement has been reached, i.e., formal contractual agreements are expected to be signed

[9]For consistency, we use the 2021 definition of local authority districts by the Office for National Statistics.

imminently, and the online listing is discontinued. We use this flag to identify the completion of the sales process, alongside a matching procedure to verify that these transactions are actually finally completed and lodged with the U.K. Land Registry, as described below.

Most of the listings are initiated by a real estate agency, and only a minority originate from individuals. This explains why multiple listings of the same property are rare. When this does occur, and a property is listed multiple times in a horizon under a week, we consider only the latest de-duplicated listing in our analysis and filter out the preceding ones.

The data further distinguish between listings where a property is available for sale or for rent. When properties are available for sale, we observe the price indicated by the seller initially, and any subsequent adjustments until the archive date. For a property that is available for rent, we observe the monthly rent indicated by the landlord, and any subsequent adjustments. In the U.K. market, the rent amount refers to the net monthly cash flow that the landlord expects to receive, excluding additional costs such as energy or telecommunication bills.

In our sample, 55% of listings are for sales of properties, and 45% for rentals. We consider a sale to be completed when its availability flag turns to "sale subject to contract", and a rental to be completed when the availability flag turns to "let agreed". The median time on the market for a sale listing is 24 weeks, which is remarkably similar to the Danish housing market over a similar time period (Andersen et al., 2022). For a rental listing, the median time on the market is much lower, at only 7 weeks.

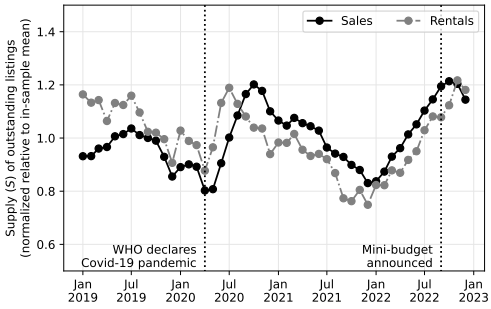
Figure 1 plot a) shows the evolution of the stock of outstanding listings, which we use as a measure of supply; and Figure 1 plot b) shows the number of completed listings, which we use as a measure of transaction volume. The average probability that an outstanding listing is completed in any given month is equal to 9.3% for sales and 20.4% for rentals. Plot c) in the figure shows the time variation in this probability. The declaration of Covid-19 as a pandemic by the WHO in March 2020, and the subsequent week-long lockdown lead to a pronounced slowing of activity in the market, but both the number of outstanding listings and the rate at which these listings translated into actual transactions increased markedly over the course of the next year.[10]

[10]Section B of the online appendix discusses the role of a fiscal policy intervention in the form of a stamp duty "holiday" for demand conditions during this period.

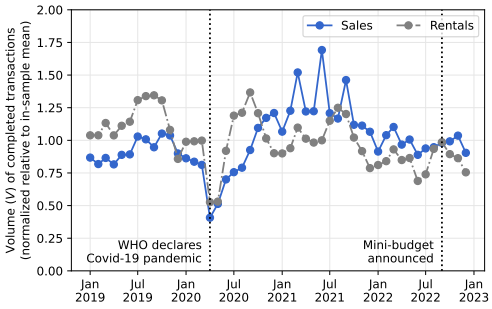
Figure 1
Outstanding listings vs. completed transactions

The figure shows the evolution of the number of listings that have been outstanding for at least one day during a particular month (Supply, S) and the number of listings that have been archived during the month with a flag that indicates a successful sale or rental (Volume, V). We report values of these variables relative to their in-sample mean. The monthly transaction probability is defined as the number of realized sales relative to the outstanding stock of listings.

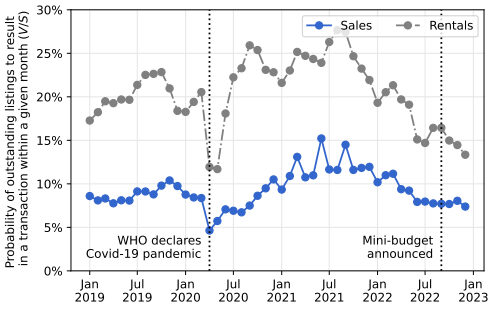
a) Outstanding supply of listings (S)



b) Realized transaction volume (V)



c) Transaction probability (V/S)



3.2 Search activity

Our data records online search activity between January 2019 and December 2022, for two layers of engagement between an online user and a listing. The first, which we denote as a "search visit", is an instance of the user clicking the "detail view" hyperlink associated with a given property. On the Rightmove.com website, first-level browsing and customized keyword search display the listing's location, price, and the number of bedrooms and bathrooms, while the "detail view" provides the full set of quantitative information (e.g., the floor area), and qualitative descriptions of features that the seller/landlord deems relevant. Any user of the website, irrespective of whether they have registered for account or not, can access this information. The second layer of engagement, which we denote as a "meeting", implies a request for direct contact with the owner of the property (if they have posted the listing directly), or the agency that maintains the listing.

We compute the number of unique users that click on a "detail view" as a measure of outstanding demand (D), the number of such views (each user can click multiple times on the same listing) to measure the users' information gathering effort (G), and the number of direct contact requests as a proxy for the number of in-person meetings (M) that they request.

In our data, the unit of observation for user demand is an anonymous IP-level key. To ensure that we appropriately account for the fact that the same person may log in using different devices at different points in time, we use the sample of registered users (they are linked across all used devices) to find the average number of unique keys assigned to a user throughout their active search period, conditional on the location where they are search from, and the month when the search takes place. We then adjust the number of observed keys in the sample of non-registered users by this number. In addition, to filter for bots, we eliminate all users with only one search, those that search over more than 1,000 listings, and those with search originating from more than 86 IP keys (which corresponds to the 99^{th} percentile of the number of IP keys in the sample).

Figure 2 shows the evolution of the number of users and meetings in both segments of the market. Search activity is highly seasonal, as in Ngai and Tenreyro (2014)—more intense during the spring, peaking mid-year, and decreasing substantially during the months of November and December of each year. The outbreak of the Covid-19 pandemic initially led to a decrease which was similar in magnitude to levels usually observed in a typical winter month, but both buyer and tenant interest immediately rebounded.

A measure of market tightness, which divides the number of searching users by the outstanding number of listings in each period, shown in plot a), increases by 50% in the period immediately after March 2020 and remains elevated until the summer months of 2022. This additional buyer interest (visible in plot b) does not lead to a corresponding increase in actual contacts, but it does generate a higher probability for listings to be converted into realized deals. Plot c) shows that the number of meetings per user (i.e., our measure of search effort) decreases by around 20% in the post-pandemic period, and becomes relatively stronger in the rental market. These patterns suggest an increasing desire by tenants to engage with their counterparties on the supply side: they gather relatively less information online, but seek more in-person meetings later on.

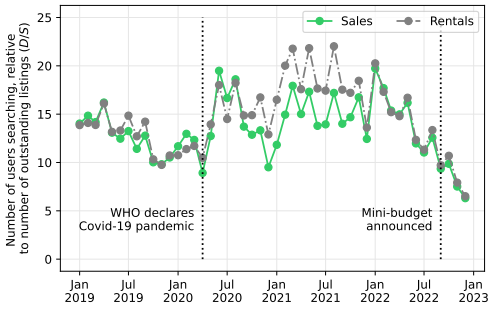
3.3 Realized transactions

While in our listings-level data we have an indicator of when a sale agreement between buyers and sellers has been reached, this does not necessarily mean that the ownership

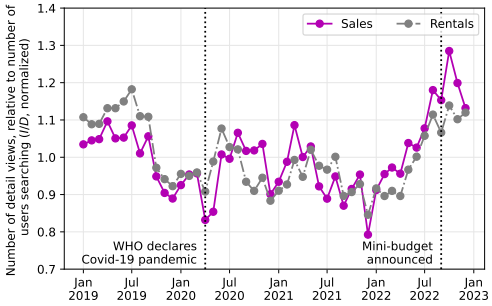
Figure 2
Demand, search and meetings

The figure shows the evolution of market tightness, defined as the ratio between the number of users visiting at least one listing during any given month, and the number of outstanding listings during that month. We report the average number of visits per user, and the average number of meetings relative to the total number of visits. In plots b) and c), we normalize reported quantities by dividing through the in-sample mean of each variable.

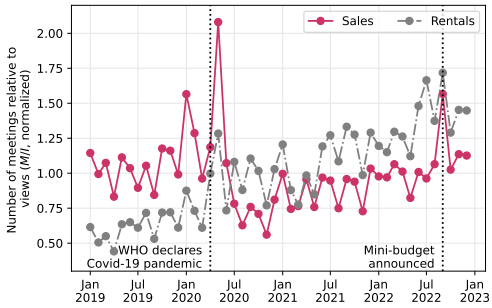
a) Market tightness ($\theta = D/S$)



b) Search effort (G/D)



c) Meeting intensity (M/I)



right has actually been transferred. To validate our measure of realized sales volume, we use the universe of residential property transactions in England and Wales, which is made available by HM Land Registry for the period between 1995 and 2022. Each record lodged with the Land Registry indicates the date when the contract has been signed, the exact address, and the transaction price.

Based on this information, we can assign listings to transactions with a high degree of confidence. However, one limitation is that the Land Registry data only covers England and Wales and not Scotland. For the part of the sample that is common across the two data sources (January 2010 - December 2022), we observe 9,493,978 listings with a "sold subject to contract" flag, while 7,038,376 listings have been matched to the Land Registry data as completed sales. This corresponds to 59.7% of the 11,788,614 transactions lodged with the Land Registry over this time period. On a monthly basis, Figure A.5 plots the share of listings with final transactions observed in the Land Registry data. As of

December 2022, 77% of Land Registry transactions can be matched to the listings on Rightmove.

There are two sources of measurement error in our inference of transaction amounts. First, the agency may fail to adjust listing status, despite the fact that the sale has actually happened. Second, a verbal agreement may have been reached, but before signing the contract, either counterparty may have decided to withdraw, and the seller then decided not to reinstate the listing as active on the website.

Figure A.3 aggregates transactions across local authority districts and months, and plots the two resulting measures against each other. Given a correlation coefficient of 0.92, we conclude that measurement error is limited, but nevertheless use transaction levels matched to the Land Registry sample for robustness checks below.

We start by implementing this approach at the level of 300 local authority districts and 48 monthly observations for the number of active searchers, outstanding listings, and contact requests. In addition, the final version of our data set is cleaned to remove outliers, i.e., we restrict market tightness per local authority to be less than 150, the average meeting intensity below 2, transaction probability below 0.4, average price adjustment between -20% and 20% in the sales market and below 100% in the rental market, and an outstanding set of listings above 500. This is necessary because some local authorities can have low turnover, which leads the set of outstanding listings to be less representative. The total number of local authority $\times$ month observations in the final sales sample is equal to 16,269, in the rental sample 16,262, and in the merged sample with transactions lodged with the Land Registry it equals 14,506.

3.4 Prices

In the case of properties listed for sale, sellers indicate an initial listing sales price which serves as an initial anchor for bilateral negotiations, and which can subsequently be adjusted upwards or downwards. To capture the listing price strategy, we first compute a hedonic valuation for each property, using the realized transaction prices in Land Registry data, alongside property characteristics reported for each listing. Our hedonic valuation model predicts the ln of the sale price P_{it} of all sold properties i in each year t:

$$\ln(P_{it}) = \zeta_w + \xi_{ly} + \psi_{rm} + \beta_{\mathbf{x}}{}' \mathbf{X_{im}} + \varepsilon_{im},$$

where ζ_w are electoral ward fixed effects, ξ_{ly} are local authority district cross year fixed effects, ψ_{rm} are region cross month fixed effects, and $\mathbf{X_{im}}$ is a vector of time-varying property characteristics: a second order polynomial augmented with an logarithmic term

of the floor area, the number of bedrooms and bathrooms, as well as dummy variables for property type, whether the property is part of a new development, and whether it is a retirement home. This version of the hedonic valuation model has a strong explanatory power for realized transaction prices, with an R^2 equal to 0.87. In a second step, we use the estimated set of coefficients and fixed effects to predict out-of-sample valuations for all properties that are either listed for sale or for rent in our sample, both at the time of the initial listing, as well as for all subsequent instances when the listing price is being revised.

For a property that is listed for sale, we define the listing *premium* as the ratio between the asking price and the hedonic valuation. For a property that is listed for rent, we define the *listing capitalization rate* as the ratio between the total annual asking rent and the hedonic valuation. Figure 3 shows the evolution of these two quantities through time and across locations.

Consistent with previous evidence from other markets (e.g., Andersen et al. (2022)), we find that sellers list for a price that is around 10.5% above the hedonic value on average, but this number fluctuates substantially across market regimes. In particular, towards the end of the sample, as demand decreased substantially, sellers seem to react by decreasing asking prices to just 3% above hedonic valuations.

At the same time, listing capitalization rates remain very stable at around 5% throughout the sample, but vary substantially across locations, in a manner that is unrelated to average listing premia. To understand this, we compute and report price revisions in Figure 3. Before March 2020, sale prices tended to be revised by around 3% downwards during each month of time on the market. This pattern is symptomatic of a more general phenomenon that is apparent when we plot histograms of the full distribution of average price revisions: sales listings premia generally vary asymmetrically, and upwards price revisions are very uncommon.

Together, the data sets described above capture the entire process of search and matching in the housing market, including market tightness, the variation of search effort, and the probability that listings result in actual realized transactions. We now turn to the estimation of matching functions, aiming to gain further insight into the nature of the frictions that affect the matching process.

Figure 3
Listing premia and capitalization rates

The top left plot shows the evolution of average listing premia, i.e., the ln difference between the listing price and the estimated hedonic value of the property at the time of listing, and the capitalization rate ("cap rate") in the rental market, i.e., the ratio between the listed annual rent and the hedonic value of the property. The top right plot computes average magnitudes of revisions of the sale price or the monthly rent, respectively. The middle plots show frequency distributions of these revisions. The bottom plot computes average listing premia and capitalization rates within each local authority district.

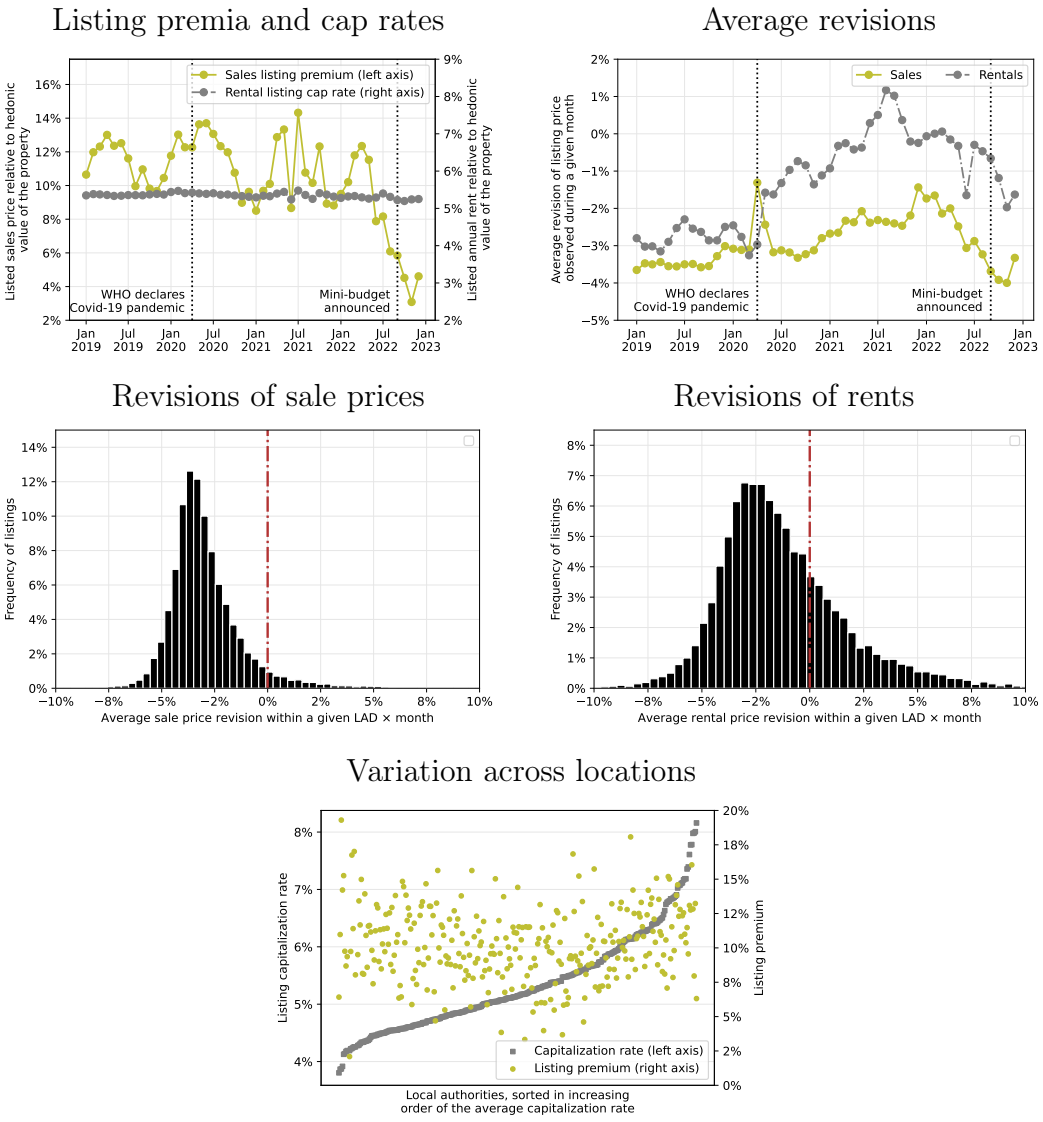


Table 1
Standard model

Panel A reports estimated coefficients from the following set of specifications:

$$\ln Y_{it} = \ln \mu + \alpha_D \ln D_{it} + \alpha_S \ln S_{it} + \varepsilon_{it},$$

where $Y_{it} \in \{G_{it}, M_{it}, V_{it}\}$ is the number of visits, meetings and the realized transaction volume, respectively, measured in local authority district i and month t. Panel B repeats the estimation by imposing the assumption of constant returns to scale:

$$\ln(Y_{it}/S_{it}) = \ln \mu + \alpha \ln \theta_{it} + \varepsilon_{it},$$

for the same set of dependent variables, and defining $\theta_{it} = D_{it}/S_{it}$ as the market tightness. In parentheses, we report standard errors clustered at the level of the local authority district. *, **, *** denote statistical significance for a 10%, 5% and 1% confidence level, respectively.

Panel A
Cobb-Douglas function with constant returns to scale

	Properties for sale			Properties for rent		
	Search per listing	Meetings per listing	Transaction probability	Search per listing	Meetings per listing	Transaction probability
Market tightness (α)	0.772***	0.351***	0.277***	0.619***	0.618***	0.400***
	(0.016)	(0.038)	(0.022)	(0.016)	(0.025)	(0.021)
No. of obs.	16,269	16,269	16,269	16,262	16,262	16,262
R^2	0.720	0.093	0.095	0.722	0.353	0.263

Panel B
Unrestricted estimation

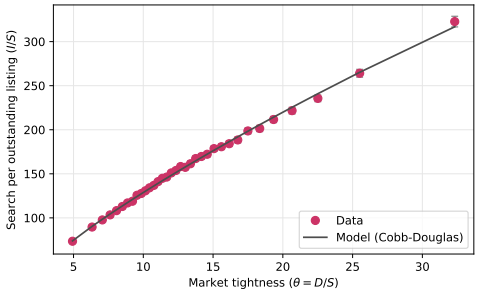
	Properties for sale				Properties for rent		
	Searches	Meetings	Transactions	Transactions (registered)	Searches	Meetings	Transactions
Demand (α_D)	0.948***	0.397***	0.272***	0.279***	0.870***	0.806***	0.349***
	(0.013)	(0.038)	(0.021)	(0.027)	(0.02)	(0.035)	(0.025)
Supply (α_S)	0.296***	0.666***	0.721***	0.738***	0.300***	0.321***	0.617***
	(0.015)	(0.041)	(0.024)	(0.032)	(0.032)	(0.014)	(0.023)
Returns to scale ($\alpha_D + \alpha_S$)	1.243	1.064	0.993	1.017	1.169	1.126	0.965
H_0: $\alpha_D + \alpha_S = 1$ (p-Value)	0.00	0.04	0.70	0.49	0.49	0.00	0.00
No. of obs.	16,269	16,269	16,269	14,506	16,262	16,262	16,262
R^2	0.936	0.593	0.685	0.616	0.964	0.796	0.851

Figure 4
Different stages of the search process

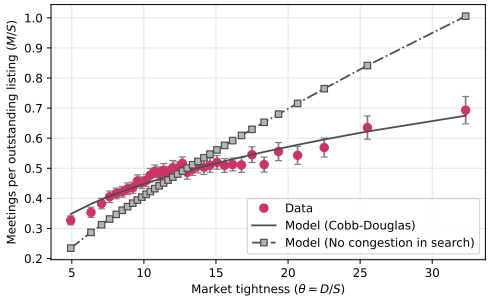
The figure reports average values of variables calculated for selected quantile bins of market tightness. The search per listing variable captures the number of online detail views per listing in each month, the meetings per listing variable is computed as the number of direct contact requests per listing, and transaction probability measures the number of realized transactions relative to the outstanding stock of listings in each given month.

Panel A
Properties for sale

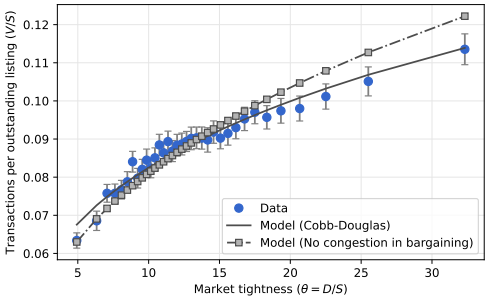
Search per listing



Meetings per listing

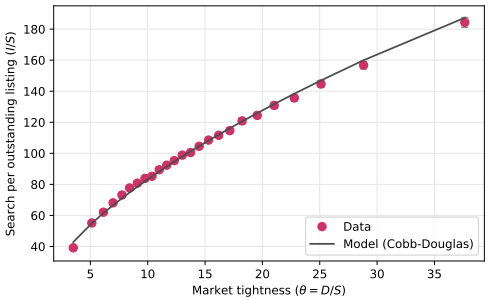


Transaction probability

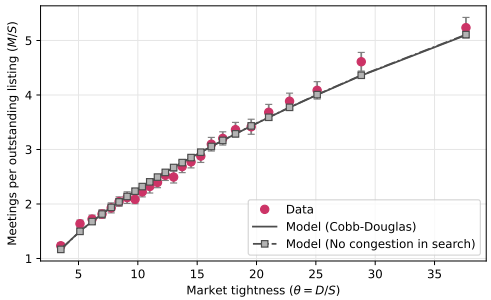


Panel B
Properties for rent

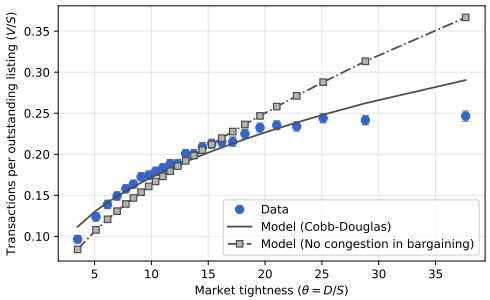
Search per listing



Meetings per listing



Transaction probability



4 Aggregate model fit

To assess the empirical fit of the standard Cobb-Douglas matching function for the entire sequence of online searches, offline meetings, and final transactions, we exploit information on the number of clicks on a listing's "detail view" page (G), the number of direct contacts (M), and the number of confirmed bilateral agreements (V).[11] We consider a three-stage process, consistent with the structure of our data: First, buyers or prospective tenants gather information about available supply. In our data, we observe the online activity of searchers who open a particular listing's dedicated "detail view" page—possibly several times by the same searcher over multiple time periods. Starting from this first layer of information obtained online, individuals then initiate meetings with potential counterparties, which we observe as requests for direct contact with the managing agency or the owner of the property. For a subset of these meetings, the process of bilateral negotiation eventually results in a contractual agreement and an archiving of the listing, which we also observe in the data.

Assuming elasticity parameters that apply separately on the demand (α_D) and supply (α_S) sides of the market, and allowing for varying degrees of search and efficiency μ at each stage of the search and matching process, the following system of three equations captures individual decisions and transaction outcomes:

$$G_{it} = \mu_G D_{it}^{\alpha_{G,D}} S_{it}^{\alpha_{G,S}}, \tag{12}$$

$$M_{it} = \mu_M D_{it}^{\alpha_{M,D}} S_{it}^{\alpha_{M,S}}, \tag{13}$$

$$V_{it} = \mu_V D_{it}^{\alpha_{V,D}} S_{it}^{\alpha_{V,S}}. \tag{14}$$

The first three columns of Panel A in Table 1 report estimation results that help pin down magnitudes of congestion effects and returns to scale at the three different stages of the search process captured by equations (12)-(14) in the sales segment of the housing market imposing the constant returns to scale assumption. We find a search elasticity equal to 0.772, which suggests that for every 1% increase in the number of interested buyers, the total number of online views that listings experience increases by 0.772%. However, more significant congestion effects arise at the meeting stage – the same increase in potential buyers is associated with a much smaller increase of 0.351% additional direct meetings, and ultimately an increase of 0.277% of the volume of final realized transactions. A large part of the congestion effects in the sales market can therefore be attributed to

[11] Appendix section A assesses the empirical fit of alternative functional forms.

the searchers' selection of properties that they want to inspect physically, after having initially scanned a much broader consideration set of outstanding listings online. The following three columns in the same panel report elasticities at each stage of the search process for the rental market. We find a search elasticity of 0.619, a meeting elasticity of 0.618 and transaction elasticity of 0.40, suggesting that much of the congestion effects in the rental segment arise in the final stage of the search process, once the renters and landlords meet offline to evaluate each other.

Panel A, Figure 4 illustrates graphically how the effect of market tightness manifests itself differently at the search and matching stage, as well as between market segments. The gray dotted lines show counterfactual levels of meetings and transactions, computed by assuming that the same elasticity from the previous stage of the search process continues to apply. In the sales market, the observed number of meetings per listing appears to be significantly lower than a counterfactual value which assumes that online views generate proportional amounts of physical inspections. In tight sales markets, online search activity is more intense, but this additional buyer interest does not necessarily lead to a higher number of physical inspections or ultimate realized transactions. However, in the rental segment, Panel B of Figure 4 shows that while online views are associated with roughly proportional amounts of physical inspections, they do not result in as many successful transactions, especially in tighter markets.

Panel B of Table 1 estimates separate elasticities for demand and supply in both market segments, i.e., without restricting the coefficients to α_D and α_S to assume constant returns to scale ($\alpha_D + \alpha_S = 1$). In the sales segment, we find that a 1% increase in the available stock of sales listings generates only 0.296% more searches, but it increases the number of meetings by 0.666% and the number of realized transactions by 0.721%. Adding another listing does not generate a great deal of online attention in tight demand conditions, but it does seem to generate significantly more meetings and final transactions.

Overall, our estimation validates the assumption of constant returns to scale in realized sale transactions, consistent with previous research. We cannot reject the hypothesis that congestion effects exactly offset each other at these two stages of the search process in the sales segment, as both demand and supply increase proportionally. However, the nature of the matching process in the rental market seems different, with suggestive evidence for increasing returns to scale at the meetings stage, and decreasing returns to scale in realized rental transactions. In the next section, we compare our results with past literature and explore the sources of congestion that lead us to observe the elasticities reported above.

4.1 Comparing with past literature

The Cobb-Douglas matching function with constant returns to scale implies a log-linear relationship between the transaction probability and market tightness. We test this relationship with the following empirical specification:

$$\ln(V_{it}/S_{it}) = \ln \mu + \alpha \ln \theta_{it} + \varepsilon_{it}, \tag{15}$$

where $\theta_{it} = D_{it}/S_{it}$ is market tightness in local authority district i and month t, and V_{it}/S_{it} is the corresponding transaction probability, measured in the same location over the same time period. Figure 4 shows that this simple version of the model is well able to capture the degree to which, conditional on the available outstanding stock of listings, a higher number of searchers is associated with additional realized transactions in both sales and rental markets. Here, the individual dots correspond to bin scatter observations obtained for 25 quantile groups of tightness in each respective market segment, and the solid line indicates the fit of the Cobb-Douglas function.

Exploiting the variation of market tightness across space and time to identify the parameter α in equation (15) has a long tradition—see Petrongolo and Pissarides (2001); Coles and Smith (1996); Genesove and Han (2012). These previous results lead us to expect a demand elasticity of volumes between 0.15 and 0.3. In Panel B of Table 1 we report an estimated effect of market tightness on the transaction probability of 0.277 in the sales market and 0.400 in the rental market, consistent with these previous results, though rental markets have a higher estimated demand elasticity.

With the assumption of constant returns to scale and the inclusion of market tightness as a single state variable, measurement error can occur if the level of aggregation that we have opted for does not correspond to searchers' actual consideration sets. In this case, the estimated coefficients will be biased upwards in the positive domain. With the separate estimation of coefficients on the demand and supply side of the market, measurement error induced by imperfect aggregation can still affect the estimated coefficients, but the associated bias is towards zero. Comparing the estimates in Panels A and B of Table 1 is very encouraging, because the estimated coefficients remain similar, despite being affected by measurement error that generates bias in opposite directions. In addition, replacing the number of transactions implied by the listings data with its directly observed counterpart in deed-level data registered with the Land Registry confirms both the estimated magnitudes and the validity of the constant returns to scale assumption.

As concerns the demand elasticity at the meeting stage, Genesove and Han (2012)

report a level of 0.84, which is much higher than both the value of 0.351 that we estimate under the assumption of constant returns to scale, and 0.397 in an unrestricted specification in the sales market. But interestingly, our estimate is similar to Genesove and Han (2012) when we look at the *information gathering* stage, i.e., in terms of online views of properties by potential buyers. Given the much earlier sample during which their estimate is obtained, we can plausibly attribute the difference in magnitude to the fact that the point at which buyers first engage in sufficient detail with properties has shifted over recent years, from a physical to a virtual environment.

4.2 Decomposing the congestion effects

Mapping the model in Section 2.5 to the data allows us to separate the contribution of different frictions to the observed congestion effects. We first assume that buyers and sellers can adjust the meeting intensity $\phi_D(\theta)$ and the processing rate $\phi_S(\theta)$ as functions of the segment-specific level of market tightness. In steady state, meeting and transaction outcomes are then characterized by the following sets of parameters:

J :	Preference segmentation
$\phi_D(\theta)$:	Buyers' search costs
$\phi_S(\theta)$:	Sellers' processing rate
$\overline{\varepsilon}$:	Threshold level of match quality

Our data on online search behavior allows us to calculate the share of the available stock of listings that the average user in the sample visits in any given month (equal to 0.75% for sales and 0.45% for rentals). This implies an upper bound for the number of segments equal to $J = 135$ and $J = 222$ for sales and rentals, respectively. The underlying assumption in the model is that segments are perfectly non-overlapping, i.e., an entire group of searchers targets a specific sub-set of listings and ignores the remaining part of the market. As potential buyers are in reality much less strictly separated, the congestion effects generated by preference segmentation are most likely lower than our theoretical assumption predicts.

In the model, the rate at which buyers initiate meeting requests is uniquely pinned down by their search intensity, and not affected by the other parameters. We therefore use the observed empirical variation of the number of meetings for different levels of market tightness to estimate $\phi_D(\theta)$ through a third-degree polynomial. To correct for the fact that in the data we only observe online meeting requests and not actual direct physical

contacts, we assume that, when market tightness becomes close to zero, buyers initiate meeting requests at a rate of one (i.e, $\phi_D = 1$).

Similarly, we assume that sellers process all buyer requests immediately (i.e., $\phi_S = 1$) when market tightness becomes close to zero, which allows us to link the average level of the probability of sale to the role of match quality. We estimate the threshold level of match quality $\bar{\varepsilon}$ to be equal to 0.73 in the sale segment and 0.25 in the rental segment. The variation of the sellers' processing rate is then given by the residual probability of sale, after accounting for the cumulative role of segmentation, buyer search and match quality.

In Figure 5, we report simulated model-implied patterns of variation of the probability of sale by the level of market tightness, accounting for the separate role of alternative frictions. We normalize the average level of market tightness by dividing through its in-sample mean, to be consistent with the previous theoretical (Head et al., 2014) and empirical (Genesove and Han, 2012) literature, which considers levels of market tightness around one. This is also important because, in the model, we assume that buyers gather information, request for a meeting and, when successfully matched with a property, immediately evaluate it and decide on a purchase–all within the same period. In reality, the different stages of the search process are spread out over longer periods of time. The normalization of the average level of market tightness aims to correct for this effect.

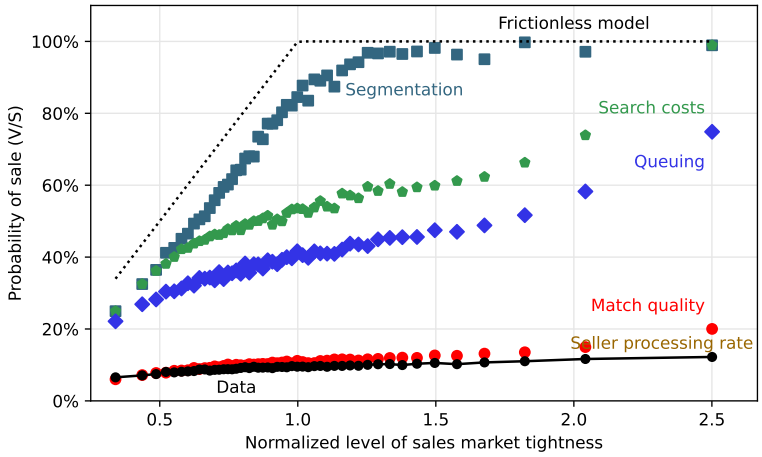
We plot the results of this estimation and model simulation procedure for binned values of market tightness, starting with the case (indicated with a dotted line) in which there is no segmentation ($J = 1$), buyers and sellers initiate and process requests instantly ($\phi_D = 1$, $\phi_S = 1$), and bilateral negotiations always generate a surplus ($\bar{\varepsilon} = 0$). Relative to a frictionless version, the model attributes some degree of sales market congestion to the role of segmentation and coordination problems ("queueing"), but the largest role accrues to variation in the rate at which buyers view properties, and the frictions that impede a successful match during the property inspection and bilateral negotiation stage. We find a relatively smaller but visible residual role for variation in the sellers' processing rate.

These broad patterns are similar in the rental market, with roughly equal contributions of search effort and match quality to the congestion effects observed in the data. However, an important distinction arises in terms of the role of seller behavior, which is found to be the most important source of congestion for properties listed for rent—especially when the market is tight. In the next section, we show that this result is consistent with variation in the negotiation strategy of landlords, as reflected in the observed price adjustment behavior.

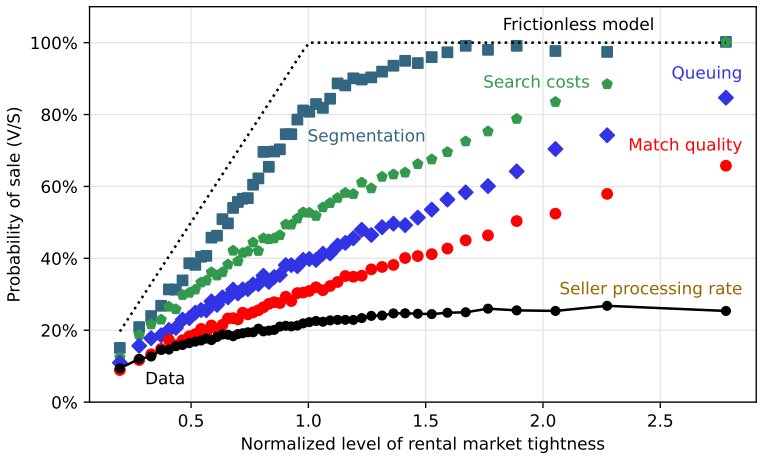
Figure 5
Decomposition of transaction outcomes

The figure reports average values of the transaction probability in the sales and the rental segments of the market, calculated for selected quantile bins of market tightness, normalized to equal to one in our sample. We compare the average probability of sale in the data with the one that would prevail in a frictionless version of the model, and with alternative measures computed by cumulatively considering additional sources of friction.

Panel A
Properties for sale



Panel B
Properties for rent



4.3 Pricing strategy

To capture the separate role of demand and supply conditions on pricing strategies in the data, we propose the following semi-log specification:

$$Y_{it} = \delta + \pi_D \ln \theta_{it} + \pi_S \ln S_{it} + \varepsilon_{it}, \tag{16}$$

where the dependent variable is either the average listing premium in local authority i in month t (or equivalently, the average capitalization rate), the price revision intensity (defined as the ratio between the total number of revisions observed and the outstanding stock of listings), or the average value of those revisions.

Table 2 shows that, for a given number of properties for sale, a 100% increase in the number of interested buyers is associated with a 5.3% increase in the listing premium that sellers ask for. Moreover, when listing prices are adjusted in such a "hot" market, they are adjusted upwards by 0.4%. On the other hand, a 100% increase in supply is associated with 4.1% lower listing premia, and price adjustments of -0.3% on average.

Figure 6 further illustrates this link between aggregate conditions, listing prices, and price adjustments. Subplots a) and b) show that when the market is tighter, i.e., when there are more potential buyers (Panel A) or tenants (Panel B) available for each unit of supply, sellers are more likely to list for a high premium relative to hedonic value and less likely to adjust the price after the initial listing. Subplot c) shows that adjustments are also less pronounced when the market is tighter.

The intensity with which sellers react to the aggregate environment indicates their willingness to negotiate: in tight markets, price revisions are rare and relatively small in magnitude. This mechanism is a critical determinant of the congestion effects that we see at the bargaining stage of the search and matching process. As the market becomes tighter and sellers and landlords are less likely to negotiate, the conversion rate of meetings into contractual agreements decreases strongly. Rather than help alleviate congestion, sellers' strategic behaviour, on the margin, appears to make matters worse.

In the next section, we further extend our exploration of how the different stages of the search process contribute to the overall likelihood that a typical listing will result in a successful transaction.

Table 2

Listing prices and price revisions: Estimation results

The table reports estimated coefficients from the following regression specification:

$$Y_{it} = \delta + \pi_D \ln \theta_{it} + \pi_S \ln S_{it} + \varepsilon_{it},$$

where Y_{it} measures the average listing premium and capitalization rate in the sales market, as well as the ln number of price revisions and the average observed level of the price revision in local authority district i and month t. In parentheses, we report standard errors clustered at the level of the local authority district. *, **, *** denote statistical significance for a 10%, 5% and 1% confidence level, respectively.

	Properties for sale			Properties for rent		
	Listing premium	Number of revisions	Average revision	Listing cap rate	Number of revisions	Average revision
Demand (π_D)	0.053***	0.103***	0.004***	-0.003**	0.170***	0.016***
	(0.003)	(0.024)	(0.001)	(0.001)	(0.039)	(0.002)
Supply (π_S)	-0.041***	0.046**	-0.003***	0.001	0.136***	-0.015***
	(0.004)	(0.023)	(0.001)	(0.001)	(0.030)	(0.001)
No. of obs.	14,506	14,506	14,506	14,465	14,465	14,465
R^2	0.082	0.023	0.005	0.013	0.183	0.072

Figure 6

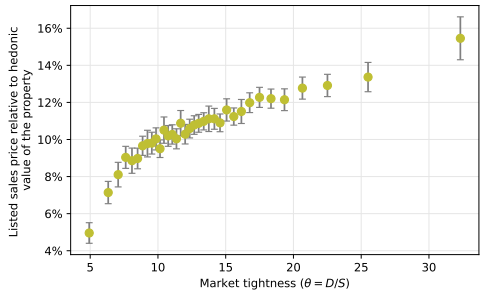
Variation of listing prices and price revisions by market tightness

The figure reports average values of listing price ratios and listing price revisions, for selected quantile bins of market tightness. We compute price revisions in the set of listings for which the quoted sale price was revised in any given local authority and month. We define the meeting conversion rate as the ratio between the number of meetings that are initiated in a given location and month, and the number of final realized transactions in the same location and the same month.

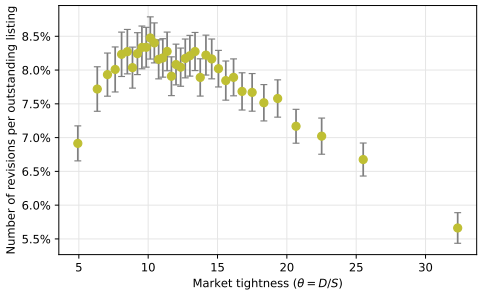
Panel A

Properties for sale

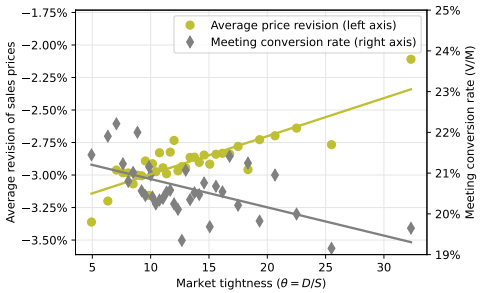
a) Listing premium



b) Number of revisions



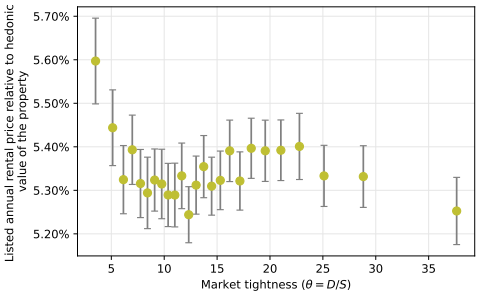
c) Average revision



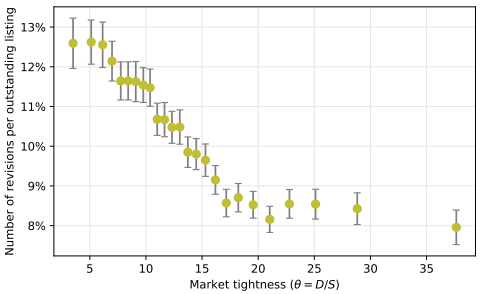
Panel B

Properties for rent

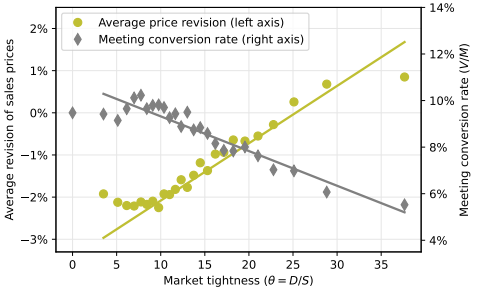
a) Capitalization rate



b) Number of revisions



c) Average revision



4.4 Extended formulation of the matching function

A formulation of the matching function with market tightness as a single state variable is able to capture the observed behaviour of counterparties at the three stages of the search process reasonably well (information gathering, meetings, final transactions). In Table 3, we explore whether there is a separate role for additional forces that accrue at different stages of the search process to explain final transaction outcomes.

First, the level of market tightness explains 7.3% of the location × month variation in the transaction probability for the average property in our sample that is listed for sale, and 30.3% of the variation in the transaction probability for the average property that is listed for rent.

But above and beyond these effects, and conditional on a given state of the market, a 1% increase in the search effort of potential buyers and tenants is associated with a higher transaction probability of around 13%. Notably, the coefficient on market tightness remains roughly unchanged when we include the users' search effort explicitly in the regression, which suggests that our measure of individual search effort carries separate and distinct information.

These results support the conclusion that beyond a Cobb-Douglas form defined on the aggregate levels of demand and supply, the matching function in the sales market needs to account for individual search effort as an additional state variable. And moving further across the remaining columns of Table 3, the meeting intensity (the degree to which virtual expressions of interest are followed by physical inspections); the listing strategy of sellers reflected in the listing premium they set; and the pattern of subsequent revisions of listing premia are all additional determinants of matching. These additional variables increase the explanatory power of the model by a factor of 2.

Table A.3 in the online appendix assesses the robustness of these conclusions by filtering out location and time fixed effects, to isolate variation idiosyncratic to a particular local authority district in a given time period. With this change of specification, the estimated demand elasticity remains of a similar magnitude, in line with previous research. In addition, the sellers' and landlords' bargaining positions continue to have an important role for the transaction outcome.[12] We further explore patterns of idiosyncratic variation and co-movement across aggregate variables in more detail in the next section.

[12]Interestingly, the role of the search effort turns negative, suggesting that unusual volumes of online search can be detrimental to listings being converted into successful deals, potentially due to information overload or decision fatigue. Both segments of the market seem to be subject to the same phenomenon, albeit with a much stronger magnitude for properties listed for sale than for rent.

4.5 Time variation: Beveridge curves and stock-flow matching

An additional lens through which search and matching equilibria are routinely viewed is the dynamic relationship between the outstanding levels of demand and supply—commonly known as the Beveridge curve. In most settings, and especially in the labor market, an increase in demand leads available supply to be exhausted, so the Beveridge curve is generally downward-sloping.

In the housing market, the situation is very different. Panel A of Figure A.4 shows that the Beveridge curve is robustly upwards-sloping, consistent with prospective and successful sellers simultaneously becoming part of the demand side of the market (Anenberg and Bayer, 2020; Gabrovski and Ortego-Marti, 2019; Grindaker et al., 2021; Moen et al., 2021); the presence of segmented search (Piazzesi et al., 2020); and strategic listing behaviour in anticipation of higher demand (Ngai and Tenreyro, 2014).

But more importantly, is the current outstanding stock of supply a good proxy for the searchers' consideration set at each point in time? One possibility, consistent with a stock-flow matching framework (Coles and Smith, 1996; Andrews et al., 2013), and with recent empirical evidence by Gilbukh (2023) and Anenberg and Ringo (2023), is that the new inflow of listings attracts a disproportionate amount of attention by active searchers, and is therefore more likely to be associated with a higher rate of matching.

To explore this phenomenon, Panel A of Figure A.7 first shows that, on average, 15% of listings and 60% of users enter the sales segment of the market in any given month. Similarly, 33% of the available listings for rent and 69% of searchers in the rental market correspond to new inflows. In Panel B of Figure A.7, we compute the variation of search and meeting activity that listings experience between the time when they initially appear on the website, and subsequent periods. We find that by the second month, the number of users decreases to less than half the initial value; a similar but somewhat more muted pattern obtains in terms of meeting requests.

Given that both buyer and tenant search is tilted towards new listings, we extend our estimation framework to account for this observation. The sixth column in Table 3 shows that a higher share of new supply is associated with a larger transaction probability in both the sales and rental segments. The explicit incorporation of the stock-flow relationship into the estimated matching function leads to a significant overall improvement in explanatory power.

5 Cross-elasticities in the sale and the rental segments

5.1 Theoretical intuition

Thus far, our framework has been limited to search and matching patterns *within* a particular segment of the market, i.e., for sales of the asset in question. However, if the asset is traded in multiple markets simultaneously, factors in each trading venue can affect outcomes in other venues. For instance, many different assets can be purchased or rented, and there are natural inter-dependencies between the mechanisms that define equilibria in each sub-market. In this section, we explore such *cross-segment* dependencies in the context of the sale and rental components of the housing market, and sketch a high-level model to guide empirical work.

Consider the optimal resource allocation problem of a household over their life cycle, with preferences defined over non-durable consumption and housing services. At any given point in time, denote by $-P$ the current cost of the representative property on the market, and $-kP$ its rental cost per period. If r is the discount rate, the present value of renting is equal to $-kP/r$, and property ownership is optimal when $P < kP/r$. In the absence of search and matching frictions, to simplify the exposition of the life-cycle portfolio allocation problem, we allow the discount rate r to capture all factors that affect the inter-temporal allocation of capital, such as the real return on financial assets, the cost of mortgage credit, and the urgency of the transaction. The household decision is then characterized by a simple rule:

$$\begin{cases} \text{own}, & \text{if } r < k, \\ \text{rent}, & \text{otherwise.} \end{cases} \tag{17}$$

Let the distribution of r capture cross-household heterogeneity (arising, for example, from a distribution of financial constraints arising from ease of borrowing or access to cash), with:

$$r \sim \text{Uniform}(r_{\min}, r_{\max}). \tag{18}$$

In this case, a fraction f of the population will optimally decide to become *owners*, and a fraction $1 - f$ will be *renters*:

$$f = \frac{k - r_{\min}}{r_{\max} - r_{\min}}. \tag{19}$$

When households face search and matching frictions in their effort to buy a house or sign a tenancy agreement, we assume they can optimally allocate search effort between

the sales and the rental market. Each unit of search comes at a cost c_S and c_L, respectively (expressed in units of the underlying property value),[13] and the chosen number of search units $G_S > 0$ and $G_L > 0$ are associated with probabilities $\phi_S(G_S)$ and $\phi_L(G_L)$ to result in successful sales/rentals. To insure an interior solution, the necessary and sufficient condition is that $\phi_j^{'}(0) = 0$, $\phi_j^{'}(G_j) > 0$ and $\phi_j^{''}(G_j) < 0$ for $j \in \{S, L\}$, i.e., the transaction probability is a positive and concave function of search effort in both markets – an assumption well founded in the data.[14] To further simplify the dynamic structure of the problem, we assume first that when search fails, i.e, no successful match gets realized within a relevant planning horizon, the searcher has the option to shift their effort to the alternative segment. Second, we assume that some owners of properties, which we call *investors* (N), do not require housing services, instead renting out their properties to potential tenants. Denoting the discounted present value of total life-time resources of the representative household by $\overline{W}$, the expected values of searching in the sales market as a potential owner; in the rental market as a potential tenant; or in the sales market as a potential investor, are then given by the following value functions, respectively:

$$W_S = \max_{G_S \geq 0} \phi_S(G_S)(\overline{W} - P) + (1 - \phi_S(G_S))\beta W_L - c_S \cdot P \cdot G_S, \tag{20}$$

$$W_L = \max_{G_S \geq 0} \phi_L(G_L)(\overline{W} - P \cdot k/r) + (1 - \phi_L(G_L))\beta W_S - c_L \cdot P \cdot G_L, \tag{21}$$

$$W_N = \max_{G_N \geq 0} \phi_S(G_N)(\overline{W} - P + \widetilde{\phi}_L \cdot P \cdot k/r) + (1 - \phi_S(G_N))\beta \overline{W} - c_N \cdot P \cdot G_N, \tag{22}$$

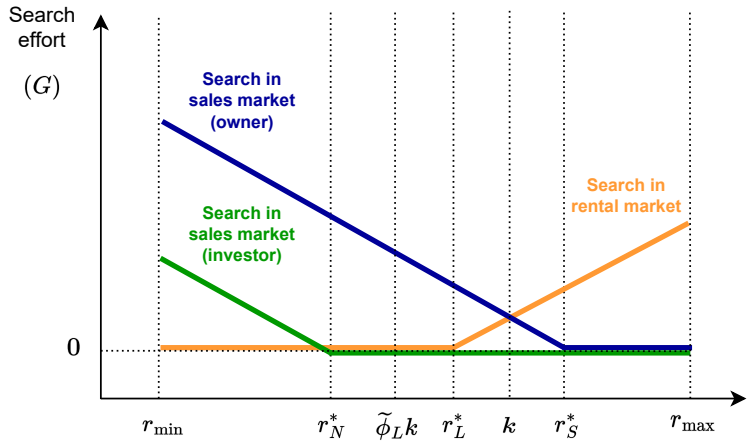
where β is an inter-temporal preference parameter. In addition to the transaction probability ϕ_S described above, investors also need to consider the eventuality that a listing in the rental market will not result in a successful tenancy agreement over a given time horizon. To avoid a notationally burdensome and analytically not insightful second layer of value functions, we simply introduce a parameter $\widetilde{\phi}_L$ to capture the expected fraction of rental income that the investor is able to realize as actual cash inflows, for an expected path of rental market vacancy in the future. For simplicity, we also assume that once an

[13] To avoid conflicting notation, we use an S subscript for the sales segment of the market, L for the rental/*lettings* segment, and N to denote an investor.

[14] Panel B of Table 3 provides an empirical validation of the assumption that the transaction probability scales positively with the *observed* search effort. We find that, on average, a higher number of both virtual and physical property inspections are associated with a higher transaction probability. However, note that the variables G_S and G_L considered in this section do not necessarily have to refer to the *observed* behaviour of households, because in some instances search can be associated with potential information overload or decision fatigue, which leads to a lower probability of transaction success. Therefore, the concept of effort used here refers strictly to the resources that searchers deploy to increase the probability that a purchase or a rental agreement becomes more likely. The model predictions developed at the end of the section are expressed in terms of the transaction probability, since this is the ultimate margin that all agents (owners, renters and investors) optimize in the model.

investment decision is taken, it cannot be undone over the planning horizon.

The solution to this system of equations is then given by three levels of r for when it is optimal to search in the rental market, the sales market as an owner, and the sales market as an investor.



Consider an agent with a draw of the discount rate $r = k$. Since they are indifferent between searching in the two segments, they allocate some amount of effort to both, in proportion to the relative search costs in the two market segments. Above $r = k$, there exists a level r_S^* for which search becomes too costly in the sales market. Below $r = k$, there exists a level $r_L^* < k$ for which search becomes too costly in the rental market.

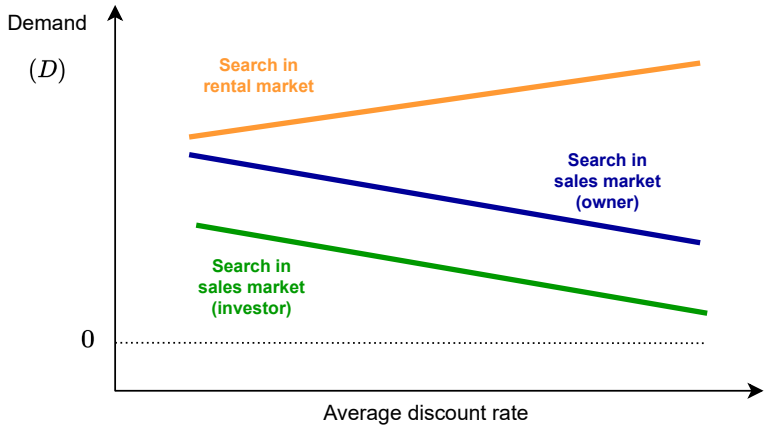
From the perspective of an investor, the expected net payoff in case of a successful transaction is positive if $r < \widetilde{\phi}_L k$, because they can only expect to harness a fraction $\widetilde{\phi}_L < 1$ of the gross annual yield. With a positive cost of search, the threshold level $r_L^* < \widetilde{\phi}_L k$ defines the point below which investors enter the market.

The total number of users searching in each segment results from the distribution of agents in equation (18):

$$D_S = \underbrace{\int_r 1_{G_S(r)>0} dr}_{\text{Owners}} + \underbrace{\int_r 1_{G_N(r)>0} dr}_{\text{Investors}}, \text{ for sales listings, and,} \tag{23}$$

$$D_L = \int_r 1_{G_L(r)>0} dr, \text{ for rental listings.} \tag{24}$$

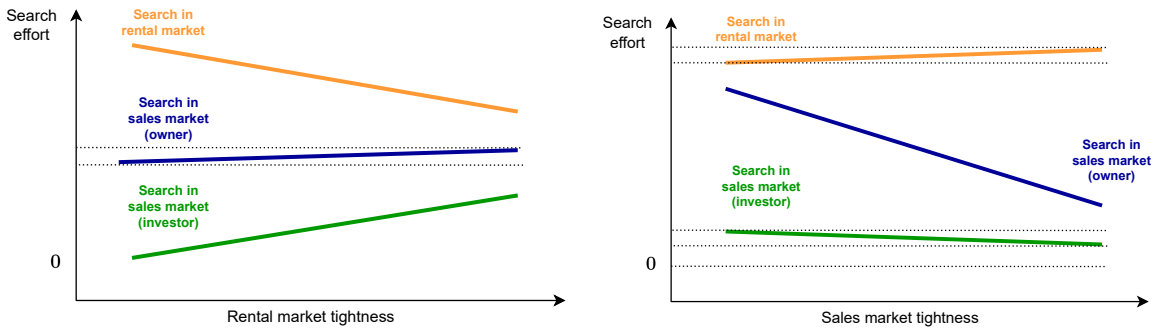
We can now analyze comparative statics with respect to the average level of the discount rate:



With a fixed pool of households interested in either buying or renting a property, a regime of higher interest rates, or an additional housing risk premium, decreases demand for property purchases. It leads potential owner-occupiers to direct their attention to the rental market instead, and potential investors to find alternative uses for their capital. While we cannot distinguish between these two categories of owners, we will still be able to test this substitution mechanism between the two market segments using a shock to financial conditions in Section 6.

To further understand how search and matching patterns can have complementary effects across segments, first consider an exogenous shock that causes the number of interested renters to rise (left-hand diagram below). As the rental market becomes tighter, the probability ϕ_L decreases for any level of effort G, and the trade-off moves in favor of the sales market for all market participants. The re-allocation of effort is strongest for those that were planning to search in the rental market in the first place (indicated with an orange line), because it immediately affects their expected probability of securing a tenancy agreement. But it also affects potential owners that search in the sales market first (blue line), because in the event that their search fails, they would eventually have to face tougher conditions in the rental market. Interestingly, from the perspective of an investor (green line), a tighter rental market means that the probability of finding a tenant, captured by the parameter $\widetilde{\phi}_L$, is *increasing*. They will therefore intensify the effort to complete a successful property purchase.[15]

[15]We present here a stylized version of optimal decisions. Figure A.6 in the online appendix illustrates the same phenomena with a numerical calibration of the model solution.



A similar cross-dependence occurs when an exogenous shock causes the number of interested buyers to rise, i.e., the sales segment of the market becomes tighter (right-hand diagram above). Directly affected searchers respond strongly to the associated decrease of the probability ϕ_S of a successful transactions; searchers that seek to rent a property exert slightly more effort in their segment, as they want to avoid a worsening fallback position. Investors respond as well, but with a lower magnitude than home-owners, because for them shifting search effort to the rental market, which makes their demand more inelastic.

Here, the key driving force of both within- and across-market outcomes is the set of probabilities ϕ_S and ϕ_L, and the adjustment factor $\widetilde{\phi}_L$. Table A.2 in the online appendix validates empirically the link between these variables and the state of the market. As expected, a tighter market makes it less likely for search effort to result in a successful transaction, both in the sales and the rental segments, but it makes it more likely for a potential landlord to successfully rent out the property. Figure A.6 further illustrates the theoretical intuition behind such cross-market dependence effects. This calibrated illustration highlights that an increase in sales market tightness has a positive but modest effect on the transaction probability in the rental market, but an increase in rental market tightness has a positive and potentially strong effect on the transaction probability in the sales market. This is plausibly driven by investors for whom a "hot" rental market is associated with a higher expected yield, in line with our predictions.

The model's predictions can therefore be summarized as follows:

a) A high-interest regime is associated with a shift of demand from the sales to the rental sector.

b) An increase in sales market tightness has a positive but modest effect on the transaction probability in the rental market.

c) An increase in rental market tightness has a positive and potentially strong effect

on the transaction probability in the sales market, driven by investors for which a "hot" rental market is associated with a higher expected yield.

Empirical results: The final set of columns in Table 3 shows that a tighter rental market is associated with a higher transaction probability in the sale market, and the estimated magnitude of this effect (0.143) is strong and statistically significant, consistent with the marginal role of investors that see a tighter rental market as an opportunity.

Table 3 also shows that a higher capitalization rate (i.e., a higher rental market yield) leads to more intense transaction activity in the sales market—consistent with the intuition that a higher capitalization rate makes the sales market more attractive both for owners (who prefer to own rather than rent) and investors (who anticipate a higher net yield from their property purchase). This effect is strong and statistically significant.

6 Exogenously induced financial constraints

To validate the quantitative magnitude of the effects described in the previous sections, we exploit an unexpected and economically large fiscal policy event. On 23 September 2022, the U.K government unexpectedly announced a set of looser policies and tax cuts, collectively known as Prime Minister Liz Truss' "mini-budget". This induced a sharp market reaction, leading to a sharp depreciation of the British Pound, and resulted in extraordinary turbulence in bond markets. The turbulence in debt markets sharply increased borrowing costs and resulted in significant rationing of mortgage credit in the economy.[16]

Panel A of Figure 7 plots average mortgage rates at various levels of loan-to-value (LTV) ratios. The increase in rates following the mini-budget announcement is evident across all LTVs – swiftly materializing in tighter financial conditions for potentially all home-buyers other than pure cash buyers. Alongside this increase in mortgage costs, accompanying monetary policy guidance issued by the Bank of England upwardly revised the mid- to long-term perspective on mortgage costs for any typical household.

The *ex-ante* distribution of owner-occupied properties with outstanding mortgages across all local authority districts in the U.K. is a useful proxy for how potentially binding such a large policy-induced financial constraint is likely to be in each region. We use the fraction (denoted by f_i^{mortgage}) of owner-occupied properties in local authority district i

[16]Another policy-induced variation within our sample is the stamp-duty holiday declared by the U.K. government in order to spur the real-estate market in the aftermath of COVID-19. We study this in Section C in the online appendix.

that have a mortgage outstanding as available from the 2011 U.K. Census to proxy for the intensity of this shock across different local authorities in the U.K.

Panel B of Figure 7 shows that the share of owner-occupied properties that have a mortgage outstanding in a local authority district varies between a low of 35% to a high of nearly 70%. We use this to condition the effect of the "mini-budget" on buyer search and matching in the housing market, thus utilizing this policy-induced variation to identify matching elasticities, in particular the cross-market search between sale and rental segments of the U.K. housing market.

This empirical design is based on the assumption that the *ex-ante* share of people with a mortgage in a local authority i before the shock is an adequate proxy for financial constraints for all those who search in the same location.[17] In particular, we run the following regression specification:

$$Y_{it} = \zeta_i + \delta_{\text{year}} + \delta_{\text{month}} + 1_{\text{post}} \times f_i^{\text{mortgage}} + \varepsilon_{it}, \tag{25}$$

for a set of dependent variables Y_{it}, measured in local authority i and week t. To isolate effects for the months between October and December 2022, we include year fixed effects as well as calendar month fixed effects. The combination of the two serves to provide a counterfactual that developments in these last three months of 2022 can be judged against.

Table 4 reports estimated coefficients for selected outcome variables. The first row presents the estimated effect of the shock to mortgage rates across all of the U.K., relative to the observations before September 2022. In response to this financial shock, we find that the number of actively searching users decrease significantly (by 9.7%), and the number of outstanding listings rises. Consequently, market tightness is much diminished. We also observe that the search and meeting activity per listing is drastically lower (32.1% and 14.4% respectively) and the transaction probability is 31% lower than before the mortgage rate shock. In terms of seller behaviour, we note that the listing premia decrease by 3 percentage points – about 33% of the average listing premium in the full sample. Outstanding listing prices are also revised downwards by 1.4 percentage points, which amounts to a large fraction of the average downward price revision of 3% for a typical sale listing.

The interaction term between the post-event period and the local exposure to mortgage costs suggests that the overall effect is principally driven by locations where households

[17] A decomposition of search by location will be the subject of further exploration in future versions of this paper.

are more likely to be financing property purchases with mortgage contracts. In such highly exposed locations, the marginal effect of the policy on market tightness is equal to -0.68, on search effort -0.61, and on the number of meetings per listing -0.39.

These effects are large and statistically robust; but more importantly, they allow us to compute corresponding demand elasticities as a result of the mortgage rate shock, which we can compare to the unconditional estimates reported in Table 1. Dividing the marginal effect on search by its counterpart in terms of market tightness, we find a value of $0.89 = (-.61)/(-0.68)$, which is close to the unconditional estimate of 0.83. For meetings, we have $0.57 = (-0.39)/(-0.68)$, slightly above the unconditional estimate of 0.37 in the aggregate sample. In terms of realized transactions, although imprecisely estimated, the demand elasticity is 0.16, consistent with the more conservative estimates in the specification with fixed effects reported in Table A.3. These results provide useful additional validation for the demand elasticities across the different stages of the search and matching process documented in the paper.

As expected, the increase in mortgage costs leads to a re-allocation of demand between the sales and the rental segments of the market. Panel B of Table 4 shows that online search activity decreases by 47% for properties listed for sale, and it increases by 35.9% for properties listed for rent. The associated search elasticity is equal to 0.875, slightly higher than the unconditional estimate (0.619). As the same time, the number of meeting requests increases by an order of magnitude more than in the unconditional sample, which suggests a sharp uptick in search effort. But despite the additional tenant interest, the number of realized rental transactions is decreasing, consistent with the presence of significant congestion effects. Supply-side behavior is very likely a major source of this congestion, as landlords increase the listing capitalization rate by 1.8% on average; this is a very significant magnitude, given that the average rental capitalization rate is equal to 5% in the data.

Table 3

Contribution of different stages of the search process to realized transactions

The table reports estimation results from regression specifications where the dependent variable is the ln probability of sale, and explanatory variables are ln market tightness, ln search effort, ln meeting intensity, the average listing premium, and ln number of revisions per listing, as well as the market tightness in the rental market, and the capitalization rate (listing premium, respectively). *, **, *** denote statistical significance for a 10%, 5% and 1% confidence level, respectively.

Panel A

Properties for sale

	Dependent variable: Probability of sale (V/S)						
	Within-market specification						Cross-market specification
Market tightness ($\theta = D/S$)	0.244***	0.275***	0.318***	0.356***	0.371***	0.134***	0.015
	(0.021)	(0.023)	(0.026)	(0.028)	(0.026)	(0.037)	(0.032)
Search intensity (I/D)		0.130***	0.160***	0.155***	0.234***	0.045	0.004
		(0.042)	(0.042)	(0.04)	(0.038)	(0.043)	(0.038)
Meeting intensity (M/I)			0.067***	0.057***	0.056***	-0.022	-0.082***
			(0.019)	(0.016)	(0.015)	(0.014)	(0.012)
Listing premium				-0.062***	-0.058***	-0.050***	-0.057***
				(0.012)	(0.011)	(0.012)	(0.007)
Number of revisions per listing					-0.137***	-0.345***	-0.288***
					(0.011)	(0.012)	(0.011)
Net supply inflow (S_{new}/S)						0.433***	0.383***
						(0.021)	(0.019)
Rental market tightness $\theta_L = D_L/S_L$							0.143***
							(0.018)
Capitalization rate in rental market							0.093***
							(0.008)
No. of obs.	14,506	14,506	14,506	14,506	14,506	14,506	14,465
R^2	0.073	0.078	0.084	0.114	0.145	0.223	0.321

Table 3
Contribution of different stages of the search process to realized transactions
(continued)

Panel B
Properties for rent

	Dependent variable: Probability of sale (V/S)						
	Within-market specification						Cross-market specification
Market tightness ($\theta = D/S$)	0.431***	0.544***	0.537***	0.528***	0.515***	0.356***	0.358***
	(0.022)	(0.024)	(0.024)	(0.024)	(0.023)	(0.031)	(0.031)
Search intensity (I/D)		0.290***	0.275***	0.245***	0.258***	0.132***	0.132***
		(0.045)	(0.046)	(0.049)	(0.049)	(0.046)	(0.045)
Meeting intensity (M/I)			-0.044***	-0.069***	-0.095***	-0.138***	-0.158***
			(0.013)	(0.012)	(0.016)	(0.017)	(0.017)
Capitalization rate				0.038***	0.038***	0.035***	0.039***
				(0.014)	(0.014)	(0.014)	(0.014)
Number of revisions per listing					-0.062***	-0.113***	-0.116***
					(0.018)	(0.02)	(0.019)
Net supply inflow (S_{new}/S)						0.390***	0.396***
						(0.039)	(0.037)
Sales market tightness $\theta_S = D_S/S_S$							0.010
							(0.033)
Listing premium in sales market							-0.040***
							(0.012)
No. of obs.	14,465	14,465	14,465	14,465	14,465	14,465	14,465
R^2	0.303	0.323	0.325	0.332	0.338	0.371	0.379

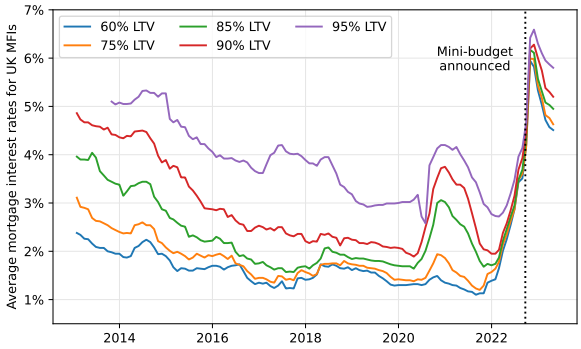
Figure 7

Mortgage borrowing costs and local exposure

Panel A shows average quoted household mortgage interest rates by U.K. monetary and financial institutions, for fixed-rate mortgage products with different initial loan-to-value (LTV) ratios for the underlying contract. The advertised interest rates used in the computation of quoted rates are obtained from an independent service ("Moneyfacts") and compiled and reported by the Bank of England. Panel B reports the variation in the local exposure to mortgage borrowing costs. We compute the fraction of owner-occupied property that has a mortgage contract outstanding, as captured by the 2011 wave of the U.K. Census.

Panel A

Mortgage interest rates



Panel B

Heterogeneity across locations

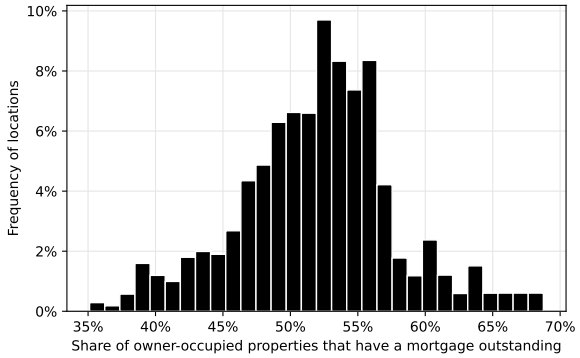


Table 4

Market response to an increase in mortgage costs

The table reports estimated coefficients from the following empirical specification:

$$Y_{it} = \zeta_i + \delta_{\text{year}} + \delta_{\text{month}} + 1_{\text{post}} \times f_i^{\text{mortgage}} + \varepsilon_{it}, \tag{26}$$

where i is a local authority, t is a week, δ_{year} and δ_{month} are year and calendar month fixed effects, respectively. The treatment indicator 1_{post} takes a value of one if the observation is after September 2022, and zero otherwise. The set of dependent variables Y_{it} are indicated in column headers. The variable f_i^{mortgage} captures the share of owner-occupied property that has a mortgage outstanding. In parentheses, we report standard errors clustered at the local authority level. *, **, *** denote statistical significance for a 10%, 5% and 1% confidence level, respectively.

Panel A

Properties for sale

	Supply	Demand	Market tightness	Search per listing	Meetings per listing	Transaction probability	Listing premium	Price revision
September 2022 - December 2022	0.203***	-0.097***	-0.299***	-0.321***	-0.144***	-0.310***	-0.034***	-0.014***
	(0.004)	(0.003)	(0.005)	(0.005)	(0.006)	(0.007)	(0.002)	(0.003)
No. of obs.	68,725	68,725	68,725	68,725	68,725	68,725	60,863	68,725
R^2	0.957	0.854	0.729	0.741	0.679	0.375	0.163	0.012
September 2022 - December 2022	0.091***	0.150***	0.059	0.000	0.050	-0.241***	-0.082***	-0.021***
	(0.016)	(0.029)	(0.051)	(0.032)	(0.116)	(0.075)	(0.013)	(0.005)
× Local mortgage share	0.204***	-0.479***	-0.683***	-0.611***	-0.390**	-0.111	0.091***	0.009
	(0.031)	(0.054)	(0.159)	(0.062)	(0.17)	(0.114)	(0.025)	(0.158)
No. of obs.	62,497	62,497	62,497	62,497	62,497	62,497	59,210	62,497
R^2	0.951	0.835	0.695	0.729	0.584	0.359	0.163	0.01

Panel B

Properties for rent

	Supply	Demand	Market tightness	Search per listing	Meetings per listing	Transaction probability	Listing cap rate	Price revision
September 2022 - December 2022	0.456***	0.087***	-0.369***	-0.332***	-0.351***	-0.383***	-0.001***	-0.015**
	(0.006)	(0.004)	(0.006)	(0.007)	(0.01)	(0.009)	(0)	(0.007)
No. of obs.	68,725	68,725	68,725	68,725	68,725	68,725	60,794	68,725
R^2	0.959	0.934	0.79	0.74	0.742	0.403	0.571	0.019
September 2022 - December 2022	0.465***	-0.101***	-0.566***	-0.505***	-0.996***	-0.105	-0.010***	-0.021
	(0.029)	(0.026)	(0.035)	(0.037)	(0.112)	(0.121)	(0.001)	(0.133)
× Local mortgage share	-0.025	0.359***	0.384***	0.336***	1.239***	-0.536**	0.018***	0.016
	(0.055)	(0.05)	(0.066)	(0.071)	(0.212)	(0.229)	(0.002)	(0.244)
No. of obs.	62,497	62,497	62,497	62,497	62,497	62,497	59,140	62,497
R^2	0.959	0.931	0.791	0.749	0.746	0.413	0.571	0.019

7 Conclusion

Search and matching models are frequently used to study markets that involve decentralized trading. Market clearing in these models is routinely characterized by defining an aggregate matching function on the outstanding levels of demand and supply. Yet, many aspects of the process through which counterparties meet, negotiate, and close deals in these settings are opaque. We open the "black box" of the matching function by exploiting granular data covering both online and physical search for the entire U.K. housing market. Using these data, we estimate the sources and magnitudes of congestion effects at different stages of the search and matching process in both sales and rental segments of this market.

We find that a standard Cobb-Douglas formulation with constant returns to scale is well able to explain matching patterns in housing sale markets. In rental markets, additional congestion effects arise and returns to scale are mildly decreasing. This difference in matching patterns is largely attributable to sell-side optimization, i.e., rents are adjusted downwards in response to the greater availability of supply, and upwards in response to increased demand. We find that a simple and useful way to capture such seller/renter pricing strategies, consistent with prior research, is to use the initial listing premium over the hedonic valuation of the property.

The average observed listing premium in a market segment is part of a larger set of variables, including online search effort, physical meeting intensity, and the rent capitalization rate, which are helpful to explain matching patterns over and above the role of market tightness. Extending the simple Cobb-Douglas matching function with these additional factors increases its explanatory power significantly.

We also develop a stylized model of cross-market search to understand cross-dependence between the sales and rental segments of the housing market. Consistent with the model's predictions, we find a strong impact of rental market tightness on the sales transaction probability.

To validate the estimated quantitative magnitude of the effects, we exploit an unexpected event, the "Truss shock," that dramatically increased borrowing costs for new mortgage borrowers. We find that the responses of listing and search patterns in our event-study research design are consistent with the estimated elasticities in the period prior to the realization of the shock.

Taken together, our findings are helpful for the future calibration and development of structural models of housing search and matching frictions. Our work additionally showcases the importance of accounting for simultaneous equilibrium determination in

both sales and rental segments of search and matching markets.

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In Search of the Matching Function in the Housing Market

Online Appendix

Cristian Badarinza, Vimal Balasubramaniam and Tarun Ramadorai

July 1, 2024

Table A.1
Literature review

The table reports a selected set of contributions to the literature on search and matching frictions, both in terms of theoretical modeling and empirical identification of elasticities. The column labeled *"Estimated"* indicates whether the parameters of the matching function are estimated in the data.

Publication			Matching function							
Authors	Year	Journal	Market	Estimated	Functional form	Matching variable	Elasticity		Returns to scale	
							Volume (V)	Meetings (M)	Value	Empirical test
Pissarides	1986	EP	Labor	Yes	Cobb-Douglas	V	0.30	-	CRS	Yes
Coles and Smith	1996	Economica	Labor	Yes	Cobb-Douglas	V	0.66	-	CRS	Yes
Burda and Wyplosz	1994	EER	Labor	Yes	Cobb-Douglas	V	0.22	-	DRS	Yes
Warren	1996	EL	Labor	Yes	Trans-log	V	-	-	IRS	Yes
Yashiv	2000	AER	Labor	Yes	Cobb-Douglas	V	0.80	-	IRS	Yes
Sahin et al.	2014	AER	Labor	Yes	Cobb-Douglas	V	0.24-0.66	-	CRS	-
Barnichon and Figura	2015	AEJ: Macro	Labor	Yes	Cobb-Douglas	V	0.34	-	CRS	-
Sedlacek	2016	RED	Labor	Yes	Cobb-Douglas	V	0.24	-	CRS	-
Hall and Schulhofer-Wohl	2018	AEJ: Macro	Labor	Yes	Cobb-Douglas	V, M	0.35	0.79	CRS	-
Lange and Papageorgiou	2020	-	Labor	Yes	Non-parametric	V	0.15-0.30	-	CRS	-
Wheaton	1990	JPE	Real estate	No	Poisson	V	-	-	CRS	-
Piazzesi and Schneider	2009	AER P&P	Real estate	Structural	Cobb-Douglas	M	-	0.57	CRS	-
Ngai and Tenreyro	2014	AER	Real estate	No	Cobb-Douglas	M	-	implicit	CRS	-
Anenberg and Ringo	2022	AEJ: Macro	Real estate	Structural	Urn-ball	V	0.12	-	CRS	-
Anenberg and Bayer	2020	IER	Real estate	No	Cobb-Douglas	M	-	0.84*	CRS	-
Piazzesi et al.	2020	AER	Real estate	Structural	Cobb-Douglas	M	-	implicit	CRS	-
Grindaker et al.	2023	R&R RFS	Real estate	Yes	Cobb-Douglas	V	0.64	-	CRS	-
Kotova and Zhang	2021	R&R RFS	Real estate	No	Cobb-Douglas	M	-	0.84*	CRS	-
Diaz and Jerez	2013	IER	Real estate	Structural	Urn-ball	M		0.48	CRS	

**Note:* The elasticity is used in model calibration to capture search and matching frictions in the housing market.

A Functional forms

How well do the alternative functional forms discussed above fit aggregate matching patterns in the data? Panel A of Figure A.1 considers the exponential matching function in equation (4). In the urn-ball model that motivates this functional form, the underlying assumption is that searchers randomly originate meetings, which they distribute across the set of available outstanding listings in a given location and month. This has several implications. First, this implies a proportional increase of meetings with the number of searchers, which we reject in the data. Second, the random distribution of meetings across listings predicts a very high rate of matching, which we do not see, indicating that coordination externalities are potentially much more pronounced in the data than in a standard urn-ball setting. That is, actual searchers are much more likely to "step on each other's feet" than predicted by the urn-ball model where they randomly pursue outstanding listings.

Panel B of the figure considers the Cobb-Douglas matching function for meetings corresponding to equation (5), under the assumption of perfect segmentation of preferences and frictionless matching within a segment.[1] This model performs very well in explaining the empirical pattern of meetings. However, the assumption of frictionless local matching generates a much higher rate of final transactions than we observe in the data. This suggests that search and matching frictions are quantitatively significant even *within* segments.

Figure A.2 shows that the CES specification in equation (6) is well able to match the patterns of both meetings and realized transactions. Interestingly, the parameter ρ is estimated to be close to zero, meaning that the functional form is indistinguishable from Cobb-Douglas. Overall the CES specification confirms that congestion effects originate at the level of physical meetings between counterparties. However, we cannot quantitatively separate whether these congestion effects come from preference heterogeneity—i.e., buyers self-selecting into their preferred segments of the market—or from the endogenous variation of search effort in response to potentially greater uncertainty about final outcomes in tighter markets.

Finally, the specification in equation (7) allows us to fit the slope of finally realized transactions as a function of market tightness. These fitted slopes are shown by the green lines in the right-hand plot of Figure A.2. The importance of allowing for additional

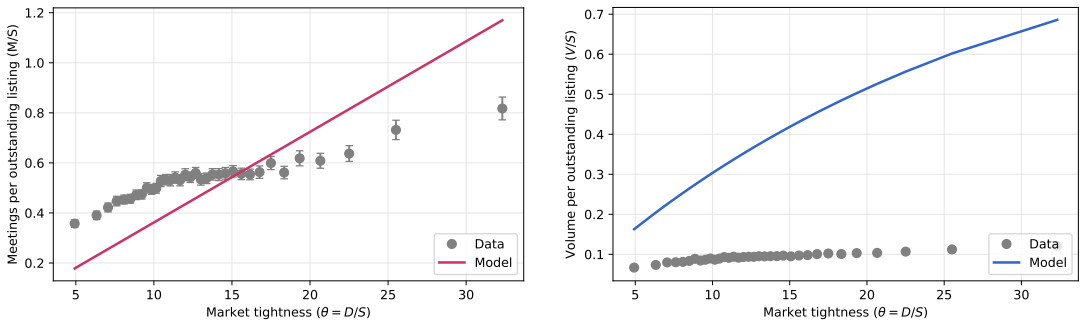
[1] We remain agnostic as to the exact dimension of the segmentation. The intuition of Shimer (2005)'s aggregation result applies in the same way to any definition of preference heterogeneity, with locally independent arrival rates of demand and supply.

congestion to occur at the bargaining stage is clearly evident in these plots, as the blue line shows the poor fit that results when we simply assume that all meetings predicted by the matching function in the left-hand panel of the figure translate directly into final transactions. In Section 4.4 in the main text, we explore the pricing effects involved in this bargaining process in more detail.

Figure A.1
Coordination and segmentation

The figure reports average values of variables calculated for selected quantile bins of market tightness. The meetings per listing variable is computed as the number of direct contact requests per listing, and transaction probability measures the number of realized transactions relative to the outstanding stock of listings in a local authority in a given month. Panel A reports the fit of a matching function that takes an exponential form, under the assumption of pure coordination frictions. Panel B reports the fit of a matching function that takes a Cobb-Douglas form, under the assumption of perfect segmentation.

Panel A
Pure coordination problem (Urn-ball model)



Panel B
Pure segmentation

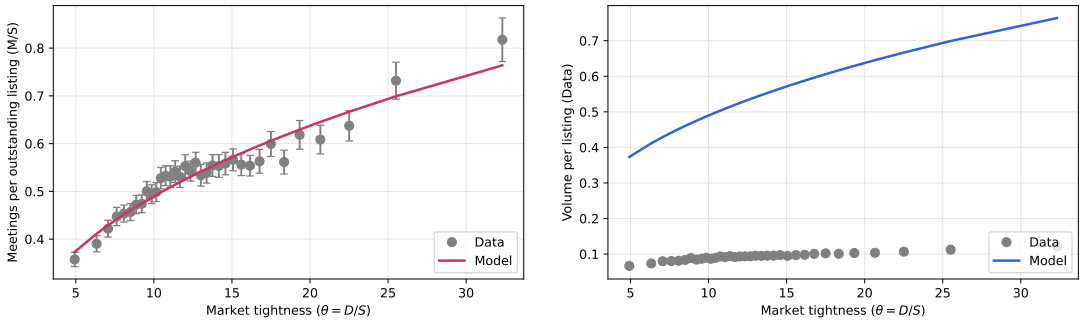
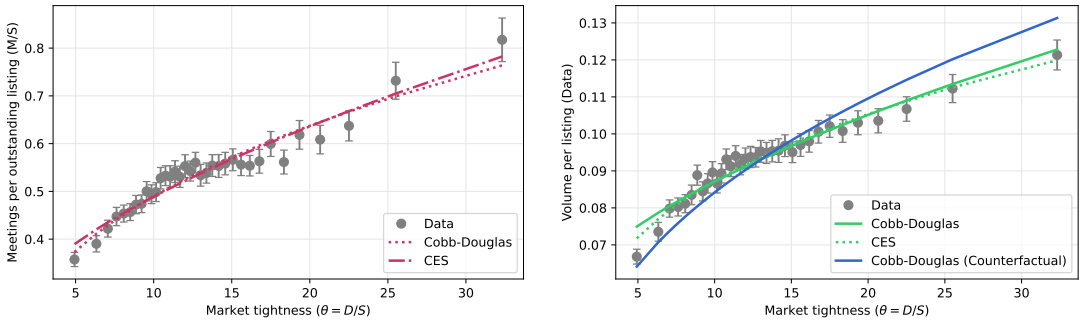


Figure A.2
Costly search and bargaining

The figure reports average values of variables calculated for selected quantile bins of market tightness. We consider the Cobb-Douglas and CES functional forms for the number of meetings, and an additional specification which flexibly estimates the impact of market tightness on final transaction outcomes, accounting for the role of bilateral bargaining.



B Additional tables and figures

Figure A.3
Validation of transaction volume

The figure compares two alternative measures for property sales transaction volume in our sample. The first, shown on the horizontal axis, is calculated as the number of listings in each local authority district for which an SSTC flag ("Sold subject to contract") is assigned in a particular month. The second, shown on the vertical axis, is calculated as the number of property sales registered with HM Land Registry in each local authority district, which indicate a given month as the contract date. The scatter plot reports ln values of these two measures.

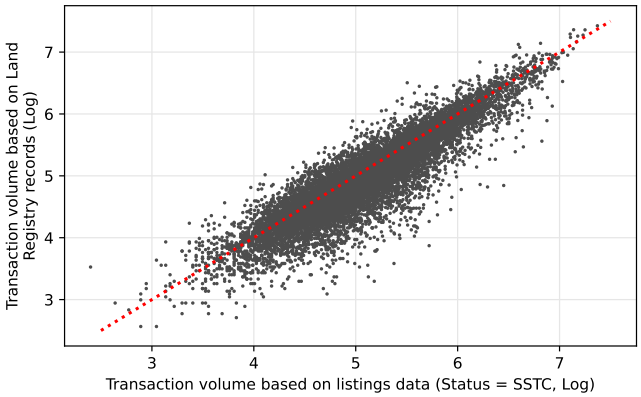


Table A.2
Effect of market tightness and pricing on transaction outcomes

The table reports estimated coefficients from regressions specifications that seek to explain two types of transaction outcomes: the conversion rate of search visits into actual transactions, and the rental transaction probability. All variables except the listing premium and rental capitalization rate are included in ln levels. In parentheses, we report standard errors. *, **, *** denote statistical significance for a 10%, 5% and 1% confidence level, respectively.

	Conversion rate of search (V/I)		Rental
	Properties for sale	Properties for rent	transaction probability (V/S)
Sales market tightness	-0.533***		
	(0.009)		
Sales listing premium	-0.088***		
	(0.005)		
Rental market tightness		-0.206***	0.443***
		(0.006)	(0.006)
Rental listing capitalization rate		0.085***	0.358***
		(0.019)	(0.018)
No. of obs.	14,141	14,465	14,465
R^2	0.252	0.073	0.284

C Demand-side policy: A stamp duty "holiday"

The fiscal treatment of residential property transactions in the U.K. requires buyers to pay stamp duty (HM Revenue & Customs, 2023). This tax is calculated as a fraction of the contractual sales price and applies progressively for a schedule of pre-defined price bands. The price bands and the associated tax schedule has remained unchanged since 2014, but during the sample period covered by our data, specific rate levels have been adjusted multiple times, in an attempt to stimulate market activity in particular segments of the market. The first adjustment took place in July 2020, when a "stamp duty holiday" was announced, which implied that lower-value properties would be exempt from paying stamp duty for a period of one year. In July 2021, when the program was due to expire, an extension was announced for some categories of properties. The pre-2020 status quo was then restored in October 2021. The table below gives an overview of these changes. Green shading indicates a relaxation of the tax regime for the respective category of property, and red shading indicates the expiration of the intervention period:

Price band	Pre-policy level	Change of stamp duty regime		
		Jul 2020	Jul 2021	Oct 2021
Below £125k	0%	0%	0%	0%
£125k to £250k	2%	**0%**	0%	**2%**
£250k to £500k	5%	**0%**	**5%**	5%
£500k to £925k	5%	5%	5%	5%
£925k to £1.5m	10%	10%	10%	10%
Above £1.5m	12%	12%	12%	12%

Panel A of Figure A.8 shows the evolution of the number of residential real estate sales transactions lodged with HM Land Registry, for five categories of prices, calculated according to the stamp duty tax bands. (We consolidate the price groups above £925k for better visualization, considering that they account for a small share of the market are not differentially affected by the policy changes.) The volume of realized transactions is stable in the pre-pandemic period, with some residual seasonality, but limited overall fluctuation at monthly frequency.

In the early months of the pandemic market activity drops to almost zero. But the pattern of recovery is intriguing, with transaction activity increasing steadily across market segments, surpassing pre-pandemic levels by up to 50 percent during 2021 and converging back to the same levels during 2022.

Where should we expect to see effects of the changes in stamp duty regimes? First, in July 2020, properties in the £250k - 500k price band experience the largest positive treatment effect, with stamp duty going from 5% to 0%. This is accompanied by a gradual shift towards this price group over the months after the policy change. A similar but more muted effect obtains for the price band £125k - 250k, for which stamp duty decreases from 2% to 0%.

Second, market participants are aware that after the 1st of July 2021 the status quo is bound to be restored, and the data confirm a very pronounced rush to complete transaction exactly during June 2021, which is the month that precedes the deadline. The bottom plots of Panel A show that these effects apply differentially across the treated price bands. Most importantly, we see a relatively more pronounced spike for the £250k – 500k group before the expiration of its tax break in July 2021, and a more pronounced spike for the £125k – 250k group before the later deadline that applies to it, in October 2021.

One puzzling observation, though, is that the higher price bands of above £500k experience increases in transaction activity that coincide with the timings described above, despite not being targeted by the policy and not being subject to an expiration of a

fiscal advantage. One possible explanation is that the widely publicized ending of the favorable stamp duty regime has lead owners to upgrade by selling a below-£500k property and buying in the higher-price segment. Such coordination between buying and selling decisions is consistent with existing evidence from both the US and the U.K. on liquidity in "hot" markets (Ngai and Tenreyro, 2014; Anenberg and Ringo, 2022).

In Panel A of Table A.4 we calculate the associated listing and search patterns around the times of the policy roll-out. For a set of dependent variables Y_{bt}, measured for 36 price bands b in increments of GBP 25,000 in each week t, we estimate the following empirical specification:

$$Y_{bt} = \zeta_b + \delta_t + \eta 1_{treat_b \times post_t} + \varepsilon_{bt}, \tag{28}$$

where $1_{treat_b \times post_t}$ is an indicator for whether the particular price band has been addressed by the policy, interacted with a time window of two months after implementation. Interestingly, demand increases by 7.6% in the treated band, but this increase is perfectly correlated with the increase in supply – i.e., sellers anticipate the additional demand in the targeted segment. Since market tightness therefore remains unaffected, equilibrium outcomes in response to the policy deviate substantially from those predicted by the unconditional elasticities estimated in Table 1. In particular, buyer interest does not seem to be directed disproportionally towards the targeted price bands, but the probability of transactions to be realized is higher. This suggest that the effects are entirely driven by the bargaining stage of the matching process.

To assess effects in the rental market, we compute hedonic price levels for each property listed for rent, and attribute the listing to a particular price band depending on this valuation. Panel B of Table A.4 reports estimated coefficients corresponding to equation (28) in the sample of properties listed for rent. We find that both demand and supply decrease significantly, which is consistent with a substitution effect between the two segments. Households respond to the policy intervention by marginally favouring a house purchase over a new rental agreement. A precise identification of elasticities is elusive, though, because of confounding responses by sellers and as an apparent rush to complete transactions in the immediate post-policy period, both in the sales and the rental market, anticipating the expiration of the tax "holiday". The observed dynamics of realized transactions allow us to attribute the observed increase in sales volumes to an increase in the unobserved component of the matching rate, as opposed to the underlying patterns of search effort.

Figure A.4
The Beveridge curve

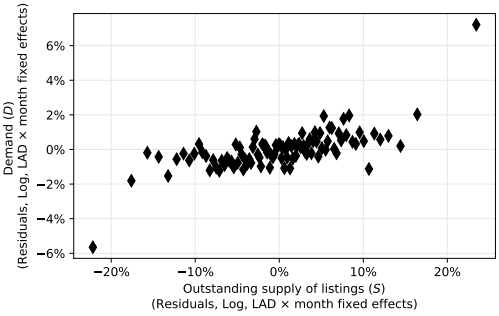
The figure reports bin scatter plots of residuals obtained from the following set of regressions:

$$Y_{it} = \zeta_i + \delta_t + \varepsilon_{it}, \tag{27}$$

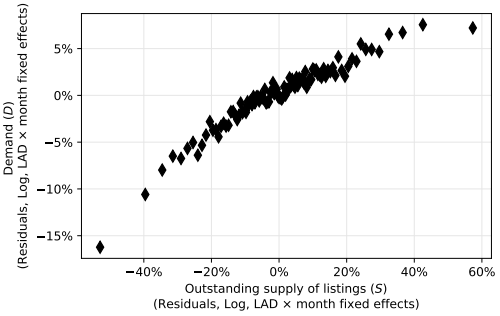
where Y_{it} measures the outstanding supply of listings and the number of users searching, the market tightness, listing premia and capitalization rates, for the sales and rental market, respectively. Panel A shows correlations within each market, and Panel B correlations between quantities in the sales and the rental market.

Panel A
Within markets

a) Properties for sale

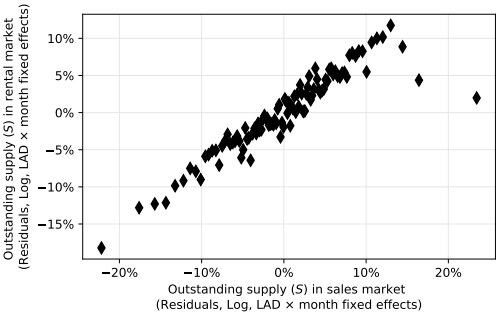


b) Properties for rent

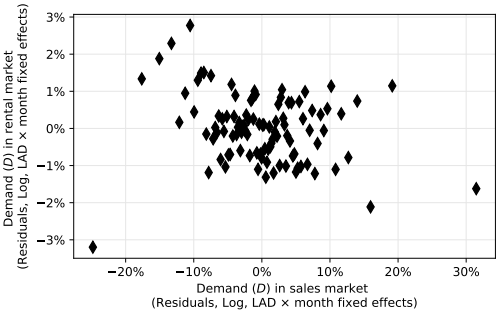


Panel B
Across markets

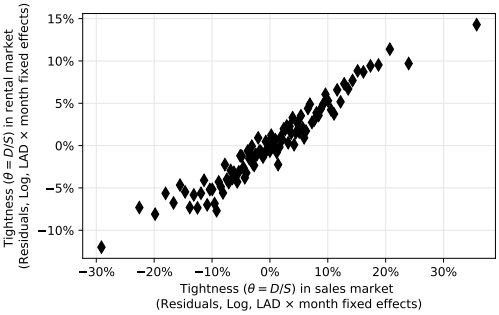
a) Supply (S)



b) Demand (D)



c) Market tightness



d) Listing prices

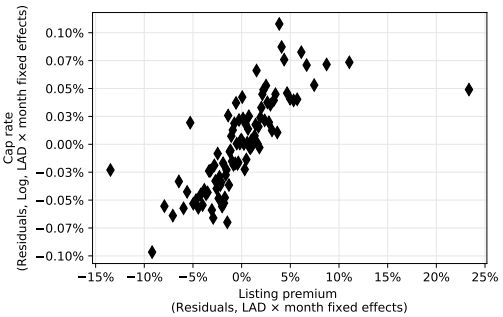


Table A.3
Contribution of different stages of the search process to realized transactions: Specifications with fixed effects

Panel A
Properties for sale (Fixed effects)

	Dependent variable: Probability of sale (V/S)						
	Within-market specification						Cross-market specification
Market tightness ($\theta = D/S$)	0.297***	0.182***	0.181***	0.182***	0.182***	0.167***	0.148***
	(0.028)	(0.032)	(0.032)	(0.032)	(0.031)	(0.032)	(0.032)
Search intensity (I/D)		-0.423***	-0.414***	-0.414***	-0.379***	-0.400***	-0.399***
		(0.047)	(0.048)	(0.048)	(0.048)	(0.05)	(0.049)
Meeting intensity (M/I)			0.018	0.018	0.002	0.001	-0.002
			(0.013)	(0.013)	(0.012)	(0.012)	(0.012)
Listing premium				-0.001	-0.001	-0.001	-0.001
				(0.002)	(0.002)	(0.002)	(0.002)
Number of revisions per listing					-0.078***	-0.084***	-0.078***
					(0.011)	(0.012)	(0.012)
Net supply inflow (S_{new}/S)						0.044**	0.046**
						(0.022)	(0.022)
Rental market tightness $\theta_L = D_L/S_L$							0.043***
							(0.013)
Capitalization rate in rental market							0.003
							(0.006)
Location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	14,506	14,506	14,506	14,506	14,506	14,506	14,506
R^2	0.757	0.761	0.761	0.761	0.763	0.763	0.763

Panel B
Properties for rent (Fixed effects)

	Dependent variable: Probability of sale (V/S)						
	Within-market specification						Cross-market specification
Market tightness ($\theta = D/S$)	0.410***	0.385***	0.391***	0.390***	0.387***	0.398***	0.402***
	(0.026)	(0.031)	(0.032)	(0.032)	(0.032)	(0.034)	(0.034)
Search intensity (I/D)		-0.130***	-0.133***	-0.145***	-0.127**	-0.124**	-0.134**
		(0.051)	(0.051)	(0.052)	(0.053)	(0.053)	(0.053)
Meeting intensity (M/I)			-0.035*	-0.034*	-0.045**	-0.044**	-0.041**
			(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Capitalization rate				-0.017*	-0.020**	-0.019*	-0.018*
				(0.01)	(0.01)	(0.01)	(0.01)
Number of revisions per listing					-0.030***	-0.027***	-0.027***
					(0.009)	(0.009)	(0.009)
Net supply inflow (S_{new}/S)						-0.027	-0.026
						(0.02)	(0.02)
Sales market tightness $\theta_S = D_S/S_S$							-0.031
							(0.035)
Listing premium in sales market							-0.003
							(0.003)
Location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	14,465	14,465	14,465	14,465	14,465	14,465	14,465
R^2	0.739	0.739	0.739	0.739	0.740	0.740	0.740

Figure A.5
Share of Rightmove Listings in Land Registry Transactions

This figure plots the monthly share of Rightmove listings matched to final transactions lodged with the Land Registry.

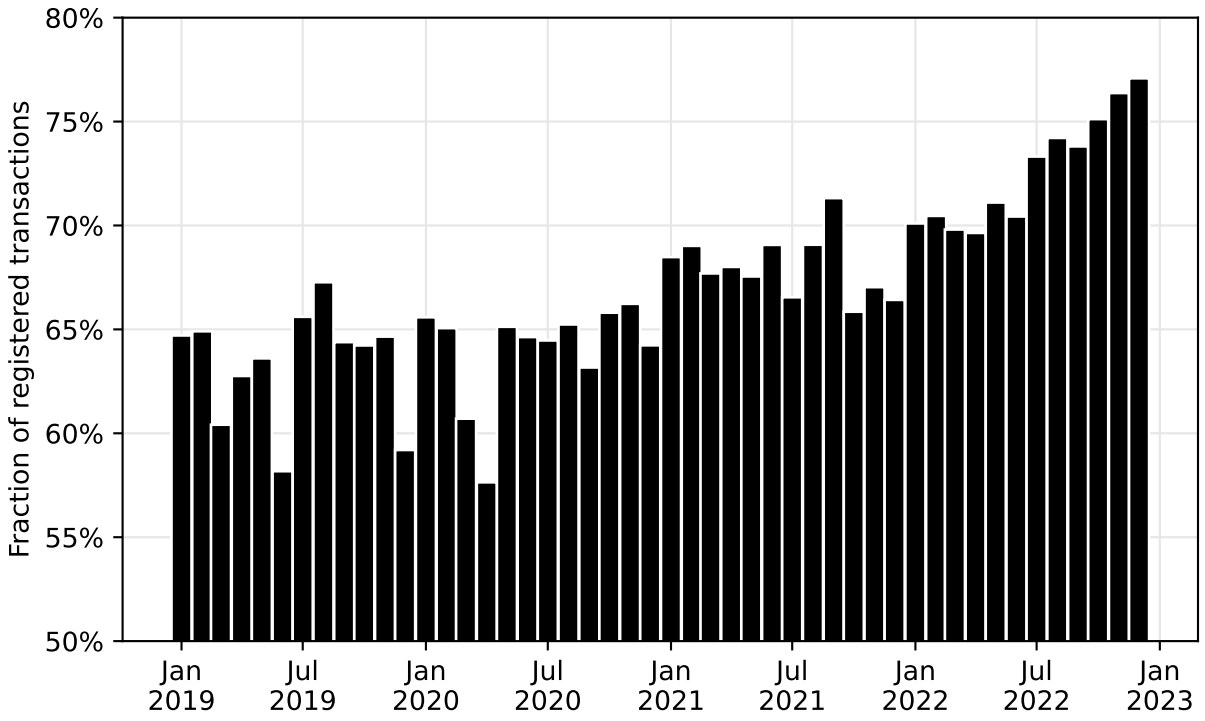
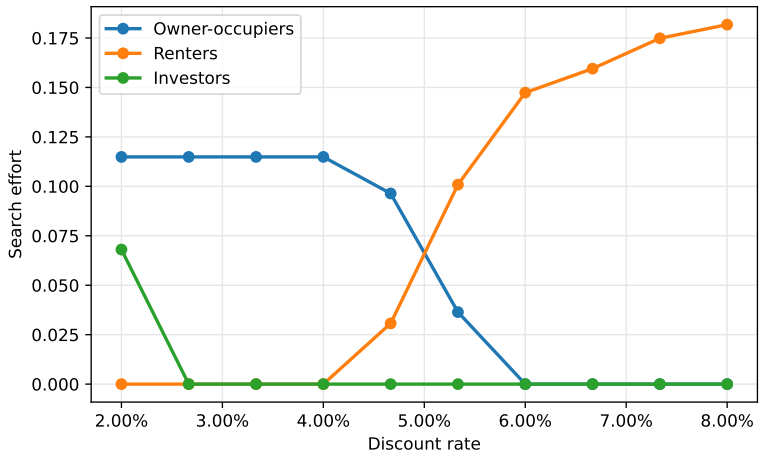


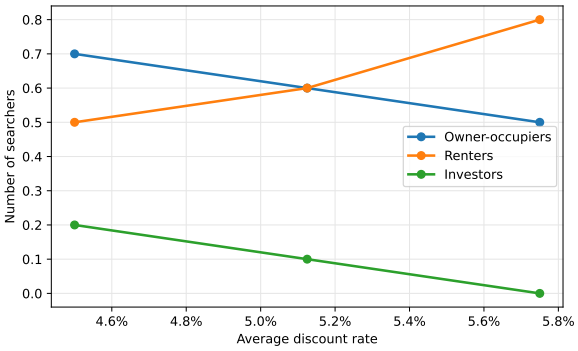
Figure A.6
Two-segment market: Model simulation

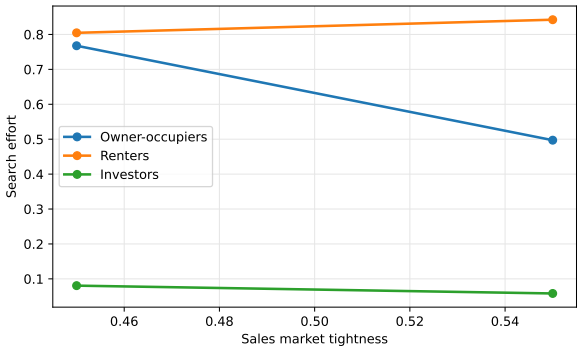
The figures report the response of optimal search in the model, for different values of market tightness and pricing in the sales and rental market, respectively. We use a version of the model that is numerically calibrated with $\overline{W} = 1, \beta = 0.96, c_S = c_L = 0.05, c_N = 0.1, P = 0.5, k = 5\%, r_{\min} = 2\%, r_{\max} = 8\%, \xi_S = \xi_L = \xi_{VL} = 0.5$.

Panel A
Optimal search effort



Panel B
Cross-market effects





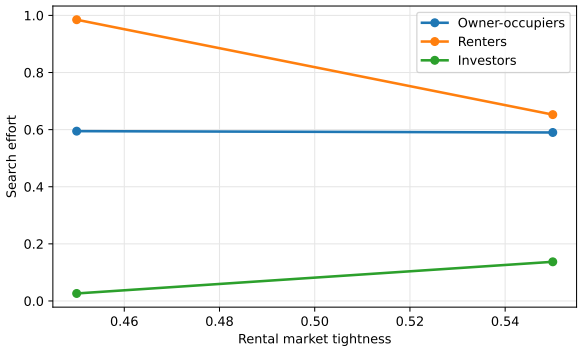
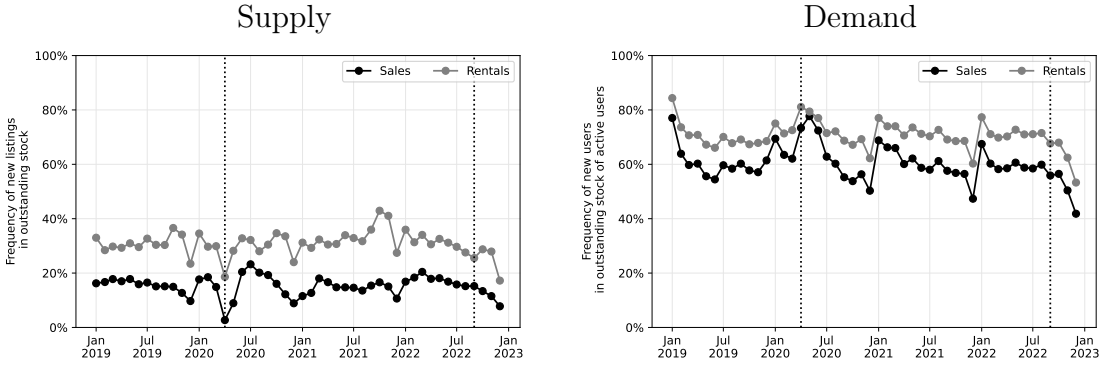


Figure A.7
Stocks and flows

Panel A calculates the share of outstanding supply that is newly listed, and the share of active users that have started searching in each month. Panel B reports the average number of searchers and the average number of meetings, calculated for each month of the listings' time on the market, normalized relative to the value in the first week after listing.

Panel A
Monthly flow into the market



Panel B
Activity by time on the market

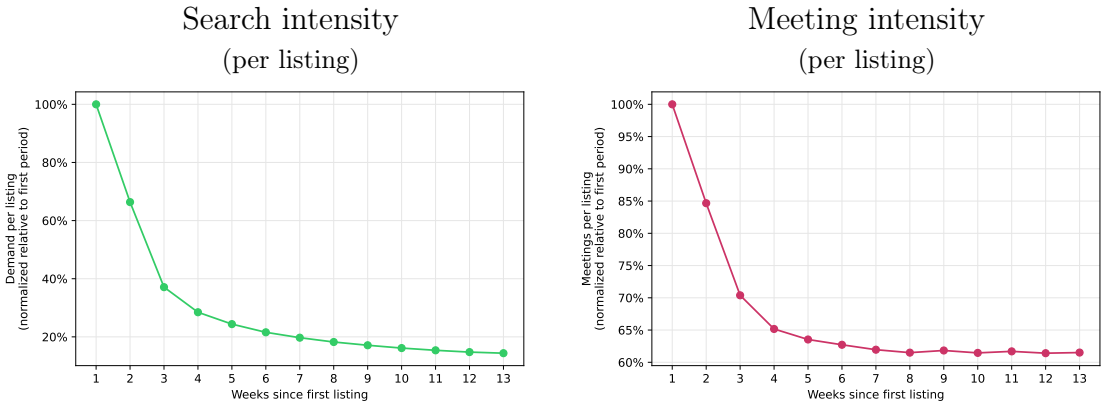


Figure A.8

Transaction outcomes before and after the expiration of the stamp duty policy

Panel A reports the evolution of transaction volumes lodged with HM Land Registry over the period between January 2019 and December 2022. We calculate aggregate numbers for price bands corresponding the stamp duty schedule. Green dotted lines indicate a decrease of stamp duty, red dotted lines indicate an increase. We show relative transaction volumes, computed as ratios between aggregate quantities for each price band.

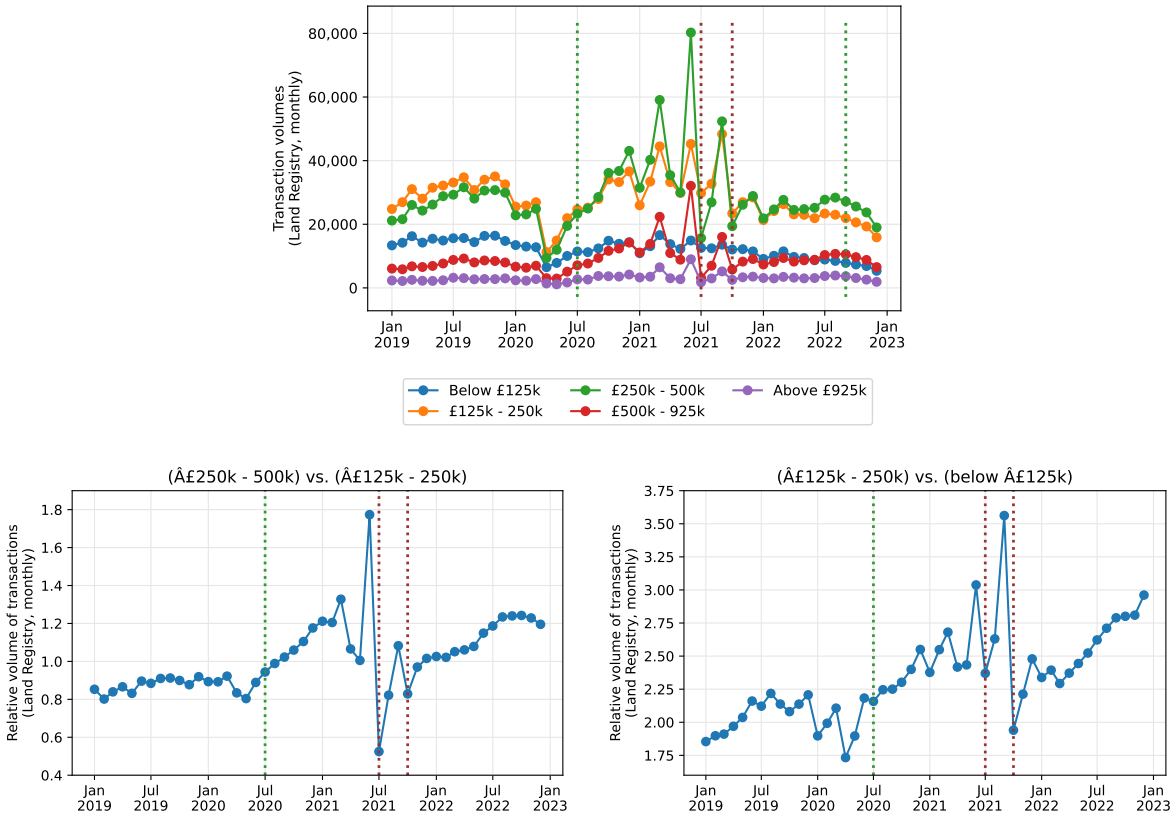


Table A.4
Market responses to the stamp duty policy

The table reports estimated coefficients η from the following empirical specification:

$$Y_{bt} = \zeta_b + \delta_t + \eta 1_{treat_b \times post_t} + \varepsilon_{bt}, \tag{29}$$

where b indicates the price band for the listing price, t is the week, and $1_{treat_b \times post_t}$ is an indicator for whether the particular price band has been addressed by the policy, interacted with a time window of one month after the date at which the policy was implemented. The set of dependent variables Y_{bt} are indicated in column headers. In parentheses, we report standard errors. *, **, *** denote statistical significance for a 10%, 5% and 1% confidence level, respectively.

Panel A
Properties for sale

	Demand	Supply	Volumes	Market tightness	Meetings per listing	Transaction probability	Price revision	Number of price revisions
July 2020 - September 2020	0.076***	0.076***	0.108***	0.000	-0.054***	0.032*	0.002	-0.033*
	(0.015)	(0.013)	(0.021)	(0.006)	(0.015)	(0.017)	(0.007)	(0.018)
No. of obs.	7,557	7,557	7,557	7,557	7,557	7,557	7,524	7,524
R^2	0.987	0.992	0.984	0.976	0.921	0.904	0.065	0.917

Panel B
Properties for rent

	Demand	Supply	Volumes	Market tightness	Meetings per listing	Transaction probability	Price revision	Number of price revisions
July 2020 - September 2020	-0.148***	-0.246***	0.064**	0.098***	0.053**	0.310***	-0.008	-0.390***
	(0.019)	(0.02)	(0.03)	(0.011)	(0.021)	(0.026)	(0.01)	(0.029)
No. of obs.	7,546	7,546	7,546	7,546	7,546	7,546	7,520	7,520
R^2	0.985	0.977	0.967	0.946	0.930	0.838	0.156	0.749