Haggle or Hammer? Dual-Mechanism Housing Search*

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Abstract

This paper concerns how trade mechanism choice affects how decentralized markets respond to shocks and policy choices. We consider this issue in the context of housing market search. We pose a dynamic search model in which agents can trade by auction or negotiation, both featuring two-sided incomplete information. We apply the model to housing data, estimating buyer and seller value distributions using a structural auction model, primitives that are used in solving for the search model equilibrium. Adding auctions as a second mechanism dampens the shock response of prices and values as agents optimally switch between mechanisms. We also find that policies that increase seller information disclosure at one mechanism can nonetheless benefit sellers and harm buyers, at odds with their intended purpose. Our estimates also highlight how mechanism efficiency assumptions influence search cost inference, with estimated seller negotiation search costs significantly lower under Nash bargaining than incomplete information.

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1. Introduction

Beginning with Diamond (1982), Mortensen (1982), and Pissarides (1985), a substantial literature has combined search processes with equilibrium models of trading, quantifying how these features determine outcomes in decentralized markets.[1] The conventional assumption is that a single trade mechanism, typically a Nash bargain, determines when trade occurs and how surplus is divided. Yet multiple trade mechanisms operate simultaneously in many markets, including housing, government procurement, ride-hailing, mineral rights leases, online consumer goods, and financial assets.[2] Agents in such settings must consider the features of each mechanism, such as whether prices are set by auction or negotiation, and the costs of continuing to search if trade does not occur. They must also consider the odds of encountering a trade partner within each mechanism, which is determined by mechanism choices on both sides of the market. Because these choices may vary with market conditions, the assessment of shocks or market design policies must account for buyers and sellers switching mechanisms in response.

This paper studies how the co-existence of mechanisms affects search and trade. We pose a dynamic equilibrium search model in which agents are free to choose between two mechanisms – negotiation and auction – through which they meet and transact, rationally choosing the one with the highest expected payoff. In contrast to the existing equilibrium search literature, we do not assume that agents learn their counterparty's value before trade. Thus, both mechanisms feature two-sided incomplete information. These mechanisms are embedded in a Diamond-Mortensen-Pissarides (DMP) equilibrium search model. The model features buyers and sellers who, in each period, choose either negotiation or auction and search for a trade partner within that mechanism. The incentive to choose a mechanism depends on the ratio of buyers to sellers, the search cost, trade probability, and the surplus conditional on trade from each mechanism. The share of transactions in each mechanism endogenously evolves with these factors over time as underlying economic conditions evolve.

The model highlights the importance of accounting for alternative trade mechanisms

[1] This approach has featured prominently in labor (Mortensen and Pissarides (1994)), housing (Head et al. (2014)), finance (Duffie et al. (2005)), and monetary exchange (Kiyotaki and Wright (1989)).

[2] For examples of these markets see Genesove and Hansen (2023), Bajari et al. (2009), Buchholz et al. (2020), Covert and Sweeney (2023), Einav et al. (2018), and Hendershott and Madhavan (2015).

in assessing price dynamics. In single-mechanism bargaining search models, increases in market tightness affect price by increasing sellers' outside options and reducing buyers'. A second mechanism breaks the identity between market tightness and mechanism tightness (the buyer-to-seller ratio at a mechanism), thus severing the direct link between the market's overall ratio of buyers to sellers and price. That mechanism switching can maintain tightness at each mechanism even as overall market tightness varies can drastically reduce price sensitivity to shocks.

Mechanism switching can also thwart policy aims. Consider a price cap introduced in a market with both auctions and negotiations. If auctions generate higher average prices than negotiations, auction sellers will initially wish to switch to negotiation, and negotiation buyers to auctions.[3] However, buyers benefit from seller numbers, and vice versa, and the mechanism switching that follows from this strategic complementarity could lead to tightness increasing at both mechanisms, possibly benefiting sellers. We show how mechanism tightnesses can either co-move or diverge in response to changes in market conditions.

Our empirical application is to the Greater Sydney metropolitan area residential housing market, with an estimated housing stock value of $4 trillion Australian dollars. Australian residential real estate markets feature trade via both auctions and negotiations (Genesove and Hansen (2023)). The advantage of Australian markets for our application lies in the formal, legal designations of auctions and negotiations and the seller's legal requirement to publicly indicate the sale mechanism before receiving buyers' offers. This setting allows us to investigate a decentralized market with dual trade mechanisms, a feature shared by other such settings, including ride-hailing (Buchholz (2022), Buchholz et al. (2020)), automobile markets (Huang (2020)), and financial markets (Hendershott and Madhavan (2015)). In housing markets, single buyer negotiations and trade with competing buyers co-exist elsewhere (Han and Strange (2014)), and to the extent that sellers indicate to searching buyers whether the property will be offered for sale under an auction-like process, our model is relevant there. Also, this market boasts detailed microdata on auction results, time-on-market, and other transaction details, allowing us to estimate each model component flexibly.

We estimate and solve the model in stages by combining structural econometric mechanism evaluation (Athey and Haile (2002)) with solution and simulation approaches to

[3]In our empirical analysis, we examine a policy with a similar effect but with mechanisms reversed: negotiation buyers are intended to benefit from the policy at the expense of negotiation sellers.

dynamic equilibrium search models (Algan et al. (2014)). We first use a structural auction model to identify and estimate the distributions of buyer and seller values and data on the number of bidders at each auction to estimate the arrival process for buyers to sellers. We then solve the model with a perturbation-based approach. We embed polynomial-based approximations of simulations from the structural mechanism estimates into the dynamic equilibrium search model: expected price conditional on trade, probability of trade, and surplus conditional on trade, for buyers and sellers, are jointly approximated as functions of the parameters characterizing the arrival (meeting) process of buyers to sellers and the distributions of buyer and seller values. These parameters will take on the endogenous values of the mechanism tightness rates and continuation values in the dynamic analysis. Fitting polynomial approximations to simulations lets the data govern functional form choices for distributions governing the transaction process, not analytical tractability. These moments are then linked using a DMP model of housing search, and we solve for the corresponding rational expectations equilibrium. This "bottom-up" approach synthesizes mechanism design theory and structural estimates of individual decisions with a dynamic equilibrium search model, where each part of the model is fit to data from the same population.

Our empirical results provide three main contributions. First, we show that equilibrium mechanism switching effects are quantitatively significant. Mechanism co-existence generates strong dampening effects on price volatility: compared to a negotiation-only model, dual-mechanism reduces volatility by 34%. This volatility reduction is a consequence of agents switching mechanisms in response to shocks; in particular, mechanism switching in response to a shock to overall market tightness reduces the shock's effect substantially. This switching is impossible in a single-mechanism environment, and the market tightness shock has lasting consequences for prices and search values.

Second, information completeness matters for inference on key search parameters. Conditional on a buyer-seller meeting, trade occurs less often under incomplete information, which prevents some positive surplus trades from taking place. This implies more buyer-seller meetings and so a 74% higher estimated tightness under incomplete than complete information negotiation models, given observed seller time-on-market. Embedded in a dual-mechanism search model, the negotiation mechanism's information completeness also has implications for the estimated search costs. Since the trades lost to inefficiency under incomplete information are the lowest positive surplus trades, rationalizing seller participation at both mechanisms requires a 26% higher search cost than Nash bargaining would have implied, again given seller time on the market.

Information completeness also affects inference about volatility. We find that incomplete information dampens price volatility, even without a second mechanism, as incomplete information bargaining exhibits less volatility than Nash bargaining when either is the sole mechanism.

Our third result emphasizes how mechanism co-existence matters for policy. We consider a commonly proposed policy: one side of the market must disclose information that reduces the counterparty's uncertainty about their value. These policies aim to advantage the counterparty. Incorporating incomplete information in our analysis allows one to explore such policies in a dynamic search environment. In housing, disclosure policy aims to benefit buyers by requiring sellers to provide such information, by disclosing information about the property (Myers et al. (2022)) or by constraining the range of values they can communicate to buyers (Gargano and Giacoletti (2020)).[4] By forcing a seller to disclose information, the buyer can extract more of the available information rent. This policy works as intended with a single mechanism: prices fall, and buyer search values improve.

When mechanisms co-exist, the outcome is not so straightforward, as both parties can switch mechanisms. Basic intuition suggests that sellers will leave negotiations, and buyers move there, so that mechanism tightness will increase at negotiations and fall at auctions. However, sellers want to be where buyers are, and vice versa, and this strategic complementarity leads to tightness increasing at both mechanisms - the net effect of which is for buyer search values to fall while seller values increase. Hence, a policy intended to benefit buyers at sellers' expense can have the opposite effect. These results show that conventional wisdom about information disclosure policies depends crucially on whether alternative trade mechanisms exist.

Related literature: Within the broader DMP literature, we primarily relate to studies of how trade mechanism design affects price determination and dynamics. Some models adopt a competitive approach, such as perfect competition or Bertrand competition (Moen

[4]Information disclosure laws have been applied in healthcare, education, and finance markets, and most notably in labor markets, including within-firm worker pay transparency (Cullen and Pakzad-Hurson (2023)) as well as a 2022 New York City law requiring firms searching for prospective employees to provide "good faith" salary ranges. See Loewenstein et al. (2014) for a review of this literature.

(1997), Postel-Vinay and Robin (2002)), and Cahuc et al. (2006), as well as Arefeva (2023), who studies housing auctions). However, by far, the most common assumption is Nash bargaining. Hall and Milgrom (2008) shows that the market volatility produced by DMP models depends on the bargaining mechanism used to set prices within a complete information environment. We build on this result by showing that both mechanism efficiency, captured in our model by two-sided incomplete information, and the presence of alternative trade mechanisms are important for inference about search parameters and price dynamics.

We also relate to empirical studies with multiple trading mechanisms. This literature is generally partial equilibrium in nature, with one side of the market choosing between two simultaneously operating mechanisms (Salz (2022), Einav et al. (2018), Gentry and Stroup (2019)). Larsen (2021) studies the sequential use of auctions and bargaining in a single trade mechanism. Gavazza (2016) considers two Nash bargaining mechanisms with dynamic search but without mechanism choice. Our model considers dynamic responses within an equilibrium two-sided search framework in which mechanisms are tied to each other through search value, and agents switch mechanisms in response to changing market conditions or economic policy. We demonstrate that mechanism switching matters for market responses to shocks and can flip the sign of a policy's effects on buyer and seller values.

In considering how tightness at different mechanisms are set by equilibrium arbitrage conditions, we are building on the competing mechanism literature (Eeckhout and Kircher (2010)). We differ in restricting mechanism choice to the auction and negotiation mechanisms used in the actual market. Thus, we exclude posted-price mechanisms, which, though typically equilibrium outcomes in the theoretical literature, are not used in this market.[5] Assuming that the mechanisms are ex-ante payoff-equivalent is analogous to the mechanism equilibrium existence condition in Eeckhout and Kircher (2010). Our contribution is to develop an empirical approach to estimating model parameters consistent with mechanism co-existence, which then permits us to explore how the market, and specifically mechanism use, responds to shocks and policy changes.

Within studies of single mechanisms, we relate to empirical studies of incomplete infor-

[5]While, theoretically, list prices can direct search (Albrecht et al. (2016)), in our empirical setting they are not always used in negotiations and are rare in auctions. Thus, we follow most of the empirical housing search papers referenced below by not incorporating them into our model.

mation in bargaining environments. A burgeoning literature shows complete information failing to explain much real-world bargaining (Backus et al. (2020), Larsen (2021), Larsen and Freyberger (2021), Byrne et al. (2022)). The impossibility of ex-post efficient trade absent complete information (Myerson and Satterthwaite (1983)) argues for models permitting inefficient trade in these settings. Modeling approaches to incomplete information bargaining have typically adopted take-it-or-leave-it offers, as in Allen et al. (2019) and Silveira (2017). Larsen and Zhang (2021) is exceptionable in adopting a mechanism design approach. We do as well, modeling bargaining outcomes by the second-best mechanism of Myerson and Satterthwaite (1983). This mechanism accounts for each side of the market's incentive to use their private information on their own value to extract rents from the other side and designs the best direct mechanism that has no need to subsidize agents' participation externally. Our contribution here is to include two-sided incomplete information within an equilibrium search model, where the payoffs to agents who fail to transact is the continuation (or 'search') value less search costs.

Finally, we add to work on housing search, such as Albrecht et al. (2007), Carrillo (2012), Guren (2018), Genesove and Han (2012), Guren and McQuade (2020), Head et al. (2014), Anenberg (2016), Wheaton (1990), Piazzesi et al. (2020), Ngai and Tenreyro (2014), Arefeva (2023) and Ngai and Sheedy (2020). These papers, which have addressed varied housing issues such as improvements in search productivity, price momentum, and foreclosure spillovers, primarily adopt Nash bargaining within the DMP framework, whereas we model private information on buyer home match quality and seller search cost and add auctions as a second mechanism.[6]

The paper continues as follows. Section 2 introduces the trading mechanisms (Section 2.1) and the dynamic equilibrium search model (Section 2.2) that embeds them. Section 3 details the institutional features of the Greater Sydney housing market and describes our data, while Section 4 gives estimation and parameterization details for our empirical implementation. Section 5 reports results for the benchmark specification and its dynamic responses, Section 6 the information disclosure counterfactual, and Section 7 concludes.

[6]Unlike these papers, we observe unaccepted offers. We are aware of only two other housing research lines with unaccepted offers: Merlo and Ortalo-Magne (2004) and Merlo et al. (2015), who exploit the UK rule requiring offers be in writing, and Anundsen et al. (2023), who study digital platform auctions in Norway. See also Genesove (1995) for unaccepted offers in non-housing auctions.

2. Theory – A Quantitative Dynamic Model of Search and Price Formation

We now describe a theoretical dual-mechanism search model. Each mechanism is characterized by buyers, who receive value draws for asset ownership, attempting to trade with sellers, who receive cost draws for asset sale. The value of an agent in search is the discounted one-period expected surplus for whatever mechanism the agent chooses plus the value of continued search, less a search cost, where surplus is relative to the continuation search value. In Section 2.1 we lay out the mechanism-specific expected surpluses, eschewing time subscripts for now.

Once we incorporate these mechanisms into our dynamic search model in Section 2.2, buyer values and seller costs will be interpreted as time-dependent transformations of more basic draws. Seller costs will represent the continuation value of search given a current period realization for the seller's search cost. Buyer values will be the value of owning the good net of the value of continuing as a buyer in the next period. Continuation values for all agents vary with aggregate, time-varying states of nature and mechanism-specific shocks.

2.1. Mechanisms of Trade

Trading mechanisms determine the allocation and payments when buyers and sellers interact. We consider three. Complete information bargaining with efficient trade serves as a comparison mechanism. The Myerson-Satterthewaite (MS) mechanism, which implements the second-best allocation under two-sided incomplete information, allows for inefficient trade. A second-price auction mechanism adds seller market power to incomplete information.

We impose several assumptions across all mechanisms we consider. $n \in \mathbb{Z}^+$ buyers attempt to trade with a seller. Buyers draw i.i.d. value v according to distribution F. Sellers receive i.i.d. cost c, with distribution G. We assume that the densities $f \equiv F'$ and $g \equiv G'$ have positive support only over the closed intervals $[\underline{v}, \overline{v}]$, $[\underline{c}, \overline{c}]$, that $\overline{c} > \underline{v}$, and that $v - \frac{1-F(v)}{f(v)}$ and $c + \frac{G(c)}{g(c)}$ are strictly increasing in v and c, respectively.

Negotiation with complete information

In the negotiation models, nature randomly chooses one of the n buyers attempting to meet the seller before values are realized. When information is complete, we assume Nash bargaining with seller surplus share $\phi \in [0, 1]$, so that trade is determined by the *ex-post* efficient allocation rule:

$$\mathcal{Q}^E(v,c) = \begin{cases} 1 & \text{if } v \geq c, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

The expected surplus for buyers, $\mathcal{W}_n^{EB}$, is thus

$$\mathcal{W}_n^{EB} = \underbrace{\frac{1}{n}\text{Pr}(\mathcal{Q}^E(v,c)=1)}_{\text{Pr(buyer selected)} \times \text{Trade prob.}} \times \underbrace{(1-\phi)\mathbb{E}[v-c \mid \mathcal{Q}^E(v,c)=1]}_{\text{Buyer's trade-conditional surplus}} \tag{2}$$

that is, the product of the probability that an individual buyer is selected by nature from the set of n potential buyers to bargain with the seller, the probability of trade, and the buyer's trade-conditional surplus. The expected surplus for sellers, $\mathcal{W}^{ES}$, is expressed similarly as

$$\mathcal{W}^{ES} = \underbrace{\text{Pr}(\mathcal{Q}^E(v,c)=1)}_{\text{Trade prob.}} \times \underbrace{\phi E(v-c \mid \mathcal{Q}^E(v,c)=1]}_{\text{Seller's trade-conditional surplus}} \tag{3}$$

Negotiation with incomplete information

When both buyer and seller have private information and the distributions of their values overlap, no bargaining mechanism exists that implements the first-best outcome of *ex-post* efficient trade, as each side of the market has an incentive to use their private information to extract rents from the other. Specifically, Myerson and Satterthwaite (1983) show that any mechanism with *ex-post* efficient outcomes requires agents to be externally subsidized, implying that the mechanism will operate at a deficit.

Given the infeasibility of the first-best under information frictions, we assume that bargaining outcomes are determined by the second-best mechanism of Myerson and Satterthwaite (1983). This mechanism maximizes *ex-ante* total surplus subject to not running a deficit and satisfying individual rationality (IR) and incentive compatibility (IC) constraints. However, it may result in inefficient *ex-post* allocations. We describe this second-best mechanism below, with additional details of its derivation in Appendix A.

Define the a-weighted virtual type function for each agent type, $a \in [0,1]$:

$$\Phi^a(v) = v - (1-a)\frac{1-F(v)}{f(v)}, \qquad \Gamma^a(c) = c + (1-a)\frac{G(c)}{g(c)}$$

and the a-weighted allocation rule:

$$\mathcal{Q}(v,c;a) = \begin{cases} 1 & \text{if } \Phi^a(v) \geq \Gamma^a(c) \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

$1-a$ captures the degree of distortion from the first best (e.g. Nash bargaining) allocation, corresponding to $a=1$. An a less than one introduces a wedge equal to $1-a$ times the sum of the information rents each side would earn under a monopoly or monopsony of the other side; the surplus must exceed that wedge for trade to occur under such a rule.

The MS mechanism prescribes allocation rule $\mathcal{Q}^N(v,c) \equiv \mathcal{Q}(v,c;a^*)$ where a^* is the highest value of a for which the a-weighted allocation rule does not run a deficit under IR and IC. Indeed, a^* is the inverse of the Lagrange multiplier on the no-deficit constraint in the MS maximizing problem. The chosen buyer pays the seller the buyer's virtual utility, in expectation and conditional on trade. Recalling that nature chooses at random one of the n buyers to meet with the seller before value realization, a buyer's expected surplus is

$$\mathcal{W}_n^{BN} = \underbrace{\frac{1}{n}\Pr(\mathcal{Q}^N(v,c)=1)}_{\text{Pr(buyer selected)} \times \text{Trade prob.}} \times \underbrace{\mathbb{E}[v-\Phi^0(v) \mid \mathcal{Q}^N(v,c)=1]}_{\text{Buyer's trade-conditional surplus}} \tag{5}$$

and the expected seller surplus is

$$\mathcal{W}^{SN} = \underbrace{\Pr(\mathcal{Q}^N(v,c)=1)}_{\text{Trade prob.}} \times \underbrace{\mathbb{E}[\Gamma^0(c)-c \mid \mathcal{Q}^N(v,c)=1]}_{\text{Seller's trade-conditional surplus}}, \tag{6}$$

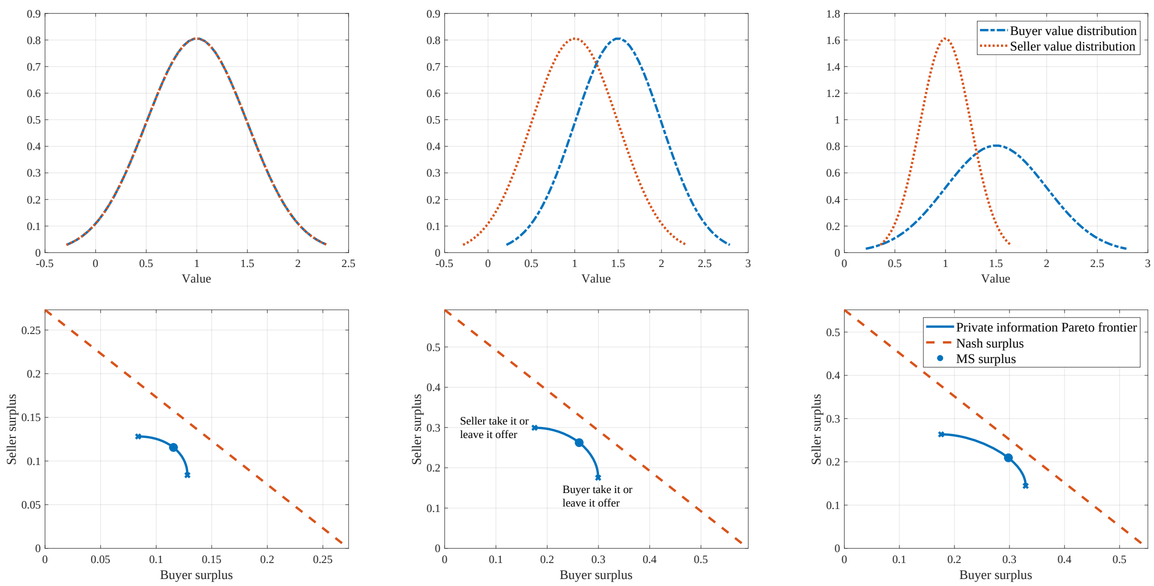
where the expectation in both expressions is taken over buyer and seller types v, c.

Figure 1 compares the MS mechanism to Nash bargaining. In panel (a), buyers and sellers have the same distribution. The Nash surplus, shown as the dashed line in the figure's lower half, can be divided between buyers and sellers by choice of ϕ without changing the total. This surplus level is unobtainable by an IC and IR mechanism not running a budget deficit under two-sided incomplete information (Myerson and Satterthwaite (1983)).

The short curved line is the private information Pareto frontier (Williams (1987)) - the set of outcomes that maximize a weighted sum of buyer and seller expected surplus subject to IC, IR and no budget deficit. This admits a much smaller range of surplus shares than the Nash set, extending from the buyer to seller take-it-or-leave-it offers, i.e., from maximum to zero buyer weight, both of which must leave substantial surplus to the other side. Points above this frontier are inaccessible to any bargaining mechanism when agents have private information; points below it are Pareto-dominated. In contrast to Nash bargaining, which admits a continuum of first-best outcomes by varying bargaining power, the MS mechanism is the unique second-best outcome that maximizes expected total surplus.

Figure 1: Buyer and seller surplus in the MS mechanism

(a) Equal distributions **(b)** Buyer mean shift **(c)** Seller variance decline



Notes: Two-sided incomplete information Pareto frontier and Nash bargaining surplus for (a) equal distributions, (b) mean-shifted buyer value distribution, and (c) lower variance seller distribution.

Panels (b) and (c) show how surplus moves with the distributions. Panel (b) shifts the buyer distribution to the right. This increases surplus, but preserves symmetry for both the Pareto frontier and the MS mechanism surpluses. Panel (c) decreases the seller distribution variance. This tilts the Pareto frontier in favor of buyers, who, facing less uncertainty about sellers than sellers do about buyers, are now informationally advantaged. This last case captures the qualitative features of the distributions that we estimate.

Auction

At auction, n buyers bid in a second-price sealed-bid auction with an optimal reserve price $\mathcal{R} : [\underline{c}, \overline{c}] \to [\underline{v}, \overline{v}]$, set by the seller and given by the solution to $\mathcal{R} = c + \frac{1-F(\mathcal{R})}{f(\mathcal{R})}$.[7]

Buyers' unique dominant strategy is to bid their value. Denote the m-th order statistic of buyer values at the auction by $v^{(m)}$. Trade occurs if the highest buyer value exceeds the seller reserve, or $v^{(n)} \geq \mathcal{R}(c)$. This gives the allocation rule for an n buyers auction:

$$\mathcal{Q}_n^A(v^{(n)}, c) = \begin{cases} 1 & \text{if } v^{(n)} \geq \mathcal{R}(c), \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

Buyer i wins the auction and is allocated the sale if $v_i > \max\{v^{(n-1)}, R(c)\}$. The winning buyer pays the seller $\mathcal{P}^A(\mathbf{v}, c) = \max\{v^{(n-1)}, \mathcal{R}(c)\}$, where $\mathbf{v}$ is the vector of n buyer values. The expected buyer surplus in an auction with n buyers is

$$\mathcal{W}_n^{AB} = \underbrace{\frac{1}{n}\text{Pr}(\mathcal{Q}^A(v^{(n)}, c) = 1)}_{\text{Pr}(V = v^{(n)}) \times \text{ Trade prob.}} \times \underbrace{\mathbb{E}\left[v - \mathcal{P}^A(\mathbf{v}, \mathcal{R}(c)) \mid \mathcal{Q}_n^A(v^{(n)}, c) = 1\right]}_{\text{Buyer's trade-conditional surplus}} \tag{8}$$

Similarly, the expected seller surplus from an auction with n buyers is

$$\mathcal{W}_n^{AS} = \underbrace{\text{Pr}(\mathcal{Q}^A(v^{(n)}, c) = 1)}_{\text{Trade prob.}} \times \underbrace{\mathbb{E}\left[\mathcal{P}^A(\mathbf{v}, \mathcal{R}(c)) - c \mid \mathcal{Q}_n^A(v^{(n)}, c) = 1\right]}_{\text{Seller's trade-conditional surplus}} \tag{9}$$

2.2. Search and Competing Mechanisms with Dynamics

We embed these mechanisms in a DMP model that allows for competing mechanisms. This entails interpreting buyer and seller values as reflecting dynamic opportunities so that $v \equiv \mathcal{V}_t^H(z) - \mathcal{V}_t^B$ and $c \equiv \mathcal{V}_t^{jS}(c^{jS})$, where $\mathcal{V}_t^H(z)$ is the value of a home with match quality z, $\mathcal{V}_t^B$ is the forgone value of continuing as a buyer when purchasing a home, and $\mathcal{V}_t^{jS}(c^{jS})$ is the seller value with realized (mechanism-specific) search cost c^{jS}. Subscript t indexes

[7] We assume that the reserve price is revealed after buyers have arrived, which is consistent with the housing market we study that uses an English auction followed in some cases by a take-it-or-leave-it seller offer to the high bidder. This English auction variant is analogous to the optimal mechanism in Bulow and Klemperer (1996) and is strategically equivalent to the sealed-bid model, given our assumptions.

the realization of a mechanism-specific or aggregate market state at time t.

We assume that time is continuous but partitioned into discrete intervals of unit length, the period over which buyers and sellers commit to a search mechanism. During any interval $[t, t+1)$, the seller first chooses a mechanism j in which to search at t, then draws c^{jS}.[8] The probability that n buyers visit a seller at mechanism j is $\gamma_{t,n}^{j}(\theta_t^j)$ – a function of mechanism tightness. Stacking these probabilities in vector $\boldsymbol{\gamma}_t^j$, the value of a seller who chooses mechanism j at t and then draws search cost c^{jS} is:

$$\mathcal{V}_t^{jS}(c^{jS}) = \beta_t \mathbb{E}_t \left[\boldsymbol{\gamma}_t^j \cdot \mathcal{W}_{t+1}^{jS} + \max_i \left\{ \mathcal{V}_{t+1}^{iS} \right\} \right] - c^{jS} \tag{10}$$

where β_t is the discount factor $\max_i \left\{ \mathcal{V}_{t+1}^{iS} \right\}$ is the maximal value of search at $t+1$, when a seller is free to re-optimize their mechanism choice, and $\mathcal{W}_{t+1}^{jS}$ is the vector of expected surpluses from trade at $t+1$ with n^{th} element, $\mathcal{W}_{t+1,n}^{jS}$, the mechanism-specific surplus when n buyers visit the seller at mechanism j, as defined in Equations (6) and (9). $\mathbb{E}_t[.]$ denotes the rational expectation formed conditional on the information at t, and taken over the distribution of aggregate and idiosyncratic states realized at $t+1$.

At t, a buyer chooses to search homes offered through mechanism j. Let $\lambda_{t,n}^{j}(\theta_t^j)$ denote the probability of visiting a seller with $n-1$ other buyers, with $\boldsymbol{\lambda}_t^j$ the vector that stacks them. We place the usual restrictions on the mechanism-specific arrival probabilities with $\lambda_{t,n}^j : \mathbb{R}^+ \to [0,1]$, $\boldsymbol{\gamma}_{t,n}^j : \mathbb{R}^+ \to [0,1]$ and $\lambda_{t,n}^j(\theta_t^j) = \frac{\gamma_{t,n}^j(\theta_t^j)}{\theta_t^j/n}$ for $n \in \mathbb{Z}^+$ and where $\mathbf{1}_{\mathbb{Z}^+} \cdot \boldsymbol{\lambda}_t^j = 1$, $\mathbf{1}_{\mathbb{Z}^+} \cdot \boldsymbol{\gamma}_t^j = 1$. With n indexing the number of buyer arrivals , $\lambda_{t,n}^j$ and $\gamma_{t,n}^j$ correspond to the n^{th} elements of the vector-valued functions $\boldsymbol{\lambda}_t^j$ and $\boldsymbol{\gamma}_t^j$.

The value from searching as a buyer through mechanism j is:

$$\mathcal{V}_t^{jB} = \beta_t \mathbb{E}_t \left[\boldsymbol{\lambda}_t^j \cdot \mathcal{W}_{t+1}^{jB} + \max_i \left\{ \mathcal{V}_{t+1}^{iB} \right\} \right] - c^{jB} \tag{11}$$

where $\max_i \left\{ \mathcal{V}_{t+1}^{iB} \right\}$ is the maximum value from search when continuing as a buyer into the next interval and choosing a mechanism, $\mathcal{W}_{t+1}^{jB}$ is the vector of expected surpluses, with n^{th} element, $\mathcal{W}_{t+1,n}^{jB}$, the surplus to the buyer given $n-1$ other buyers also visit that seller,

[8] Agents on each side of the market are ex-ante identical before choosing a mechanism, and mechanism choice is driven by aggregate market conditions and not private information or agents' idiosyncratic preferences. We discuss alternative models of mechanism selection in Appendix F.

from Equations (5) and (8), and c^{jB} is the cost of buyer search through mechanism j.

Finally, we consider the value from home-ownership to a successfully matched buyer. With probability φ_t^m, a homeowner receives a shock that dissolves the value of the match with the current home and becomes a seller. Conditional on the shock, with probability $1-p^m$ they also become a buyer in the market; with probability p^m they become a seller only and receive a fixed exogenous payoff from exiting the market. The flow utility from homeownership is a function of idiosyncratic match quality z, drawn at the start of the match and constant for its duration. Thus, the homeowner value is:

$$\begin{aligned}\mathcal{V}_t^H(z) \quad = \quad & \underbrace{r_t^H + z}_{\text{Ownership flow utility}} \quad + \beta_t \mathbb{E}_t \Big[\underbrace{\varphi_t^m (1-p^m) (\mathcal{V}_{t+1}^S + \mathcal{V}_{t+1}^B)}_{\text{Pr(Within-city move)} \times \text{(Buyer + seller value)}} \\ & + \underbrace{\varphi_t^m p^m (\mathcal{V}_{t+1}^S + \Upsilon)}_{\text{Pr(Leave city)} \times \text{Leaving seller value}} + \underbrace{(1-\varphi_t^m) \mathcal{V}_{t+1}^H(z)}_{\text{Pr(Remain matched)} \times \text{Homeowner value}} \Big]\end{aligned} \tag{12}$$

where r_t^H denotes the common component of flow utility. Υ is the exogenous payoff when exiting the market, and $\mathcal{V}_{t+1}^S \equiv \max_i \left\{\mathcal{V}_{t+1}^{iS}\right\}$ and $\mathcal{V}_{t+1}^B \equiv \max_i \left\{\mathcal{V}_{t+1}^{iB}\right\}$ are the maximum values from selling and buying when choosing the mechanism with the highest expected payoff (before drawing search costs).

2.2.1. Closing the Model

We close the model assuming that tightness – the ratio of buyers to sellers – by mechanism adjusts to ensure equal expected payoffs across mechanisms, for both buyers and sellers. Thus, we have equilibrium indifference conditions for each side of the market:

$$\mathbb{E}\left[\mathcal{V}_t^{NB}\right] = \mathbb{E}\left[\mathcal{V}_t^{AB}\right] \tag{13}$$

$$\mathbb{E}\left[\mathcal{V}_t^{NS}\right] = \mathbb{E}\left[\mathcal{V}_t^{AS}\right] \tag{14}$$

that hold for all t, where the expectation is taken over the distribution of the idiosyncratic shocks. We next account for the evolution of measures of homeowners, buyers and sellers (and thus market tightness) over time. The measure of homeowners ($\mathcal{H}_t$) evolves as:

$$\mathcal{H}_{t+1} = (1-\varphi_t^m)\mathcal{H}_t + \sum_{j \in A,N} \left(\boldsymbol{\lambda}_t^j \cdot \mathbf{Q}_{t+1}^j\right) \mathcal{B}_t^j \tag{15}$$

where $\mathbf{Q}^{j}_{t+1}$ is the vector of ex-ante probabilities that the buyer acquires the home when using mechanism j. The measure of total buyers on the market B_t evolves as:

$$\mathcal{B}_{t+1} = \varphi^{m}_{t}\left(1-p^{m}\right)\mathcal{H}_t + I_t + \sum_{j\in A,N}\left(1-\boldsymbol{\lambda}^{j}_{t}\cdot\mathbf{Q}^{j}_{t+1}\right)\mathcal{B}^{j}_{t} \tag{16}$$

$$\mathcal{B}_t \equiv \mathcal{B}^{A}_{t} + \mathcal{B}^{N}_{t} \tag{17}$$

where I_t denotes the inflow of new buyers from outside the market and $\mathcal{B}^{N}_{t}$ and $\mathcal{B}^{A}_{t}$ the measures of buyers using negotiation and auction. With S^{N}_{t} and S^{A}_{t} the measures of sellers using negotiation and auction, the total measure of sellers is:

$$\mathcal{S}_{t+1} = \varphi^{m}_{t}\mathcal{H}_t + \sum_{j\in A,N}\left(1-\boldsymbol{\gamma}^{j}_{t}\cdot\mathbf{Q}^{j}_{t+1}\right)\mathcal{S}^{j}_{t} \tag{18}$$

$$\mathcal{S}_t \equiv \mathcal{S}^{A}_{t} + \mathcal{S}^{N}_{t} \tag{19}$$

This completes the model description.

2.3. Rational Expectations Equilibrium

We focus on a rational expectations equilibrium, defined as sequences of:

i. Probabilities Ψ^{jk}_{t} with which sellers and buyers choose mechanism j at time t such that they are indifferent to trading through either mechanism ((13) and (14));

ii. Allocation rules $\mathbf{Q}^{j}_{t} \equiv \mathbf{Q}^{j}(\mathcal{V}^{H}_{t}(z) - \mathcal{V}^{jB}_{t}, \mathcal{V}^{jS}_{t}(c^{jS}))$, given the distributions F_t of net homeowner values $(\mathcal{V}^{H}_{t}(z) - \mathcal{V}^{jB}_{t})$ and G_t of seller values, that satisfy (4) and (7) given the optimal seller reserve at auction ;

iii. Distributions of values for homeowners, sellers and buyers, $\mathcal{V}^{H}_{t}(z), \mathcal{V}^{jB}_{t}, \mathcal{V}^{jS}_{t}(c^{jS})$, that satisfy (10) to (12) given the vector-valued surplus functions $\mathcal{W}^{jS}_{t}, \mathcal{W}^{jB}_{t}$ and trade probabilities, $\boldsymbol{\gamma}^{j}_{t}, \boldsymbol{\lambda}^{j}_{t}$; and

iv. Homeowner, seller and buyer measures $\mathcal{H}_t, \mathcal{S}^{j}_{t}, \mathcal{B}^{j}_{t}$ satisfying laws of motion (15)-(19);

for each $j \in \{\text{Auction }(A), \text{Negotiation }(N)\}$, $k \in \{\text{Buyer }(B), \text{Seller }(S)\}$, for all z and c^{jS}, and for all t.

2.4. How mechanism tightness varies with relative surplus changes

We now analyze how shocks to mechanism payoffs around the steady state levels generate changes in the tightness at each mechanism. We define $\Delta\mathcal{W}^{k}$ for $k \in \{B, S\}$ as the weighted sum over the number of buyers n of the change in log surplus at negotiation, where the weights are the product of the probability of n buyers and the mechanism surplus share, within market side, less the equivalent expression for auctions.

Definition 1. *Define the changes in relative trade-surplus as*

$$\begin{aligned}\Delta\mathcal{W}^B &:= \sum_n \mathcal{S}_n^{NB} d\ln\mathcal{W}_n^{NB} - \sum_n \mathcal{S}_n^{AB} d\ln\mathcal{W}_n^{AB}\\ \Delta\mathcal{W}^S &:= \sum_n \mathcal{S}_n^{NS} d\ln\mathcal{W}_n^{NS} - \sum_n \mathcal{S}_n^{AS} d\ln\mathcal{W}_n^{AS}\end{aligned}$$

where $\mathcal{S}_n^{jB} \equiv \frac{\lambda_n^j \cdot \mathcal{W}_n^{jB}}{\sum_i \boldsymbol{\lambda}^i \cdot \mathcal{W}^{iB}}$ *is the expected surplus share obtained by buyers with* n *buyers arriving at mechanism* j *and* $\mathcal{S}_n^{jS} \equiv \frac{\gamma_n^j \cdot \mathcal{W}_n^{jS}}{\sum_i \boldsymbol{\gamma}^i \cdot \mathcal{W}^{iS}}$ *is the analogous expression for sellers.*

This definition considers changes in the expected surplus from both exogenous changes and endogenous changes in the value distributions while keeping arrival rates constant. The primary factor influencing agents' mechanism choice is the expected surplus at a given mechanism relative to the other mechanism after accounting for search costs. Weighting by $\mathcal{S}_n^{jk}$ expresses the relative expected surplus changes in terms of the percentage change in mechanism surplus for each side of the market k multiplied by mechanism j's share of the summed surplus across mechanisms. Framing surplus changes this way captures that even substantial percentage increases in mechanism j surpluses may not strongly affect agents' mechanism choice if the surplus at this mechanism is small relative to the alternative. Proposition 2, proved in Appendix A, shows how movements in mechanism tightness relate to these changes in surplus for buyers and sellers.

Proposition 2. *Given Definition 1, for given changes in relative trade-surplus* $\Delta\mathcal{W}^B$ *and* $\Delta\mathcal{W}^S$ *mechanism tightness follows:*

$$\begin{bmatrix} d\ln\theta^A \\ d\ln\theta^N \end{bmatrix} = \mathcal{E}^{-1} E \begin{bmatrix} \Delta\mathcal{W}^B \\ \Delta\mathcal{W}^S \end{bmatrix}$$

where $\mathcal{E} \equiv \begin{bmatrix} \mathcal{E}^{AB} & -\mathcal{E}^{NB} \\ \mathcal{E}^{AS} & -\mathcal{E}^{NS} \end{bmatrix}$, $\mathcal{E}^{jB} \equiv \sum_n \mathcal{S}_n^{jB}\left(\frac{\partial\lambda_n^j}{\partial\theta^j}\frac{\theta^j}{\lambda_n^j}\right)$, $\mathcal{E}^{jS} \equiv \sum_n \mathcal{S}_n^{jS}\left(\frac{\partial\gamma_n^j}{\partial\theta^j}\frac{\theta^j}{\gamma_n^j}\right)$.
If $\operatorname{sgn}(-\mathcal{E}^{NS}\Delta W^B + \mathcal{E}^{NB}\Delta W^S) = \operatorname{sgn}(-\mathcal{E}^{AS}\Delta W^B + \mathcal{E}^{AB}\Delta W^S)$ *then mechanism tightnesses co-move in response to mechanism changes* $\Delta W^B, \Delta W^S$*, and diverge otherwise.*

That is, changes in mechanism tightness are related to changes in mechanism-specific surplus differences through the weighted elasticities of arrival rates with respect to mechanism tightness. Weighting is by the within-market side-k mechanism surplus share $\mathcal{S}_n^{jk}$.

The following corollaries restrict the analysis to cases when $\mathcal{E}^{jB} < 0$ and $\mathcal{E}^{jS} > 0$. These correspond to settings in which higher tightness decreases meeting probability for buyers and increases it for sellers. The condition holds for negotiation, where the seller and randomly chosen buyer surpluses are independent of buyer numbers, and it is reasonable (and holds in our application) for auctions under the mixed Poisson.

Corollary 3. *Suppose that* $\mathcal{E}^{jB} < 0$ *and* $\mathcal{E}^{jS} > 0$ *for all* $j \in \{A, N\}$ *and* $\mathrm{sgn}(\Delta\mathcal{W}^B) = \mathrm{sgn}(\Delta\mathcal{W}^S)$. *Then mechanism tightnesses co-move.*

Intuitively, if negotiations become more attractive to both sides, tightnesses must co-move; otherwise, one side will still prefer negotiations after the tightness adjustments.

The other corollary considers a sub-case of the opposite situation.

Corollary 4. *Suppose that* $\mathcal{E}^{jB} < 0$ *and* $\mathcal{E}^{jS} > 0$ *for all* $j \in \{A, N\}$, $\Delta\mathcal{W}^B$ *and* $\Delta\mathcal{W}^S$ *are of opposite signs, and* $|\Delta\mathcal{W}^B + \Delta\mathcal{W}^S|$ *is sufficiently small. Then if the absolute arrival elasticities* $\mathcal{E}^{jk}$ *for both mechanisms of one side of the market exceed those of the other side, then mechanism tightnesses co-move. Otherwise, the mechanism tightnesses move in opposite directions.*

This analysis highlights that even when a change to mechanism payoffs benefits one side of the market at the other's expense, the resulting change in mechanism tightnesses (and therefore prices) is ambiguous and depends on the meeting probability elasticities. Hence, determining whether policies that shift surplus in this manner will have their intended effect requires empirical evaluation. We analyze such a policy in Section 6.

3. Institutional Background and Data

We apply the model to New South Wales (NSW) housing market data, which accounts for one-third of Australian real estate transactions. Recent estimates place the value of turnover in NSW residential real estate at about \$240 billion Australian dollars per year.[9] Housing is the single largest asset owned by Australians, making up just over one-half (54%) of all household assets. Beyond its national macroeconomic significance, this market

[9] See Australian Bureau of Statistics release "Total Value of Dwellings: Mar 2022".

is ideal for studying price formation and search through alternative mechanisms, given the substantial use of formal auctions alongside the usual negotiations seen elsewhere.

Negotiations work as in many other property markets and take place between a single buyer and seller. Negotiation can commence any time after listing. It typically begins after a visit to the home, with the buyer invited to make an offer and negotiations ensuing.

Residential property auctions are regulated under NSW law, requiring sellers to use an open-outcry, ascending price auction. The seller retains the services of a third-party auctioneer, which is a separate service from a listing agent that nearly all sellers retain. Bidders are required to register before the auction. During the auction, the auctioneer solicits increasing bids until no bidder is willing to make a higher bid.

During the auction, the seller has the opportunity to make a single bid. Called a vendor bid, this must be announced as such by the auctioneer so that all bidders are aware that it is placed on the seller's behalf. It cannot be reduced or altered once placed. No other bidding on behalf of the seller, including shill bidding, is allowed. If all bids placed by bidders are lower than the vendor bid, no sale occurs.

At the conclusion of bidding, the seller decides whether to sell to the highest bidder. The seller is essentially committed to selling if the winning bid exceeds a minimum price (which we term the commitment price) agreed to with the auctioneer but not announced to the bidders before the auction. If the seller decides to sell to the highest bidder, that bidder wins the auction and pays the winning bid. A home that does not sell may then be listed for sale again through negotiation or auction.

This institutional setting is ideal for studying the dynamic equilibrium effects of incomplete information and multiple mechanisms. Negotiation and auction mechanisms operate simultaneously in the market, with each seller selecting a sales mechanism. There is also a strong basis for two-sided incomplete information. Buyers are privately informed about their idiosyncratic housing tastes. Sellers are privately informed about their carrying costs, which will vary over time according to whether they have purchased another home, or across other sellers not simultaneously buying; varying time obligations may also play a part. The very use of ascending, open outcry auctions indicates incomplete information, as English auctions are specifically designed to elicit bidders' private values via drop-out prices. Each sales mechanism has separate procedures, suggesting mechanism-specific search costs. For example, sellers at auction must typically pay an additional fee for the auctioneer's services. Finally, the market is inherently dynamic, with prices and sales rates responding to economic changes over time.

Several features of the auctions are useful in estimation: i) before the auction, sellers must *privately* commit to a price at which they are willing to sell; ii) buyers' offers are publicly disclosed to the seller and other buyers; iii) the winning bid and the number of bidders are recorded; and iv) the requirement to publicize information on failed auctions implies that we observe data on both successful and unsuccessful auctions. These features, along with standard structural auctions methods, allow us to identify and directly estimate the distributions of both buyer and seller values for homes and arrival rates by mechanism.

3.1. Data

We use unique data sets on housing transactions covering auctions and negotiation. The auction data come from a specialist auctioneer agency in NSW,[10] and contain records for approximately 47,000 scheduled auctions for Sydney and the broader NSW region between January 2009 and October 2019. These data are highly representative of the wider Sydney and NSW housing markets. Summary statistics for the greater Sydney metropolitan area, including average sales rates, price growth, and the distributions of price and location, are very similar to those of a census of all auction sales in that region (Genesove and Hansen (2023)). We focus on a subset of 14,482 completed auctions for the Sydney area, both successful and unsuccessful, with complete information on the seller commitment price, the highest bid placed, the number of bidders, and the auction result.

Panel A of Table 1 reports summary statistics on the auction estimation sample; Appendix B describes its construction. The mean sale price is $1.31 million AUD, while the mean commitment price is $1.32 million. Conditional on at least one bidder participating, the sale rate is 73 percent, and there are an average 4.41 bidders. Including scheduled auctions where no bidder participates lowers that to 3.99 and the sale rate to about 65 percent. The data show how seller use of the vendor bid frequently results in no sale.

We combine the auction data with transaction-level data for the universe of sales in the greater Sydney metro area. Summary statistics for this data appear in Panel B of Table 1. These data are sourced from state administrative data merged to listings information that

[10]The auction data are sourced from Cooley Auctions and the transaction data from APM; copyright and disclaimer notices are in the Online Appendix.

Table 1: Summary statistics

Panel A: Auction summary statistics	Mean	Std	Min	Max
Highest bid (AUD in millions)	1.31	0.70	0.50	4.96
Commitment price (AUD in millions)	1.32	0.72	0.42	4.70
Sale	0.73	0.44	0.00	1.00
Number of bidders	3.99	3.64	0.00	25.00
Panel B: Housing transaction summary statistics	Mean	Std. Dev.	P10	P90
Δlog auction price	0.001	0.026	-0.030	0.033
Δlog negotiation price	0.001	0.012	-0.013	0.016
Auction sales rate	0.593	0.113	0.456	0.740
Auction sales share	0.186	0.083	0.076	0.296
Neg. seller TOM (weeks)	5.827	1.491	3.893	7.696

Notes: *Panel A:* This table displays summary statistics for the auction data. There are 14,482 auctions with at least one bid placed and 18,203 observations in the full sample; see Appendix B for details on sample construction. *Panel B:* Δ *log auction (negotiation) price* denotes the weekly change in the estimated log auction (negotiation) price. *Auction sales rate* is the fraction of auctions resulting in a sale, *Auction sales share* is the share of auction sales in all home sales, and *Neg. seller TOM (weeks)* is the time-on-market for a negotiation seller.

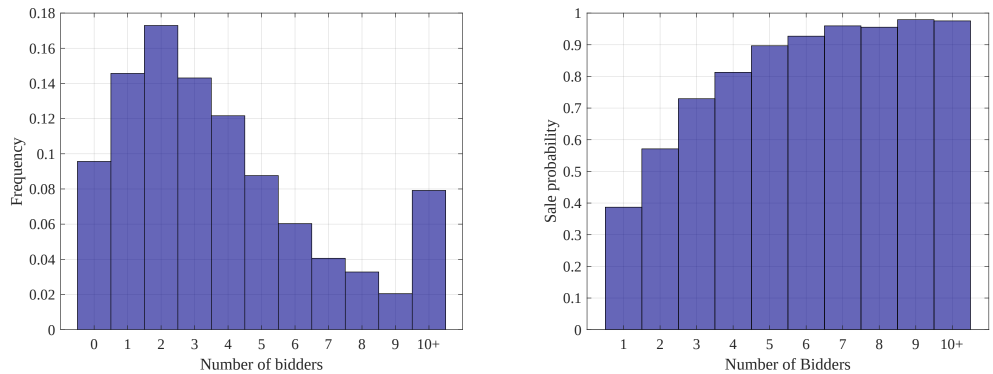
records the sale mechanism, the listing date, and the sale date. From this data, we compute a weekly distribution of time-on-market for negotiated sales.

Figure 2 shows the empirical bidder density and the sales rate by bidder numbers. The mean number of bidders is just under four, but there is significant mass in the right tail, with 8% of auctions having 10 or more bidders. Low levels of competition are also common, with slightly under 10% of auctions drawing no bidders and over 14% only one. As expected, the sales rate increases with bidder numbers. Less than 40% of single bid auctions end in a sale, while auctions with seven or more bidders have a sales rate exceeding 95%.

4. Parameterizing and Solving the Model

The challenge to parameterizing and solving the model lies in utilizing the information contained in the microdata on the distributions of buyer and seller values and arrival rates while ensuring the analytic tractability required to solve the dynamic equilibrium search model. Previous work has often adopted simplifying assumptions, such as uniform or exponential value distributions, that admit closed-form representations for endogenous variables like prices. Such an approach in our context would constrain our ability to match

Figure 2: Bidder frequency and sale probability by number of bidders



Notes: (a) Empirical bidder density and (b) sales rate by number of bidders (N) from Sydney auction data.

the distribution of outcomes observed in the data. Instead, we flexibly estimate value and buyer arrival rate distributions and use a simulation-based approach to generate tractable functional representations for endogenous variables.

We proceed with a 'ground-up' approach that estimates the model in stages. *Step 1* uses standard structural auction identification methods (Athey and Haile (2002)) to directly estimate the buyer and seller value distributions, yielding steady state search values and measures of match quality and seller search cost dispersion. Direct estimation is novel for dynamic two-sided search equilibrium models, as data on failed trades is rarely available. We also estimate the buyer arrival rate function and steady state tightness at auction. Combining seller time on the market for negotiation then yields steady state negotiation tightness. Finally, moving rate estimates and setting a discount rate and a flow utility allow us to decompose mean buyer value $\overline{\mathcal{V}}^H(0) - \overline{\mathcal{V}}^B$ into mean homeowner value $\overline{\mathcal{V}}^H(0)$ and buyer search value $\overline{\mathcal{V}}^B$, all at steady state. Solving the four Bellman equations with these estimates yields the buyer and mean seller search cost parameters.

Step 2 uses Section 2.1's models to solve for expected (i) price, (ii) trade probabilities, and (iii) trade-conditional surpluses, by mechanism, over a grid of (a) mechanism tightness rates, (b) mean buyer values, and (c) mean seller values, centered around steady state values. For auctions, we use (pseudo-) Monte Carlo integration. For negotiation, both MS and Nash, we use numerical (Gauss-Hermite) integration. The grid covers empirically plausible ranges of the three variables. Appendix E details the implementation.

Step 3 approximates each mechanism's computed outcomes (i)-(iii) by polynomials of the grid values of (a)-(c). A low-order polynomial regression proves highly accurate.

Step 4 combines these polynomials with the indifference conditions governing mechanism tightness, the Bellman search value equations, and the laws of motion for the measures of buyers, sellers and homeowners to perturb the full solution of the dynamic model. The final step (*Step 5*) parameterises the aggregate shock distributions. We use Simulated Method of Moments (SMM), estimating the standard deviation and persistence of aggregate shocks implied by the approximating solution of Step 4. We elaborate on each step below.

Step 1: Estimating Buyer and Seller Distributions and Buyer Arrival Rates by Mechanism

We estimate the distributions of buyer and seller values $v \equiv V^H(z) - \mathcal{V}^B$ and $c \equiv V^S(c^S)$ by applying structural auction methods to our auction data, accounting for the institutions detailed in Section 3. Standard auction approaches (Athey and Haile (2002)) identify the buyer distribution. The seller distribution is identified from vendor bids and sale occurrence. Our estimation allows for unobserved home quality à la Roberts (2013).

The auction model used in estimation closely corresponds to the auction mechanism of Section 2.1. Trade occurs if the highest buyer value exceeds the seller's reserve price, and price is determined by the maximum of the second highest bidder value and the reserve.[11] Our estimation accounts for the institutional details of Section 3, such as the commitment price, and allows for both observable and unobservable heterogeneity. We tried several specifications for buyer and seller values, including Weibull, log-normal, and logistic, with the normal distribution fitting the data best. We describe the likelihood function used in estimation below, for clarity omitting the conditioning on observed characteristics and unobserved home quality; fuller details appear in Appendix D.

Recall that vendor bids are recorded in the data only when bid first or last.[12] We observe four types of auction outcomes associated with the combinations of whether a sale occurred and whether the vendor bid was observed. Where there is no sale, we have separate likelihood terms for whether the vendor bid was observed (case 1) or not (case 2). Where there is a sale, we distinguish between a sale below the commitment price (case 3)

[11] As discussed in Section 2.1, the English auction variant used in practice is observationally equivalent to the sealed bid model, so we can estimate the latter without loss of generality. See Appendix D for details.

[12] Vendor bids are the first recorded bid mostly in single-bidder auctions, consistent with being used as a take-it-or-leave-it offer to the last remaining bidder.

or above the commitment price (case 4). When a sale occurs below the commitment price (case 3), we assume that the highest bid was a take-it-or-leave-it offer made by the seller through a vendor bid that was accepted by the buyer. Let $\bar{b}$ be the highest submitted bid in the auction. The log-likelihoods for an observation from each of the four cases are

$$\begin{aligned}
l_1 &= \log\left(F(\bar{b})^n\right) + \log\left[g\left(\bar{b} - \frac{1-F(\bar{b})}{f(\bar{b})}\right)\right] \\
l_2 &= \log\left(nF(\bar{b})^{n-1}(1-F(\bar{b}))\right) + \log(1-G(\bar{b})) \\
l_3 &= \log\left(n(1-F(\bar{b}))F(\bar{b})^{n-1}\right) + \log\left[g\left(\bar{b} - \frac{1-F(\bar{b})}{f(\bar{b})}\right)\right] \\
l_4 &= \log\left(n(n-1)F(\bar{b})^{n-2}(1-F(\bar{b}))f(\bar{b})\right) + \log(G(\bar{b}))
\end{aligned}$$

The overall log-likelihood sums up the four components: $\mathcal{L} = l_1 + l_2 + l_3 + l_4$.

Buyer arrivals

Data on bidder numbers allow us to estimate the arrival process for auction buyers directly. We assume that arrival depends only on tightness and not on buyer or seller values. A Poisson mixture accurately approximates the probability of observing n buyers:

$$\gamma_n\left(\theta^A\right) = \sum_{i=1}^{I} w_i \frac{(\delta_i \theta^A)^n e^{-\delta_i \theta^A}}{n!} \tag{20}$$

where $\sum_i w_i = \sum_i w_i \delta_i = 1$, $w_i \geq 0$, $\delta_i \geq 0\ \forall i$ and $n \geq 0$. As we assume that the negotiation buyer arrivals shares this same function, differing only in its argument, we omit the mechanism superscript in the definition of γ. This specification generalizes the standard urn-drawing process by adding heterogeneous (e.g., weather) shocks δ_i to the effective buyer-seller ratio in any interval while maintaining the condition that the average number of arrivals equals the buyer-to-seller ratio in the mechanism. Appendix D shows how we estimate $\{w_i, \delta_i\}_i$ using an Expectation-Maximization algorithm with $I = 4$.

To capture the scheduling of the auction at a future date beyond the listing date, we take a stochastic approach and assume that the event that an auction takes place occurs only with some probability ρ^A, with buyers arriving only upon the realization of the event. Requiring an assumption on the time interval on which buyers and sellers are committed to a mechanism, we assume it to be one week.[13]

We assume that the buyer arrival process in negotiation $\boldsymbol{\gamma}(\theta^N)$ has the same mixed Poisson functional form and parameters $\{\hat{w}_i, \hat{\delta}_i\}$ as that for auctions. To estimate negotiation tightness θ^N, we minimize the squared distance between the model-implied per-week (in line with our time interval assumption) sale probability $\gamma(\theta^N) \cdot \mathbf{Q}$ and the per-period sale probability estimated from time-on-market data $\widehat{\boldsymbol{\gamma} \cdot \mathbf{Q}}$. In generating the former, we impose the equilibrium condition that buyer and seller values distributions are the same across mechanisms, i.e., we use $\hat{F}$ and $\hat{G}$ estimated from the auctions. The nonlinear least squares estimator for negotiation tightness is $\hat{\theta}^N = \arg\min_\theta \| \boldsymbol{\gamma}(\theta) \cdot \tilde{\mathbf{Q}} - \widehat{\boldsymbol{\gamma} \cdot \mathbf{Q}} \|$.

Step 2: Computing price, conditional surpluses, and trade probabilities

With estimates for buyer and seller value distributions and mechanism arrival rates, the next step is to compute price, conditional surpluses, and trade probabilities, by simulation for auctions and numerical quadrature for negotiations, over a grid of values for the mean buyer value, mean seller value, and the mean arrival rates of buyers to a seller.

Steps 3 & 4: Function approximation and perturbing the model solution

For each function $\mathcal{F}$ computed in Step 2, and $\mathbf{y}$ the vector of its endogenous variable arguments, the approximating polynomial of $\mathcal{F}$ of order l is $\widehat{\mathcal{F}}_l\left(\boldsymbol{\nu}_l; \mathbf{y}\right) \equiv \sum_{|\alpha_\mathbf{y}|=0}^{l} \mathbf{v}_{\alpha_\mathbf{y}} \mathbf{y}^{\alpha_\mathbf{y}}$, with $\boldsymbol{\nu}_l \in \arg\min_\mathbf{v} \left\| \mathcal{F} - \widehat{\mathcal{F}}_l\left(\mathbf{v}; \mathbf{y}\right) \right\|$, where (i) multi-index $\alpha_\mathbf{y} = (\alpha_1, \ldots, \alpha_Y)$ denotes a Y tuple of non-negative integers with $|\alpha_\mathbf{y}| = \alpha_1 + ... + \alpha_Y$, α_s the s^{th} element of $\alpha_\mathbf{y}$, (ii) multi-index power $\mathbf{y}^{\alpha_\mathbf{y}} \equiv \prod_{s=1}^{Y} y_s^{\alpha_s}$, y_s the s^{th} element of $\mathbf{y}$, (iii) $\mathbf{v}_{\alpha_\mathbf{y}}$ is the parameter coefficient on term $\mathbf{y}^{\alpha_\mathbf{y}}$ of the polynomial approximation, (iv) $\boldsymbol{\nu}_l$ is the stacked vector of coefficients, and (v) the sum $\sum_{|\alpha_\mathbf{y}|=0}^{l}$ is taken across all multi-indices from $|\alpha_\mathbf{y}| = 0$ to $|\alpha_\mathbf{y}| = l$. We restrict the arrival rate approximations to be a function of tightness only and not buyer and seller values. Experiments with different orders of approximation l showed $l = 2$ to be a parsimonious but accurate approximation, as seen below and in Appendix E.

Replacing the true functions with their polynomial approximations, and then integrating over the distributions of home match quality and seller search costs, we can then solve the approximate aggregate representation of the model using standard methods. Using a SMM estimator in the next step, we solve the model using a second-order perturbation of the

[13] Any finer time interval choice is at odds with the weekly cycle on which residential real estate markets operate in Australia, and, from the evidence in Arefeva (2023) and Røed Larsen (2021), elsewhere as well.

model's solution around the steady state with idiosyncratic but not aggregate shocks.

Step 5: Parameterizing the Dynamic Model

Let ζ be the vector of persistence and standard deviation parameters governing the dynamics of aggregate shocks, and X a data matrix. The SMM estimator $\widehat{\zeta}$ minimizes $\|\mathbf{m}(\zeta|X)\|_{\mathbf{\Omega}}$, where $\mathbf{m}(\zeta|X) \equiv \frac{1}{sT-b}\sum_{t=1+b}^{sT} m_t(\zeta) - \frac{1}{T}\sum_{t=1}^{T} m_t(X)$ is the vector difference of the model-implied simulated moments $m_t(\zeta)$ and their sample counterparts $m_t(X)$, $\mathbf{\Omega}$ is a symmetric positive definite weighting matrix, s a multiple of the data length used, T, in the simulations, and b the 'burn-in' number of simulated data points dropped to mitigate the effects of initial conditions when simulations are drawn.

For model-simulated moments, we set $s = 20$ and $b = 1000$, simulating with independent AR1 dynamic shocks perturbed by Gaussian white noise and Gaussian white noise measurement errors in auction and negotiation log-prices. For the weighting matrix $\mathbf{\Omega}$, we use an iterative Newey-West estimator, with a diagonal sample moment weighting matrix in the first step, a diagonal estimate of the model-implied weighting matrix in the second, and an estimate of the optimal model-implied weighting matrix in subsequent steps. Following Ruge-Murcia (2012), we use a Bartlett Kernel with optimal lag selection parameter $[4(T/100)^{2/9}]$. We experimented with different numbers of iterative steps and found 8 sufficient for convergence when assessing model identification.

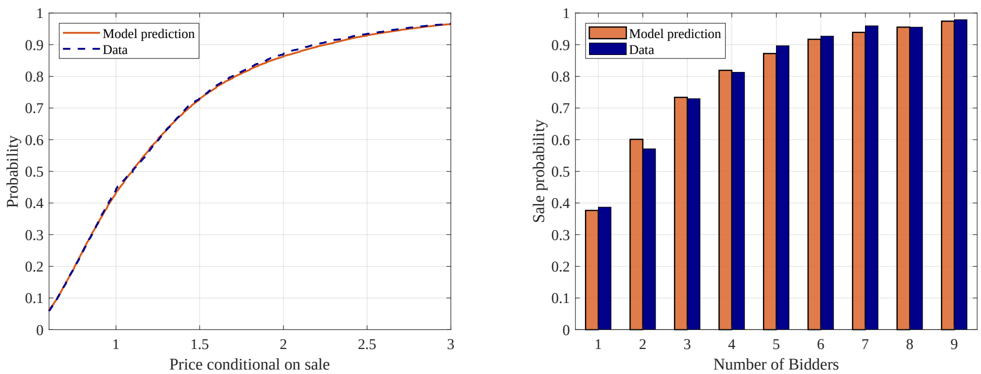
5. Results

5.1. Mechanism Models Results

Figure 3 shows the auction model's fit on two dimensions. Panel (a) shows the distribution of price conditional on sale. The estimated model matches the empirical distribution closely. Panel (b) shows the sales rate as a function of the number of bidders. Again, the model matches the empirical distribution well, even for single-bidder auctions. This suggests that our structural auction model and parametric assumptions on buyer and seller values are a reasonable approximation to the greater Sydney housing auction market. Appendix D shows the underlying estimates. It also shows that other common choices for the distribution of values, or the use of the (single) Poisson distribution, fit the data less well.

Figure 3: Auction model fit – prices and sale probability

(a): CDF of price conditional on sale (b): Sale probability by number of bidders



Notes: Sydney auction data. Model predictions are from the estimated structural auction model.

5.1.1. Comparative Static Simulations

For shocks or policies to generate meaningful mechanism switching, mechanisms must differ in how a given side of the market's expected surplus changes in response. Figure 4 displays simulation results showing how the expected surplus for each mechanism and side of the market varies with net homeownership value and mechanism tightness. Panel (a) shows how buyer and seller expected surplus gains differ across mechanisms as the buyer net ownership value $\mathcal{V}^H(0) - \mathcal{V}^B$ increases from the benchmark estimates, fixing mechanism tightnesses at steady state levels. Expected surplus increases more at negotiation than auction for both sides of the market. However, the figure suggests buyers have a greater incentive to switch mechanisms than sellers in response to an increase in buyer valuations, as the difference between the mechanisms' surplus growth is larger for them than for sellers.

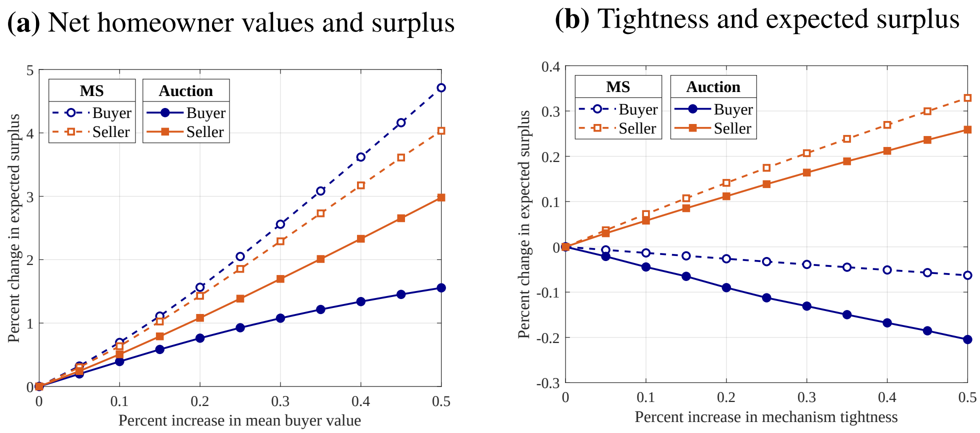
Panel (b) plots the changes in ex-ante expected surplus for buyers and sellers as tightness increases, holding buyer and seller values fixed. Unsurprisingly, expected surplus is increasing in mechanism tightness for sellers and decreasing for buyers. Buyer surplus is less sensitive to tightness at both mechanisms, especially at negotiations.[14]

The effects shown in the two panels, being partial in nature only, do not consider that both values and tightness change together in equilibrium. From Proposition 2, whether tightnesses will move together or not is determined by the relative tightness-conditional

[14]Thus the greater buyer downward shift of the buyer indifference curves in Figure 8 below.

surplus changes and the relative tightness elasticities for each mechanism.[15] Below, we present the full equilibrium response, including for price, values and mechanism share, to dynamic shocks in Section 5.4 and to a policy counterfactual in Section 6.

Figure 4: Mechanism surplus responses to value and tightness changes



Notes: Percent changes in expected surplus by mechanism for changes in mean net homeowner value (Panel (a)) and mechanism tightness (Panel (b)).

5.2. Dynamic Search Model Steady State

Table 2 reports estimated parameters and steady state values for the benchmark MS-Auction model (with those for the Nash-Auction model below). Parameters (denoted P in the table) and steady state values (S) appear in the order of their estimation. Step (i) provides the steady state net ownership value for buyers, the seller search value, and dispersion in match quality and seller search costs. Buyer match quality dispersion exceeding seller search cost dispersion is central to buyer surplus increasing with net ownership value more at negotiation than auction. Step (ii) estimates buyer arrival rate parameters and auction tightness. These values are estimated from the auction data following the model of Section 2.1. Step (iii) combines the buyer arrival rate parameters with the sales data on homes sold by negotiation, and with the MS model of Section 2.1 estimates negotiation tightness.[16]

[15] Buyer and seller surpluses both increasing with net homeowner value more at negotiations implies co-movement from Corollary 3 without reference to the tightness elasticities. This is especially evident in Figure 6, where the flow utility shock has a direct effect on net homeowner value.

[16] Given the estimated mixed Poisson, $\overline{\theta}^N = 0.432$ implies an elasticity of the seller meeting rate with respect to negotiation-tightness of 0.80 not far from the value of 0.83 found in Genesove and Han (2012).

Step (iv) lists parameters estimated from transaction or census data or assigned. Moving rates for intracity moves and intercity moves are chosen to match population census data for NSW. The weekly probability that an auction is held is set to match the time-on-market for auction sales in the transaction data. Weekly buyer search probabilities are set to match the buyer time-on-market reported in Gargano et al. (2023) for the Australian real estate market. We set a weekly discount factor of 0.9988, corresponding to a 6% annual housing interest rate.[17] Flow utility for homeownership, which is not separately identified from buyer search costs, is set to 0.0016. This is consistent with an annual user cost of housing (excluding match-specific benefits) in Australia of about 5%, well within the range of estimates in the literature, plus an imputed rent of owner-occupier premium of 2.2% per annum. Results are robust to alternative calibrations. Finally, the intercity buyer payoff is set to the buyer search value, and the inflow of new entrants is set to match the intercity moving rate, as required by the model's steady state conditions.

Steps (v-vi) report the steady state homeowner value, buyer search value, and the mechanism-specific search costs for buyers and sellers. These are determined from the previous steps and the Bellman equations of 2.2 and are identified up to a choice of discount factor, with the buyer search costs and homeowner and buyer search values additionally dependent on a choice of homeownership flow utility. Appendix C proves this result.

Alongside our main results for the baseline MS-auction model, we also show results for an equal bargaining weight Nash-auction model. These show how assumptions on the trade mechanism(s) affect empirical inference on search. Search frictions are a crucial determinant of the value from trade, net surplus, and deviations from competitive outcomes (Satterthwaite and Shneyerov (2007)). Mismeasuring these frictions may lead to incorrectly assessing market performance; thus accurately characterizing the information environment and mechanism efficiency is vital to empirical studies of frictional search markets.

Replacing the two-sided incomplete information MS mechanism with Nash bargaining has two main implications. First, implied negotiation tightness is much less, by 43%, under Nash bargaining. Lower negotiation tightness follows naturally from greater mechanism efficiency. Since negotiation tightness is estimated to fit time-on-market for negotiated sales and the fully efficient bargaining mechanism results in trade more often than inefficient

[17] This is the average nominal variable rate housing loan for owner occupiers from 2011 to 2019, Table F5, Indicator Lending Rates, Reserve Bank of Australia.

bargaining, conditional on a buyer-seller meeting, fewer meetings are needed to match observed time-on-market, and the implied buyer to seller ratio is correspondingly lower.

Second, implied seller search costs at negotiation are lower when assuming Nash bargaining. This is driven by low-surplus trades that occur under Nash bargaining but not the MS mechanism. Loss of these trades raises trade-conditional surplus for MS compared to Nash. The unchanged auction surpluses combined with the mechanism indifference condition, implies that all seller value terms in equation (10) remain equal to the steady state seller value implied by the auction estimates. Hence, the trade-conditional surplus contained within $\mathcal{W}^{NS}$ falls under Nash, while all value terms and probabilities remain unchanged, requiring seller search costs c^{NS} to decline as well to maintain equality. Our estimates imply 21% lower seller search costs at negotiation under complete information Nash bargaining than under two-sided incomplete information.

5.3. SMM Estimation

We estimate 8 structural parameters governing the dynamics of aggregate shocks: six for the persistence and standard deviation of shocks to flow utility r_t^H, the discount factor β_t, and match dissolution (becoming both a buyer and seller) probability $\alpha_t^b \equiv \varphi_t^m(1-p)$, where we assume all shocks are independent AR1 processes with Gaussian innovations and two for the standard deviations of Gaussian white noise measurement errors in the construction of log hedonic auction (log auction) and the log hedonic negotiation (log negotiation) price. The measurement errors allow for weekly compositional change in sold homes not accounted for by the log hedonic pricing model used to construct price by mechanism.[18]

The SMM estimation uses the 75 variances, covariances, and autocovariances up to a four-week lag of (i) the log auction price less the log negotiation price, (ii) the change in the log negotiation price, (iii) the auction sales rate, (iv) time on market for homes sold by negotiation, and (v) the auction sales share, on a 505 weekly observation sample from 2010W8:2019W44. All five observables are detrended using a constant and linear time trend prior to estimation, except for negotiation price growth which is simply demeaned. The pre-detrended variables are summarized in Table 1 and graphed in Appendix Figure B.1. Table 3 reports the SMM results.

[18]The hedonic specifications used are reported in Appendix B.2.

Table 2: Steady State Parameterization

Step	Name	Symbol	Value	Type	Source
i	Net Ownership Value	$\overline{\mathcal{V}}^H(0) - \overline{\mathcal{V}}^B$	1.1956	S	Auction Data
i	Seller Search Value	$\overline{\mathcal{V}}^S$	1.1019	S	Auction Data
i	Match Quality Dispersion	σ_B	0.1962	P	Auction Data
i	Seller Search Cost Dispersion	σ_S	0.1264	P	Auction Data
ii	Meeting Function Parameters	$(\mathbf{w}; \boldsymbol{\delta})$	Appendix D	P	Auction Data
ii	Auction Tightness	$\overline{\theta}^A$	3.9924	S	Auction Data
iii	Negotiation Tightness	$\overline{\theta}^N$	0.4324	S	i, Transaction Data
iv	Discount Factor	β	0.9988	P	Yearly interest of 6%
iv	Flow Utility	r^H	0.0016	P	7.2% annual R/P
iv	Intracity Mobility Rate	α^b	0.0011	P	Population Census
iv	Intercity Mobility Rate	α^s	0.0003	P	Population Census
iv	Holding Auction Probability	ρ^A	0.1556	P	Transaction Data
iv	Buyer Search Probability	ρ^B	0.1050	P	Gargano et al. (2023)
iv	New Entrants	I	0.0003	P	Steady State Condition
iv	Intercity Buyer Payoff	Υ	0.0729	P	Steady State Condition
v	Homeownership Value	$\overline{\mathcal{V}}^H(0)$	1.2685	S	i-iv, Eqn (12)
v	Buyer Search Value	$\overline{\mathcal{V}}^B$	0.0729	S	i-iv, Eqn (12)
vi	Mean Seller Auc. Search Cost	c^{AS}	0.0188	P	i-iv, Eqn (10)
vi	Mean Seller Neg. Search Cost	c^{NS}	0.0142	P	i-iv, Eqn (10)
vi	Buyer Auc. Search Cost	c^{AB}	0.0015	P	i-v, Eqn (11)
vi	Buyer Neg. Search Cost	c^{NB}	0.0044	P	i-v, Eqn (11)
	Nash-Auction Model Estimates				
iii	Negotiation tightness	θ^N	0.2483	S	i, Transaction Data
v	Mean Seller Auc. Search Cost	c^{AS}	0.0187	P	i-iv, Eqn (10)
v	Mean Seller Neg. Search Cost	c^{NS}	0.0113	P	i-iv, Eqn (10)
vi	Buyer Auc. Search Cost	c^{AB}	0.0014	P	i-v, Eqn (11)
vi	Buyer Neg. Search Cost	c^{NB}	0.0048	P	i-v, Eqn (11)

Notes: All parameters are estimated at a weekly frequency. Type denotes steady state value (S) or parameter (P). Search costs are reported as a percentage of the overall mean price. The intracity (intercity) moving rate is defined as $\alpha^b \equiv \varphi^m(1-p^m)$ ($\alpha^s \equiv \varphi^m p^m$). Identification of buyer search costs relies on all parameters in step (iv), while that of seller search costs does not rely on the choice of r^H. See Appendix C for details on identification.

5.4. Results from Dynamic Simulations

We use the dynamic model to examine the role of dual mechanisms in market responses to shocks. Comparing responses under the benchmark model and a negotiation-only model solved for the same parameters but with auctions removed, shows how a second mechanism

Table 3: Estimated Dynamic Shocks

Parameter	Value	Parameter	Value
Persistence		*Standard Deviation*	
Flow utility shock	0.018	Flow utility shock	0.021
ρ_{r^H}	(3.835e-04)	σ_{r^H}	(6.232e-04)
Intracity moving shock	0.890	Intracity moving shock	2.543e-05
ρ_{α^b}	(0.054)	σ_{α^b}	(8.621e-06)
Discount factor shock	0.998	Discount factor shock	8.620e-06
ρ_β	(0.001)	σ_β	(4.383e-06)
		NP meas. error	0.007
		σ_N	(3.518e-04)
		AP meas. error	0.021
		σ_A	(5.082e-04)
		J-test statistic of over-identifying restrictions:	64.530
		p-value of J-test statistic:	0.563

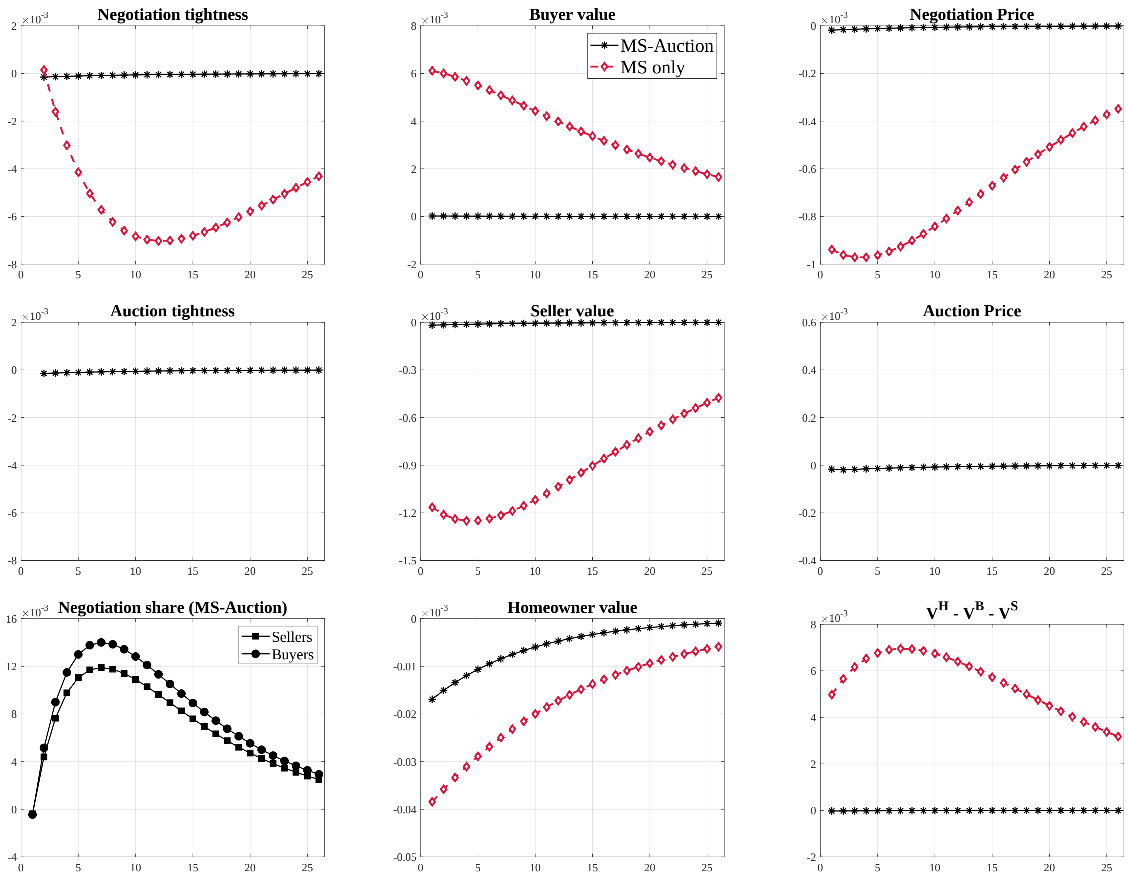
Notes: Estimates from the SMM estimator $\widehat{\zeta} = \arg\min_\zeta \|\mathbf{m}(\zeta|X)\|_\Omega$ assuming Gaussian mean zero shocks and using an iterative Newey-West optimal model-implied weighting matrix with 8 steps. Standard errors are reported in parentheses. The J-test statistic is from a Chi-square test of the overidentifying restrictions.

opens up an additional margin of response to shocks through mechanism switching. We find that the presence of a second mechanism essentially eliminates initial responses in price and value for moving shocks, which directly affects the overall ratio of buyers to sellers in the market, but not for an ownership flow utility shock. Yet the persistence in price and value responses, which operates through a follow-through increase in market tightness, is also dampened with dual-mechanisms, through the same channel.

Figure 5 shows the effects of a shock that increases the within-market moving rate α^b, plotting the percentage deviation from steady-state against weeks since the shock's onset. The shock increases buyer and seller measures equally, thus decreasing overall market tightness, as it exceeds one. In the negotiation-only model (indicated by red), this lower tightness improves buyers' search value and worsens sellers', a deterioration in seller's relative bargaining position that lowers price, as is standard.

In contrast, with dual mechanisms (in black), the fall in market tightness is accommodated by buyers and sellers switching from auctions to negotiations, with mechanism tightness rates nearly unchanged. As a result, prices in both mechanisms are nearly completely unaffected. Only the extensive persistence in the shock, whose higher future values

Figure 5: Moving shock IRFs

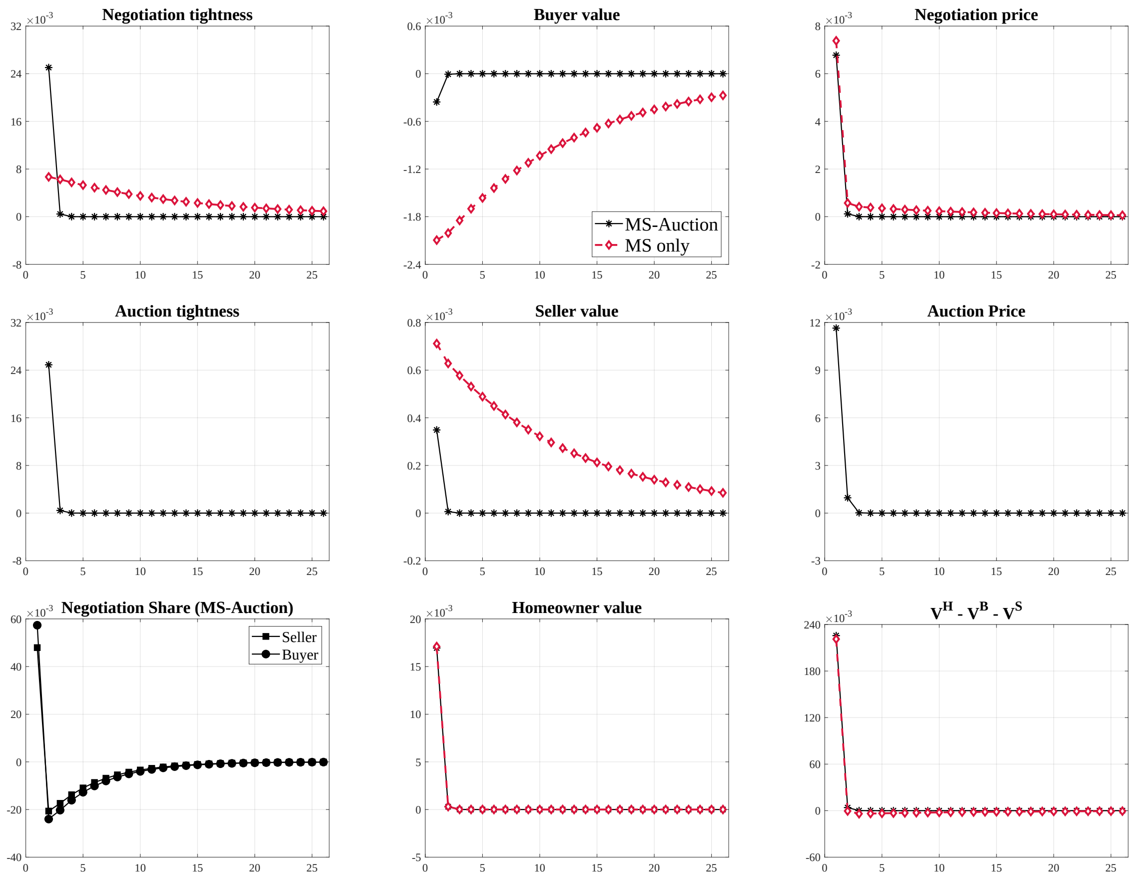


Notes: Impulse response functions for a shock to intra-city moving rate. Values on the y-axis are percent deviations from steady state (except for negotiation share, which shows percentage point deviations).

portend a shorter stay in homeowner status and so reduce its value, prevents the price effect from being fully eliminated by mechanism switching.

The initial responses to an ownership flow utility r^H shock are, by contrast, common to both models (Figure 6). This shock increases homeowner value but has limited effects on buyer and seller search values, given the shock's small persistence and the forward-looking nature of search values. With the increased value to homeowner dominating the change to search values (by two orders of magnitude), negotiated price increases in both models, and to a similar degree; unsurprisingly, the auction price, which is relatively more sensitive to buyer values, increases more. Under dual mechanisms, the increase in net value leads to increases in both *mechanism* tightness rates (see Section 2.4), while sellers switch to the

Figure 6: Flow utility shock IRFs



Notes: Impulse response functions for a shock to intra-city moving rate. Values on the y-axis are percent deviations from steady state (except for negotiation share, which shows percentage point deviations).

less tight mechanism to ensure a constant *market* tightness, which only responds, through the laws of motion, in the subsequent period.

Yet the subsequent dynamics do vary between the models. The higher transactions engendered by the increased ownership flow utility during the shock deplete buyer and seller stocks equally, implying higher than steady state market tightness, given that this exceeds one. With dual mechanisms, the quick dissipation of the r^H shock quickly returns homeownership and search values nearly to steady state, and, with them, *mechanism* tightness rates, but *market* tightness above steady state means that use of the high tightness mechanism - auctions - must exceed its steady state share.[19] Thus, the seller negotiation share is high in the first period to accommodate higher mechanism tightness rates and an unchanged market tightness, then low to accommodate near-steady state mechanism tightness rates but unusually high market tightness before converging back to steady state along with market tightness.

With negotiations only, mechanism tightness is market tightness, and so can only get back to steady state with the gradual inflow and outflow of market participants, depressing buyers' search values and elevating sellers'. This explains why the search values respond more with negotiations only than with dual mechanisms, and converge more slowly back to steady state, and thus also the persistence in price under the negotiation-only model.

We have repeated the analysis with auctions as the sole mechanism instead (see Appendix E.6). The results are very similar to the negotiation-only model, especially compared to the dual-mechanism model. We have also found that models where one side of the market's mechanism choice probabilities are kept constant at steady state values, with the indifference condition holding only for the other side, act similarly to single-mechanism models. It is thus the addition of a second mechanism, not which mechanism is added, and the ability of both sides to switch mechanisms, that matters for our results.

How do incomplete information and auctions affect overall volatility? Table 5 shows simulated standard deviations of key model variables, assuming trade using (i) only full-information bargaining, (ii) only incomplete-information bargaining (the MS mechanism), and (iii) either MS bargaining or an auction (the benchmark model). For nearly all variables, the standard deviations from the steady state in levels are lower under incomplete- than full-information bargaining. Introducing the auction as a second trading mechanism then further *dampens* volatility in response to shocks.

6. Information disclosure

We use the model to investigate and quantify the effects of information disclosure on prices and other search outcomes. Information disclosure policies typically require one side of the market to partially divulge private information. For example, wage disclosure laws may require employers to post a good faith range of wages an employee could expect to receive, and some housing markets require sellers to reveal an expected price range. The

[19] Were steady state market tightness less than one, negotiations would be used more intensely instead.

Table 4: Volatility with Incomplete Information and Auctions

Endogenous variable	Weekly standard deviation in levels: Incomplete information & auctions	Incomplete information	Full-information bargaining
Net surplus from buying	0.060	0.086	0.103
Buyer search value	0.005	0.008	0.004
Seller search value	0.055	0.084	0.102
Ownership values	0.065	0.094	0.099
Negotiation price	0.056	0.084	0.102
Average price	0.056	0.084	0.102
Negotiation tightness	0.011	0.016	0.015
Seller trade probability	0.009	0.009	0.010
Buyer trade probability	0.021	0.021	0.025
Auction price	0.058	-	-
Auction tightness	0.100	-	-

Notes: Volatilities are simulated with Incomplete information and auctions (see Table 3); Incomplete information (excluding the auction mechanism); and Full-information bargaining (Nash bargaining) only.

stated purpose of these policies is often to help the other side of the market: job searchers in the case of wage disclosure and buyers for housing price range requirements.

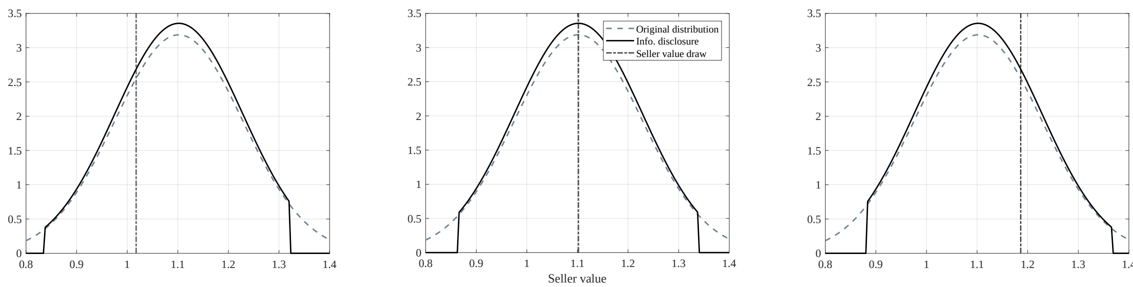
Sellers providing a more precise signal of their value will benefit negotiating buyers in a single-mechanism environment. However, its effect on buyer and seller values in a dual-mechanism search environment is theoretically ambiguous. Information disclosure in one mechanism, say negotiation, may induce buyers to switch from auctions, raising tightness at negotiation. If the increased tightness compensates for the loss in trade-conditional seller surplus, auction sellers may also find switching to negotiation worthwhile. These switches may increase or decrease tightness at either mechanism.

To study such policies, we assume that negotiating sellers must reveal additional information about their private value; we leave auctions unchanged. Specifically, under a $\Delta\%$ information disclosure policy, the seller distribution used in the MS mechanism is a truncation of the original between quantiles $q\Delta$ and $1-(1-q)\Delta$, where q is the (original) CDF of the seller's draw. Figure 7 shows some examples.

This representation aims to capture the essence of policies requiring a wage or price range announcement while abstracting from the mechanism design of information disclosure rules, which lies outside this paper's scope. Importantly, our model's buyers need not be aware of the specific seller value distribution used by the MS mechanism, provided they

Figure 7: Implementation of 5% Information Disclosure on Seller Value Distribution

(a) 25th percentile seller value **(b)** Median seller value **(c)** 75th percentile seller value



Notes: Example implementations of seller information disclosure.

Table 5: Information disclosure before and after mechanism switching

		5% Information Disclosure	
	Benchmark Steady State	Fixed Mech. Tightness	After Switching
Neg. tightness	0.43	0.43	0.46
Auc. tightness	3.99	3.99	4.08
Neg. buyer value	0.07	0.26	0.04
Auc. buyer value	0.07	0.07	0.04
Neg. seller value	1.10	0.87	1.14
Auc. seller value	1.10	1.06	1.14
Homeowner value	1.27	1.23	1.28

Notes: Results of a 5% information disclosure policy for negotiations only. The first column reports the benchmark steady state using the MS-Auction parameterization of Table 2. The second imposes information disclosure at negotiation but fixes tightness at each mechanism to baseline steady state levels; this shows the effects of information disclosure absent mechanism switching. The last shows the steady state equilibrium with information disclosure, allowing mechanism tightnesses to adjust to equilibrate search values across mechanisms.

know that the mechanism satisfies individual rationality and incentive compatibility. Our framework assumes that sellers communicate their value draw to the mechanism, which truncates the seller distribution according to the rule above and combines this with the buyer's reported value draw to determine allocation and payment.

We implement the policy by solving for a new steady state using functional approximations of simulated values for the MS-negotiation surpluses under the information disclosure rule in place of the baseline MS-surpluses, holding the parameters constant. To close the model in the counterfactual, we keep total housing supply $H + S$ fixed.

The results of a 5% information disclosure policy on negotiation sellers are displayed in Table 5. The first column presents benchmark steady state values for the endogenous variables. The second and third columns show how the policy changes these variables before and after equilibrium mechanism switching. The second column fixes tightness in each mechanism at the benchmark steady state levels and does not allow buyers and sellers to change mechanisms.[20] Negotiation buyers benefit from the information disclosure at the initial tightness values, as the additional expected surplus conditional on trade raises their expected value from search. Correspondingly, on the other side of the market, negotiation sellers are worse off under the policy, as they suffer surplus losses conditional on trade.

These effects are reversed after allowing for mechanism switching, as shown in the third column of Table 5. Mechanism switching causes tightness at both mechanisms to increase relative to the benchmark levels, benefiting sellers, and harming buyers.

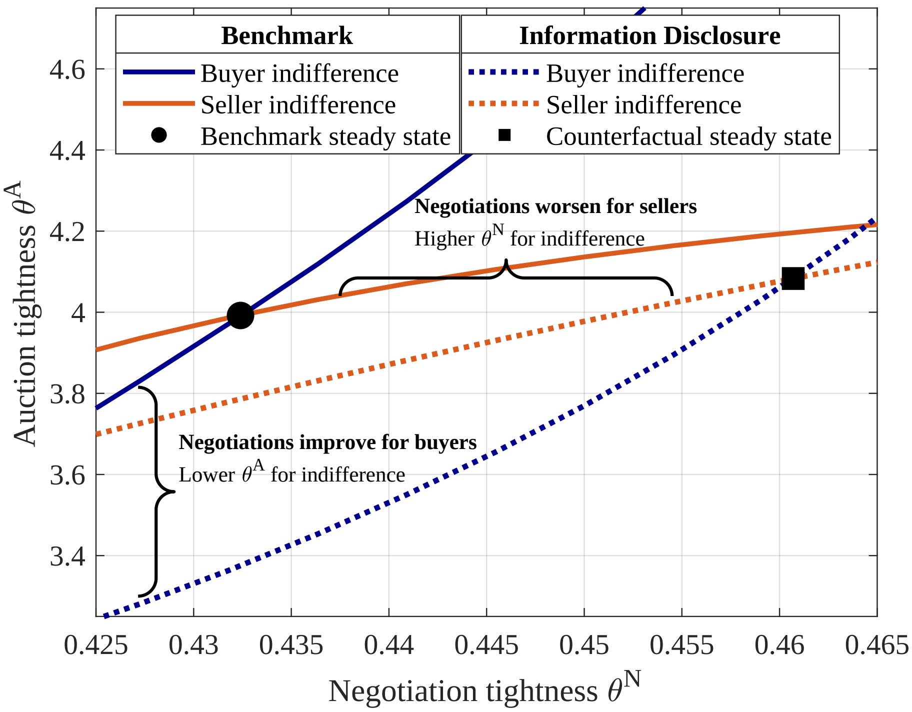
Note that one's basic intuition would be for buyers to leave auctions for the bettered conditions at negotiations and sellers to leave the now worsened conditions for them there for auctions, thus increasing negotiation tightness and decreasing auction tightness. That auction tightness can nonetheless increase follows from the strategic complementarity between buyers' and sellers' mechanism choices: buyers want to be where the sellers are, and sellers where the buyers are.

Some intuition as to why auction tightness does indeed increase in our case can be seen in Figure 8. This figure plots the locuses of the mechanism tightness pairs (θ^N, θ^A) that make each side of the market indifferent between the two mechanisms. These indifference curves for the benchmark model show, for each θ^N, the θ^A that ensures mechanism indifference for buyers and the θ^A ensuring it for sellers, which we generate by first jointly solving for V^{NB} and V^{NS} using negotiation value equations (10 - 11), fixing V^H to its steady state level. Both curves slope up, as buyer and seller values are strictly monotonic in mechanism tightness. The two curves' intersection is a steady state equilibrium.

The information disclosure policy counterfactual shifts both buyer and seller indifference curves down. For buyers, information disclosure at negotiation increases surplus given tightness. Because higher auction tightness decreases the attractiveness of auctions for them, buyers require lower than benchmark auction tightness to be indifferent between the two mechanisms. For sellers, the policy reduces negotiation surplus; as higher tightness

[20]Specifically, we assume that buyers and sellers must remain in a given mechanism until they transact and are replaced by new buyers and sellers in that mechanism when they leave the market. This gives unknowns, V^{NB}, V^{AB}, V^{NS}, V^{NS}, and V^H, that correspond to the five equations characterized by equations (10 - 12).

Figure 8: Equilibrium mechanism indifference with information disclosure



Notes: Mechanism indifference loci for buyers and sellers in the benchmark model (solid) and information disclosure counterfactual (dashed).

benefits sellers, lower auction tightness is needed to match this, which also shifts the seller indifference curve down. Crucially, the seller indifference curve shifts down less, because sellers' auction surplus is more sensitive to auction tightness than is buyers' (see Figure 4(b)). The seller shift is sufficiently smaller that both tightnesses increase.

Table 6 shows that these effects, as well as a shift towards auctions among sales, increase steadily with the extent of information disclosure, as we consider disclosure rates of 5% and 10%. Auctions account for just under 19% of sales in the benchmark case but nearly one third of sales with 10% information disclosure at negotiation.

The findings suggest that implementing information disclosure policies in frictional search markets should account for agents' responses by switching mechanisms. Although these policies' stated goal is often increased buyer welfare (employee welfare in the case of labor markets), mechanism switching may have the unintended consequence of benefiting the information-divulging side at the expense of the intended beneficiaries.

Table 6: Information disclosure and mechanism intensity

	Benchmark	5% Info. disclosure	10% Info. disclosure
Buyer value V^B	0.073	0.044	0.018
Seller value V^S	1.102	1.143	1.181
Homeowner value V^H	1.269	1.278	1.288
Buyer negotiation share Ψ^{BN}	0.682	0.549	0.498
Seller negotiation share Ψ^{SN}	0.755	0.627	0.575
Fraction of sales via auction	0.186	0.285	0.326

Notes: Results of a 5% and 10% information disclosure policy on mechanism intensity. The first column reports the benchmark steady state using the MS-Auction parameterization of Table 2. The second and third columns impose information disclosure at negotiation at 5% and 10% levels, respectively.

7. Conclusion

This paper formulates a dynamic equilibrium model of two-sided search and trade across multiple mechanisms with incomplete information. As such, it combines the search and competing mechanism literatures. We estimate structural model primitives from auction and other housing transaction data and use them to solve for the steady state and dynamics of a housing search model with auction and negotiation mechanisms.

Our empirical findings have important implications for understanding markets when search is costly. First, they suggest that models featuring Nash bargaining can *understate* the importance of search costs if there is two-sided incomplete information, as the higher expected trade-conditional surplus in incomplete information bargaining requires higher search costs to rationalize seller participation in our model.

Second, single mechanism models may *overstate* price responsiveness, as mechanism switching dampens the response to shocks. With a second mechanism, mechanism tightness rates equilibrate to ensure buyer and seller indifference between mechanisms and so are impervious to market tightness shocks. This leaves price unchanged and sellers' share of auctions accommodating the change in the buyer-to-seller ratio. Demand changes that work through the flow utility of housing lack this effect, and price reacts initially to such shocks how we would expect from simple demand-supply logic; however, a follow-through increase in market tightness leads, through the same channel, to price persistence in the sole-, but not the dual-, mechanism model. Overall, we find moving shocks, which directly affect market tightness, to be sufficiently important for a second mechanism to reduce price volatility substantially.

Third, our findings show the importance of considering mechanism choice when evaluating policy changes that differentially affect surplus across mechanisms. We show that an information disclosure policy that benefits negotiating buyers at sellers' expense, given mechanism choices, actually harms buyers and benefits sellers when they are free to choose mechanisms and tightness equilibriates to ensure indifference across the mechanisms.

References

ALBRECHT, J., A. ANDERSON, E. SMITH, AND S. VROMAN (2007): "Opportunistic Matching in the Housing Market," *International Economic Review*, 48, 641–664.

ALBRECHT, J., P. A. GAUTIER, AND S. VROMAN (2016): "Directed search in the housing market," *Review of Economic Dynamics*, 19, 218–231.

ALGAN, Y., O. ALLAIS, W. J. DEN HAAN, AND P. RENDAHL (2014): "Chapter 6 - Solving and Simulating Models with Heterogeneous Agents and Aggregate Uncertainty," in *Handbook of Computational Economics Vol. 3*, ed. by K. Schmedders and K. L. Judd, Elsevier, vol. 3 of *Handbook of Computational Economics*, 277–324.

ALLEN, J., R. CLARK, AND J.-F. HOUDE (2019): "Search Frictions and Market Power in Negotiated-price Markets," *Journal of Political Economy*, 127, 1550–1598.

ANENBERG, E. (2016): "Information Frictions and Housing Market Dynamics," *International Economic Review*, 57, 1449–1479.

ANUNDSEN, A., A. LYSHOL, P. NENOV, AND E. R. LARSEN (2023): "Match Quality and House Price Dispersion: Evidence from Norwegian Housing Auctions," Tech. rep., Norges Bank Working Paper 12/2023.

ARCIDIACONO, P. AND R. A. MILLER (2020): "Identifying Dynamic Discrete Choice Models off Short Panels," *Journal of Econometrics*, 215, 473–485.

AREFEVA, A. (2023): "Housing Markets: Auctions, Microstructure Noise, and Weekly Patterns," *Available at SSRN 2980095*.

ATHEY, S. AND P. A. HAILE (2002): "Identification of Standard Auction Models," *Econometrica*, 70, 2107–2140.

BACKUS, M., T. BLAKE, B. LARSEN, AND S. TADELIS (2020): "Sequential Bargaining in the Field: Evidence from Millions of Online Bargaining Interactions," *The Quarterly Journal of Economics*, 135, 1319–1361.

BAJARI, P., R. MCMILLAN, AND S. TADELIS (2009): "Auctions versus Negotiations in Procurement: An Empirical Analysis," *The Journal of Law, Economics, & Organization*, 25, 372–399.

BUCHHOLZ, N. (2022): "Spatial Equilibrium, Search Frictions, and Dynamic Dfficiency in the Taxi Industry," *The Review of Economic Studies*, 89, 556–591.

BUCHHOLZ, N., L. DOVAL, J. KASTL, F. MATĚJKA, AND T. SALZ (2020): "The Value of Time: Evidence from Auctioned Cab Rides," Tech. rep., National Bureau of Economic Research.

BULOW, J. AND P. KLEMPERER (1996): "Auctions Versus Negotiations," *The American Economic Review*, 86, 180–194.

BYRNE, D. P., L. A. MARTIN, AND J. S. NAH (2022): "Price Discrimination by Negotiation: A Field Experiment in Retail Electricity," *The Quarterly Journal of Economics*, 137, 2499–2537.

CAHUC, P., F. POSTEL-VINAY, AND J.-M. ROBIN (2006): "Wage Bargaining with On-the-job Search: Theory and Evidence," *Econometrica*, 74, 323–364.

CARRILLO, P. E. (2012): "An Empirical Stationary Equilibrium Search Model of the Housing Market," *International Economic Review*, 53, 203–234.

COVERT, T. R. AND R. L. SWEENEY (2023): "Relinquishing Riches: Auctions versus Informal Negotiations in Texas Oil and Gas Leasing," *American Economic Review*, 113, 628–63.

CULLEN, Z. B. AND B. PAKZAD-HURSON (2023): "Equilibrium Effects of Pay Transparency," *Econometrica*, 91, 765–802.

DECAROLIS, F. (2018): "Comparing Public Procurement Auctions," *International Economic Review*, 59, 391–419.

DIAMOND, P. A. (1982): "Wage Determination and Efficiency in Search Equilibrium," *The Review of Economic Studies*, 49, 217–227.

DUFFIE, D., N. GÂRLEANU, AND L. H. PEDERSEN (2005): "Over-The-Counter Markets," *Econometrica*, 73, 1815–1847.

EECKHOUT, J. AND P. KIRCHER (2010): "Sorting versus Screening: Search Frictions and Competing Mechanisms," *Journal of Economic Theory*, 145, 1354–1385.

EINAV, L., C. FARRONATO, J. LEVIN, AND N. SUNDARESAN (2018): "Auctions Versus Posted Prices in Online Markets," *Journal of Political Economy*, 126, 178–215.

GARGANO, A. AND M. GIACOLETTI (2020): "Cooling Auction Fever: Evidence from the Housing Market," *Available at SSRN 3561268*.

GARGANO, A., M. GIACOLETTI, AND E. JARNECIC (2023): "Local Experiences, Search, and Spillovers in the Housing Market," *The Journal of Finance*, 78, 1015–1053.

GAVAZZA, A. (2016): "An Empirical Equilibrium Model of a Decentralized Asset Market," *Econometrica*, 84, 1755–1798.

GENESOVE, D. (1995): "Search at wholesale auto auctions," *The Quarterly Journal of Economics*, 110, 23–49.

GENESOVE, D. AND L. HAN (2012): "Search and Matching in the Housing Market," *Journal of Urban Economics*, 72, 31–45.

GENESOVE, D. AND J. HANSEN (2023): "Auctions and Negotiations in Housing Price Dynamics," *Review of Economics and Statistics*, Forthcoming.

GENTRY, M. AND C. STROUP (2019): "Entry and Competition in Takeover Auctions," *Journal of Financial Economics*, 132, 298–324.

GUREN, A. M. (2018): "House Price Momentum and Strategic Complementarity," *Journal of Political Economy*, 126, 1172–1218.

GUREN, A. M. AND T. J. MCQUADE (2020): "How do Foreclosures Exacerbate Housing Downturns?" *The Review of Economic Studies*, 87, 1331–1364.

HALL, R. E. AND P. R. MILGROM (2008): "The Limited Influence of Unemployment on the Wage Bargain," *The American Economic Review*, 98, 1653–74.

HAN, L. AND W. C. STRANGE (2014): "Bidding Wars for Houses," *Real Estate Economics*, 42, 1–32.

HEAD, A., H. LLOYD-ELLIS, AND H. SUN (2014): "Search, Liquidity, and the Dynamics of House Prices and Construction," *The American Economic Review*, 104, 1172–1210.

HENDERSHOTT, T. AND A. MADHAVAN (2015): "Click or Call? Auction versus Search in the Over-The-Counter Market," *The Journal of Finance*, 70, 419–447.

HUANG, G. (2020): "When to Haggle, When to Hold Firm? Lessons from the Used-Car Retail Market," *Journal of Economics & Management Strategy*, 29, 579–604.

KIYOTAKI, N. AND R. WRIGHT (1989): "On Money as a Medium of Exchange," *Journal of Political Economy*, 97, 927–954.

KRISHNA, V. (2009): *Auction Theory*, Hoboken, NJ: Academic press.

LARSEN, B. AND J. FREYBERGER (2021): "How Well Does Bargaining Work in Consumer Markets? A Robust Bounds Approach," Tech. rep., National Bureau of Economic Research.

LARSEN, B. AND A. L. ZHANG (2021): "Quantifying Bargaining Power Under Incomplete Information: A Supply-side Analysis of the Used-Car Industry," *Available at SSRN 3990290*.

LARSEN, B. J. (2021): "The Efficiency of Real-world Bargaining: Evidence from Wholesale Used-Auto Auctions," *The Review of Economic Studies*, 88, 851–882.

LOEWENSTEIN, G., C. R. SUNSTEIN, AND R. GOLMAN (2014): "Disclosure: Psychology Changes Everything," *Annual Review of Economics*, 6, 391–419.

MERLO, A. AND F. ORTALO-MAGNE (2004): "Bargaining over Residential Real Estate: Evidence from England," *Journal of Urban Economics*, 56, 192–216.

MERLO, A., F. ORTALO-MAGNÉ, AND J. RUST (2015): "The Home Selling Problem: Theory and Evidence," *International Economic Review*, 56, 457–484.

MOEN, E. R. (1997): "Competitive Search Equilibrium," *Journal of Political Economy*, 105, 385–411.

MORTENSEN, D. T. (1982): "The Matching Process as a Noncooperative Bargaining Game," in *The Economics of Information and Uncertainty*, University of Chicago Press, 233–258.

MORTENSEN, D. T. AND C. A. PISSARIDES (1994): "Job Creation and Job Destruction in the Theory of Unemployment," *The Review of Economic Studies*, 61, 397–415.

MYERS, E., S. L. PULLER, AND J. WEST (2022): "Mandatory Energy Efficiency Disclosure in Housing Markets," *American Economic Journal: Economic Policy*, 14, 453–487.

MYERSON, R. B. AND M. A. SATTERTHWAITE (1983): "Efficient Mechanisms for Bilateral Trading," *Journal of Economic Theory*, 29, 265–281.

NGAI, L. R. AND K. D. SHEEDY (2020): "The Decision to Move House and Aggregate Housing-market Dynamics," *Journal of the European Economic Association*, 18, 2487–2531.

NGAI, L. R. AND S. TENREYRO (2014): "Hot and Cold Seasons in the Housing Market," *The American Economic Review*, 104, 3991–4026.

PIAZZESI, M., M. SCHNEIDER, AND J. STROEBEL (2020): "Segmented Housing Search," *The American Economic Review*, 110, 720–59.

PISSARIDES, C. A. (1985): "Short-run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages," *The American Economic Review*, 75, 676–690.

POSTEL-VINAY, F. AND J.-M. ROBIN (2002): "Equilibrium Wage Dispersion with Worker and Employer Heterogeneity," *Econometrica*, 70, 2295–2350.

ROBERTS, J. W. (2013): "Unobserved Heterogeneity and Reserve Prices in Auctions," *The RAND Journal of Economics*, 44, 712–732.

RØED LARSEN, E. (2021): "Intra-Week Price Patterns in the Housing Market," *The Scandinavian Journal of Economics*, 123, 327–352.

RUGE-MURCIA, F. (2012): "Estimating Nonlinear DSGE Models by the Simulated Method of Moments: With an Application to Business Cycles," *Journal of Economic Dynamics and Control*, 36, 914–938.

SALZ, T. (2022): "Intermediation and Competition in Search Markets: An Empirical Case Study," *Journal of Political Economy*, 130, 310–345.

SAMUELSON, W. F. (1985): "Competitive Bidding with Entry Costs," *Economics Letters*, 17, 53–57.

SATTERTHWAITE, M. AND A. SHNEYEROV (2007): "Dynamic Matching, Two-Sided Incomplete Information, and Participation Costs: Existence and Convergence to Perfect Competition," *Econometrica*, 75, 155–200.

SILVEIRA, B. S. (2017): "Bargaining with Asymmetric Information: An Empirical Study of Plea Negotiations," *Econometrica*, 85, 419–452.

WHEATON, W. C. (1990): "Vacancy, Search, and Prices in a Housing Market Matching Model," *Journal of Political Economy*, 98, pp. 1270–1292.

WILLIAMS, S. R. (1987): "Efficient Performance in Two Agent Bargaining," *Journal of Economic Theory*, 41, 154–172.

Online Supplementary Appendix

Appendix A. Mechanism description and proofs

Appendix A.1. Myerson-Satterthewiate Mechanism

A direct mechanism inputs agents' types and outputs a determination of whether trade occurs and payments paid by buyers and received by sellers. The problem is to find the optimal expected outcome within the set of direct mechanisms that do not run a budget deficit. We denote the allocation rule by $Q : [\underline{v}, \overline{v}] \times [\underline{c}, \overline{c}] \to \{0, 1\}$ and payment functions by $M^k : [\underline{v}, \overline{v}] \times [\underline{c}, \overline{c}] \to \mathbb{R}$ for each agent $k \in \{B, S\}$. We define the a-weighted virtual type functions as $\Phi^a(v) = v - (1-a)\frac{1-F(v)}{f(v)}$ for buyers and $\Gamma^a(c) = c + (1-a)\frac{G(c)}{g(c)}$ for sellers, with $a \in [0, 1]$. The payments M^k can be represented by the 0-weighted virtual type functions (Krishna (2009), Section 5.1), so that $M^B(v) = \Phi^0(v),\ M^S(c) = \Gamma^0(c)$.

The problem is to maximize the equally weighted expected surplus from buyers and sellers, $\mathbb{E}\left[\left(\left(v - M^B(v)\right) + \left(M^S(c) - c\right)\right) Q(v, c)\right]$, subject to the no-deficit constraint $\mathbb{E}[(M^B(v) - M^S(c))Q(v, c)] \geq 0$, where expectations are taken over buyer and seller values. The solution procedure searches over all rules that do not run a deficit and selects the one with the highest expected surplus. The impossibility of obtaining the first-best solution means that the no-deficit constraint always binds – i.e., the Lagrange multiplier ρ on the no-deficit constraint must exceed one.[21] For any given $\rho > 1$, the allocation rule that maximizes the expected surplus is given by $Q^\rho(v, c) = 1$ if $\Gamma^{1/\rho}(c) \leq \Phi^{1/\rho}(v)$ and 0 otherwise. The optimal mechanism selects the smallest ρ such that $\mathbb{E}[(M^B(v) - M^S(c))Q^\rho(v, c)] \geq 0$.

Appendix A.2. Proofs of Proposition 2 and Corollary 3

Proof of Proposition 2 . Buyer and seller value functions in stationary equilibrium (with idiosyncratic and aggregate shocks) are $E\left[V^{jB}\right] = \beta E\left[\sum_n \lambda_n^j \mathcal{W}_n^{jB}\right] + \beta E\left[V^{jB}\right] - c^{jB}$, and $E\left[V^{jS}\right] = \beta E\left[\sum_n \gamma_n^j \mathcal{W}_n^{jB}\right] + \beta E\left[V^{jS}\right] - c^{jS}$. Differencing across mechanisms,

$$
\begin{aligned}
E\left[\sum_n \lambda_n^A \mathcal{W}_n^{AB}\right] &= E\left[\sum_n \lambda_n^N \mathcal{W}_n^{NB}\right] - \Delta c^B \\
E\left[\sum_n \gamma_n^A \mathcal{W}_n^{AS}\right] &= E\left[\sum_n \gamma_n^N \mathcal{W}_n^{NS}\right] - \Delta c^S
\end{aligned}
$$

[21] If $\rho < 1$, the shadow price of running a deficit is lower than the benefit of transferring money directly to participants, so surplus is maximized by running an infinite deficit and paying this to buyers and sellers.

with $\Delta c^B \equiv \beta^{-1}\left(c^{NB} - c^{AB}\right)$, $\Delta c^S \equiv \beta^{-1}\left(c^{NS} - c^{AS}\right)$ and where we have used mechanism indifference, $E\left[V^{AB}\right] = E\left[V^{NB}\right]$ and $E\left[V^{AS}\right] = E\left[V^{NS}\right]$. Totally differentiating,

$$E\left[\sum_n \left(\frac{\partial \lambda_n^A}{\partial \theta^A}\mathcal{W}_n^{AB} d\theta^A + \lambda_n^A d\mathcal{W}_n^{AB}\right)\right] = E\left[\sum_n \left(\frac{\partial \lambda_n^N}{\partial \theta^N}\mathcal{W}_n^{NB} d\theta^N + \lambda_n^N d\mathcal{W}_n^{NB}\right)\right] \quad \text{(A.1)}$$

Dividing through by $\boldsymbol{\lambda}^A \cdot \mathcal{W}^{AB} + \boldsymbol{\lambda}^N \cdot \mathcal{W}^{NB}$, we can re-write the LHS of (A.1) as

$$E\left[\sum_n \mathcal{S}_n^{AB}\left(e_n^{AB} d\ln\theta^A + d\ln\mathcal{W}_n^{AB}\right)\right]$$

where $e_n^{AB} \equiv \frac{\partial \lambda_n^A}{\partial \theta^A} \times \frac{\theta^A}{\lambda_n^A}$ is the elasticity of arriving at a seller with $n-1$ other buyers with respect to mechanism tightness, $\mathcal{S}_n^{AB} \equiv \frac{\lambda_n^A \mathcal{W}_n^{AB}}{\boldsymbol{\lambda}^A \cdot \mathcal{W}^{AB} + \boldsymbol{\lambda}^N \cdot \mathcal{W}^{NB}}$ is the expected surplus share obtained by a buyer at auction with $n-1$ other buyers arriving (relative to total buyer surplus across all mechanisms). Applying the same steps for a buyer at negotiation (A.1) becomes

$$E\left[\sum_n \mathcal{S}_n^{AB}\left(e_n^{AB} d\ln\theta^A + d\ln\mathcal{W}_n^{AB}\right)\right] = E\left[\sum_n \mathcal{S}_n^{NB}\left(e_n^{NB} d\ln\theta^N + d\ln\mathcal{W}_n^{NB}\right)\right]$$

Using a similar argument for sellers, the cross-mechanism arbitrage condition for is

$$E\left[\sum_n \mathcal{S}_n^{AS}\left(e_n^{AS} d\ln\theta^A + d\ln\mathcal{W}_n^{AS}\right)\right] = E\left[\sum_n \mathcal{S}_n^{NS}\left(e_n^{NS} d\ln\theta^N + d\ln\mathcal{W}_n^{NS}\right)\right]$$

These equations can be expressed as a linear system of $(d\ln\theta^A, d\ln\theta^N)$ as follows:

$$E\begin{bmatrix} \mathcal{E}^{AB} & -\mathcal{E}^{NB} \\ \mathcal{E}^{AS} & -\mathcal{E}^{NS} \end{bmatrix}\begin{bmatrix} d\ln\theta^A \\ d\ln\theta^N \end{bmatrix} = E\begin{bmatrix} \Delta\mathcal{W}^B \\ \Delta\mathcal{W}^S \end{bmatrix}$$

Since the $\mathcal{E}^{jk}$ are invariant to shocks, the conclusions of the proposition follow provided $\mathcal{E}^{NB}\mathcal{E}^{AS} - \mathcal{E}^{AB}\mathcal{E}^{NS} \neq 0$. ■

Proof of Corollary 3. This follows directly from the last line in the proposition, given the signs of the terms. ■

Proof of Corollary 4. $\operatorname{sgn}(-\mathcal{E}^{NS}\Delta W^B + \mathcal{E}^{NB}\Delta W^S) = \operatorname{sgn}(|\mathcal{E}^{NB}| - \mathcal{E}^{NS})\operatorname{sgn}(\Delta W^B)$

and $\operatorname{sgn}(-\mathcal{E}^{AS}\Delta W^B + \mathcal{E}^{AB}\Delta W^S) = \operatorname{sgn}(|\mathcal{E}^{AB}| - \mathcal{E}^{AS})\operatorname{sgn}(\Delta W^B)$. The conclusions follow from the last line in the proposition. ■

Appendix B. Data and Sample Construction

Appendix B.1. Auctions microdata

From a large real estate auction company headquartered in Sydney, Australia, we obtained data on the 50,378 auctions it ran from 2008 until September 2019. Removing properties classified as commercial leaves a sample of 46,939.

We apply several criteria to generate the final sample. First, we require that the auction be held, as the listings data contain many entries for auctions that were canceled, postponed, or otherwise withdrawn from the market. Second, for the number of bidders sample, we require the number of bidders, auction outcome, date, and region. For the full auction sample, we additionally require the commitment price and highest bid.[22] Third, we remove outliers: the approximately 0.1% of observed auctions with more than 25 bidders; listings with low (<\$500,000) or very high (>\$5 million) highest bids, which is a small fraction of the overall sample; and observations with highest bid-to-commitment price ratios below 0.75 or above 1.25, which typically correspond to typos in the raw data. Fourth, we remove any auctions outside NSW. We are left with 14,482 observations for the full auction sample and 18,203 observations for the number of bidders sample.

Appendix B.2. Auctions and Negotiations Sales Data

We also use an overlapping census of sales transactions, sourced from Australian Property Monitors (APM) (see the Copyright and Disclaimer Notices at the end of this Appendix), from 2010:W8 to 2019:W44 inclusive and covering the same postal codes in the Sydney metropolitan area as the auctions microdata. The data include the sale price, listing date, sales (contract) date, sale mechanism, and if an auction was the selected mechanism whether it was successful or not. We use these data to construct log hedonic prices by mechanism, the auction sales rate, the auction sales share, and negotiated seller time on market, all at a weekly frequency. Details of their construction follow.

[22]Institutionally, the commitment price is called the reserve price. We relabel it for clarity as it differs from the reserve price of auction theory in that sellers are allowed to sell below it. Sellers may refuse to sell at a bid above it, but are then obliged to pay the sales fees to the listing agent and auctioneer, and so exercising this option is extremely uncommon in practice.

For log hedonic prices, we estimate a log price regression using the transaction data:

$$\ln P^j_{hzt} = \kappa^j_z + \vartheta^j_t + \sum_r H_{hrt}\chi^j_r + \sum_s X_{hst}\delta^j_s + \sum_r\sum_s H_{hrt}X_{hst}\omega^j_{rs} + \nu^j_{hzt} \tag{B.1}$$

where home h is sold in postal code z in week t via mechanism $j \in \{\mathrm{N}, \mathrm{A}\}$. The weekly log hedonic price by mechanism is constructed using the estimates of the (ϑ^j_t) coefficients. In addition to them, we control for postal (Zip) code (κ^j_z) fixed effects, the type of home (H_{hrt}) (e.g., detached house, townhouse, semi-detached home, apartment or villa), and other home attributes including the number of bedrooms, number of bathrooms, the log lot/building size (X_{hst}) and the interactions of these attributes with home type $(H_{hrt}X_{hst})$.

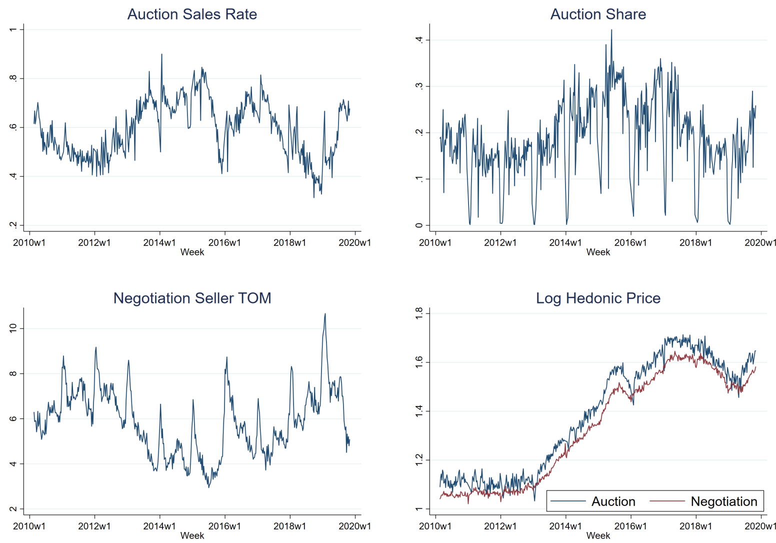
The auction sales rate is the ratio of auction sales to the sum of auction sales and the number of homes that failed to sell at auction (whether on a buyer or vendor bid, or where no bids were offered). The auction sales share is the ratio of auction sales to the sum of auction and negotiation sales. Negotiation seller time on market is the number of weeks from date of listing to date of sale, that is, the day the sale contract is signed (and not the settlement date). We date all variables, including prices, by contract date.

Figure B.1 reports the original source data with outliers removed by the R-package "tsclean".[23] All data are measured at weekly frequency. There are seasonal patterns, with the auction sale share falling in the last weeks of December and early weeks of January, which increases the volatility of log prices in those periods. Before estimation, we compute the demeaned log change in price by mechanism and detrend the auction sales share, sales rate, and negotiation seller time-on-market using a constant and linear time trend.

Steady state weekly moving rates are calibrated to match Sydney and NSW 3-year mobility data published in ABS Catelogue: 3240.0 - Residential and Workplace Mobility, and Implications for Travel: NSW and Vic., October 2008. We fit mutually independent Poisson processes for the arrival of intracity shocks (moves of less than 50km) and intercity shocks (all other moves to the state, i.e. interstate or from overseas).

[23]This package uses an automated, robust STL decomposition for seasonal series and linear interpolation to replace missing values and outliers.

Figure B.1: Observables used in SMM Estimation



Note: Original data are sourced from housing transactions data provided by APM. Outliers are removed using the R-package "tsclean". These figures are before detrending. Data are detrended before SMM estimation.

Appendix C. Identification of Steady-State Values

Proposition 5 shows that the model is identified up to a choice of time discount factor β and flow utility from ownership r^H.[24] This result is similar to identification results of other dynamic models, such as Arcidiacono and Miller (2020), that show that identification depends upon a choice of time discount factor and a fixed value of one of the flow payoffs.

We first recap the main assumptions of the mechanism models that are necessary to generate the mapping from the data on auction and negotiation outcomes into the mechanism-specific surplus, trade probability, and mechanism tightness.

Assumption 1 (Auction mechanism). *The auction mechanism is an independent private values second-price sealed bid auction with an optimal seller reserve. Values for buyers $V^H(z) - V^{AB}$ are i.i.d draws from a distribution F. Values for sellers V^{AS} are i.i.d. draws from a distribution G.*

Assumption 2 (Exogenous N). *Buyers in the auction market are matched to auction sellers such that the distribution of the number of buyers n_t at any given auction t is determined*

[24]While we assume that other parameters are known in the proof of Proposition 5, we later generalize this result to allow for other data sources to identify these parameters without impacting the main result.

by a mixed-Poisson probability mass function $\gamma_n^A(\theta^A) = \sum_{i=1}^I w_i \frac{(\delta_i\theta^A)^n e^{-\delta_i\theta^A}}{n!}$ that is independent of value realizations for buyers and sellers, where θ^A is auction tightness, and the probability that a given auction buyer is at an auction with n total buyers is $\lambda_n^A(\theta^A)$. The probability that n buyers arrive at a given negotiation seller is the same as the auction arrival probabilities up to a change in tightness:$\gamma_n^N = \gamma_n^A, \lambda_n^N = \lambda_n^A$.

Assumption 3. *The distribution of buyer and seller values at negotiations is the same as the distribution of buyer and seller values at auctions: $V^H(z) - V^{NB} \sim F$, $V^{NS} \sim G$.*

Assumption 4. *The negotiation mechanism is the second-best mechanism of Myerson and Satterthwaite (1983) with buyer value distribution F and seller value distribution G.*

Assumption 5. *The time discount factor β, owner match dissolution probability α^m, probability of leaving the market p^m, ownership flow utility r^H, seller auction arrival rate ρ^A, and buyer search probability ρ^B are known.*

Proposition 5. *The steady-state equilibrium values B, S, and $\{\mathcal{W}^{jk}, \gamma^j(\theta^j), \lambda^j(\theta^j), c^{jk}, \Psi^{Nk}\}$ for $j \in \{A, N\}$, $k \in \{B, S\}$ are identified by the joint set of bidders at each auction, highest auction bid, auction result $\{n_t, \bar{b}_t, r_t\}_{t=1}^T$, the distribution of negotiation seller time-on-market TOM_S^N, and the auction sales share $\mathcal{S}^A$.*

The proof of Proposition 5 proceeds in three steps. First, we show that the buyer and seller trade probabilities, auction tightness, and buyer and seller value distributions at auction are identified from the auction data, auction model, and buyer arrivals. Second, we show that negotiation trade probabilities and tightness are identified by negotiation seller time-on-market, assuming that the distributions of buyers' and seller values at negotiation are the same as at auction - as implied by the search model - and that the MS mechanism determines negotiation outcomes. Together, these results imply the identification of steady-state mechanism-specific surpluses $\mathcal{W}^{jk}$. Finally, we show that the remaining steady-state equilibrium values, which are the measures of buyers and sellers and the probabilities that buyers and sellers choose the negotiation mechanism, along with the mechanism-specific search costs, are identified from the steady-state equilibrium conditions of the dynamic model, the auction sales share $\mathcal{S}^A$, and Assumption 5.

Lemma 1 (Auction identification). *$\lambda_n^A(\cdot)$, $\gamma_n^A(\cdot)$, θ^A, $F(\cdot)$, and $G(\cdot)$ are identified from the data on auction outcomes $\{n_t, \bar{b}_t, R_t\}_{t=1}^T$, the auction model of Assumption 1, and the buyer arrival process of Assumption 2.*

Proof. The auction data consists of the number of bidders at each auction t, n_t, the highest bid submitted $\bar{b}_t$ (which may be the seller's vendor bid), and the result of the auction R_t which takes values of $\{$Sale, No Sale, No Sale (Vendor bid)$\}$. Recall that "No Sale" results do not specify who placed the final bid (sellers or buyers) while "No Sale (Vendor bid)" means that the final bid placed was a binding bid on behalf of the seller. Our model uses a sealed bid auction with optimal reserve abstraction to capture the ascending oral auction with a single vendor bid which is actually used. For simplicity, our identification argument focuses on cases in which a sale occurred or the auction failed on a vendor bid, as these cases suffice to establish the identification of buyers' and seller values. In "No Sale" cases we treat the vendor bid as unobserved, generating bounds on seller values. Including these cases improves the precision of the estimates but does not affect the identification argument.

Identification of the distribution of buyer values F follows standard arguments in the auctions literature (Athey and Haile (2002)). The simplest argument for identification focuses on the case in which $n = 1$. When $n = 1$, the highest bid always corresponds to the seller's optimal reserve. Because the buyer and seller have independent value draws, the optimal reserve price is independent of the buyer's value v, so $F(\bar{b})$ is identified by the proportion of auctions that result in a sale when the reserve price is $\bar{b}$. With F identified, there is a one-to-one mapping from the observed reserve prices r_t to seller values given by $c_t = r_t - \frac{1-F(r_t)}{f(r_t)}$; applying this mapping to all auctions yields identification of G. Finally, because n_t is assumed to be exogenous, the $n = 1$ case suffices for identification.

Data on bidder numbers at each auction n_t non-parametrically identifies the probability mass function (pmf) for bidder numbers at auction. Separately identifying θ^A and the buyer arrival function $\lambda_n(\cdot)$, a necessary first step to determining θ^A in counterfactuals and outside of steady state, and inferring θ^N, requires a parameterization, however. We use a finite Poisson mixture distribution as a flexible parametric representation, . Auction tightness is identified from the average number of buyers at each auction. Identification of the remaining parameters of the auction buyer arrival function follows from the non-parametric identification of this distribution. Finally, γ^A is the pmf associated with λ^A conditional on $n_t \geq 1$. ■

Lemma 2 (Negotiation identification). *θ^N is identified by negotiation seller time-on-market TOM^{NS} and Assumptions 4, 3 and 2.*

Proof. In steady-state there is a constant, per-period probability of sale for negotiation sellers. This depends on (i) the distribution of buyer and seller values, (ii) the negotiation mechanism, and (iii) the arrival rate of buyers to sellers. Both (i) and (ii) are known. The arrival rate *function* is known. So per-period sale probability for a negotiating seller is known up to θ^N. Since this is an increasing function of θ^N and per-week sale probability is obtainable from seller time-on-market data, θ^N is identified. ■

Lemma 3 (Steady-state identification). *Suppose Assumption 5 holds and that the auction sales share $\mathcal{S}^A$ and $\theta^j, \mathcal{W}^{jk}, \lambda^j(\cdot), \gamma^j(\cdot)$ for $j \in \{A, N\}$ and $k \in \{B, S\}$ are known. Then B, S, Ψ^{Nk}, and c^{jk} for $j \in \{A, N\}, k \in \{B, S\}$ are identified from the steady-state equilibrium of equations (12-19).*

Proof. For simplicity, assume $\rho^A = \rho^B = 1$ and that the probability of leaving the market $p^m = 0$. We denote $V^k \equiv \max_j\{\mathcal{V}^{jk}\}$ as the steady state search value for side of the market k. Equation (10) implies that for mechanism j we have $c^{jS} = \beta\gamma^j(\theta^j)\mathcal{W}^{jS} + (\beta - 1)V^S$. Because all terms on the right-hand side are identified or known, c^{AS} and c^{NS} are identified.

For buyers, from equation (11) we have $(1-\beta)V^B = \beta\lambda^j(\theta^j)\mathcal{W}^{jB} - c^{jB}$, and from the ownership value equation (12) we have $(1 - \beta)V^H = r^H + \varphi^m\beta V^S - \varphi^m\beta(V^H - V^B)$. Taking the difference of the buyer and owner value equations yields

$$r^H + c^{jB} = \varphi^m\beta V^S - [1 - \beta + \varphi^m\beta](V^H - V^B) - \beta\lambda^j(\theta^j)\mathcal{W}^{jB}$$

All terms on the right-hand side are identified or known for each mechanism j, so mechanism-specific buyer search costs c^{jB} are identified up to the ownership flow utility r^H.

The seller and buyer negotiation choice probabilities Ψ^{NB} and Ψ^{NS}, and seller and buyer measures S and B remain to be identified. The first of these can be inferred from the observed auction sales share $\mathcal{S}^A$ (the fraction of all trades that occur via auction):

$$\mathcal{S}^A = \frac{p^{AS}(1 - \Psi^{SN})}{p^{NS}\Psi^{NS} + p^{AS}(1 - \Psi^{NS})} \quad \Rightarrow \quad \Psi^{NS} = \frac{p^{AS} - \mathcal{S}^A p^{AS}}{\mathcal{S}^A p^{NS} + p^{AS} - \mathcal{S}^A p^{AS}}$$

where, for simplicity, we have defined $p^{jS} = \sum_{n=1}^{\overline{N}} \lambda_n^j \mathbb{E}[Q^j|N = n]$ and $p^{jB} = \sum_{n=1}^{\overline{N}} \gamma_n^j \mathbb{E}[Q^j|N = n]$ as the ex-ante probability of seller trade at mechanism j and the ex-ante probability of buyer trade at mechanism j, respectively. This identifies Ψ^{NS}.

Then, as mechanism tightnesses are $\theta^N = \frac{\Psi^{NB}B}{\Psi^{NS}S}$ and $\theta^A = \frac{(1-\Psi^{NB})B}{(1-\Psi^{NS})S}$, we can solve for Ψ^{NB} and market tightness B/S. The steady-state mass of buyers and sellers are then identified from the laws of motion (16) and (18), completing the proof:

$$B = \frac{\alpha^m}{p^{NB}\Psi^{NB} + p^{AB}(1 - \Psi^{NB})}, \quad S = \frac{\alpha^m}{p^{NS}\Psi^{NS} + p^{AS}(1 - \Psi^{NS})}$$

■

Appendix D. Structural Auction Model Estimation

This describes the estimation of the structural auction model and presents full parameter estimates for buyer and seller values and the distribution of buyer numbers at auction.

Buyer and seller values: We parameterize buyer and seller values as Normal distributions with mean and standard deviation determined by auction k covariates and the quality term η_k, so that $V_k^i \sim \mathcal{N}\left(\zeta_\mu^i X_k^\mu + \alpha_\mu^i \eta_k,\ [\zeta_\sigma^i X_k^\sigma + \alpha_\sigma^i \eta_k]^2\right)$ for $i \in \{B, S\}$. We assume that home quality η_k is observed by all buyers and the seller but unobserved by the econometrician. The set of variables determining the mean is $X_k^\mu = [\ell_k, \tau_k, D_k]$ where ℓ_k indicates whether the auction took place at the property or in a separate auction room, and τ_k and D_k are year and region dummy variables, respectively. To economize on the number of estimated parameters, we assume that the standard deviation is time- and space-invariant, so that $X_k^\sigma = [1, \ell_k]$, with unobserved quality η_k entering into both the mean and the variance.

Estimation of the model takes place in two stages. First, we estimate the distribution of the unobserved quality term following Roberts (2013). Instead of the seller's reserve, we use the commitment price to proxy for house quality. Specifically, we assume that $\underline{R} = m(\eta_k; X_k)$ for some known function $m(\cdot)$ strictly increasing in η. In estimation, we assume that m is linear, and use the set of variables defined above for X_k^μ. This assumes that the commitment price is completely described by the observed characteristics and the home quality and that the idiosyncratic component of the seller's value after controlling for observed covariates and home quality does not determine the commitment price.[25] Appendix D.1 shows that deconvolution methods yield a similar unobserved quality distribution.

After obtaining estimates $\hat{\eta}_k$, we estimate the parameters $\{\zeta_\mu^i, \zeta_\sigma^i, \alpha_\mu^i, \alpha_\sigma^i\}$ for $i \in \{B, S\}$

[25] We see this assumption as reasonable, as sellers have no reason to reveal information about their private value when the commitment price is set – the commitment price is agreed upon by the seller and listing agent/auctioneer prior to auction as a commitment device for the listing agent to "force" a sale with a sufficiently high bid, thus obtaining their commission. Since the commitment price is never revealed to buyers, the seller's incentive is to set it as high as possible regardless of their private value.

by maximizing the likelihood in Section 4.[26] The estimation procedure makes a first guess for all parameters except time dummies τ and region dummies D_k, and then uses the output as the initial guess in estimating all parameters. We find the initial guess and estimate the parameters by the Nelder-Mead algorithm and verify that we have found a maximum by using the resulting estimates as the initial guess in an optimizer using the BFGS algorithm. The estimated parameters for buyer and seller values are listed in Table D.1. The distributions $\hat{F}$ and $\hat{G}$ used in the dynamic equilibrium search model average over the observed characteristics in the data (e.g., location) and assume the mean value for unobserved quality, where we re-scale unobserved quality estimates to be strictly positive.

Buyer arrival parameters: We estimate the distribution over the number of buyers N at auction t as a four-component Poisson mixture, using the standard Expectation-Maximization algorithm applied to finite mixture models. For given vectors of Poisson parameters δ and mixture weights w, we compute the type expectation Z_{ti} for each observation $t = 1, ..., T$ and type $i = 1, .., 4$ as $\mathbb{E}[Z_{ti}|N, \delta, w) = w_i f(N_t|\delta_i)/[\sum_{k=1}^{4} w_k f(N_t|\delta_k)]$. Next, we maximize the expected log-likelihood $\sum_{t=1}^{T}\sum_{i=1}^{4} \ln(f(N_{ti}|\delta_i)\mathbb{E}[Z_{ti}|N, \delta, w] + \sum_{t=1}^{T}\sum_{i=1}^{4} \ln(w_i)\mathbb{E}[Z_{ti}|N, \delta, w]$ with respect to δ, w. We then re-compute the expectation using the updated δ, w values. We iterate until the difference in likelihoods between steps is less than 10^{-5}. Table D.2 presents the results with confidence intervals generated by the asymptotic distribution for the maximum likelihood estimator.

To estimate the arrival rate of buyers at negotiation, we fit observed time-on-market to weekly sale probability. Our model generates a stationary distribution for per-week sale probability so that the probability of a seller on the market in time T is $\Pr(T = t) = \alpha(1-q)^t q$, where q is the weekly hazard of sale and α accounts for low and high values of t being inflated. We regress $\log(\Pr(T = t))$ on time-on-market in using a histogram of sale probabilities where the slope coefficient is equal to $\ln(1-q)$.

Appendix D.1. Alternative specifications

Buyer and seller values: Figure D.1 shows the same fit measures of Figure 3 applied to estimated results using the Lognormal and Weibull distributions for buyer and seller value distributions. The Lognormal specification incorrectly generates the predicted distribution

[26] As referenced in Section 2.1, the sealed bid model can be estimated without loss of generality. This assumes that bidding is frictionless and the English auction is well-approximated by a Japanese auction.

Table D.1: Results: buyer and seller values

	Buyers		Sellers	
	Coeff.	95 pct. CI	Coeff	95 pct. CI
Mean				
Const.	-0.63606	[-0.64898, -0.62103]	-0.60713	[-0.62324, -0.58872]
Quality	0.88262	[0.87632, 0.88753]	0.86503	[0.85831, 0.87277]
In-room	-0.03239	[-0.03895, -0.02732]	-0.05712	[-0.06451, -0.04827]
Year				
2012	0.08593	[0.07501, 0.09944]	0.07321	[0.06149, 0.08397]
2013	0.09226	[0.08098, 0.10318]	0.04417	[0.03271, 0.05630]
2014	0.17409	[0.16213, 0.18583]	0.11583	[0.10278, 0.12681]
2015	0.33638	[0.32502, 0.34938]	0.26604	[0.25456, 0.27876]
2016	0.41469	[0.40152, 0.42651]	0.35006	[0.33696, 0.36335]
2017	0.50478	[0.49250, 0.51635]	0.44842	[0.43407, 0.46075]
2018	0.51558	[0.50262, 0.52753]	0.49139	[0.47776, 0.50515]
2019	0.44841	[0.43661, 0.45883]	0.41682	[0.40064, 0.43047]
Region				
City and East	0.58741	[0.57762, 0.59573]	0.53470	[0.52268, 0.54686]
Inner West	0.48716	[0.47569, 0.49635]	0.44790	[0.43415, 0.46066]
Lower North Shore	0.68679	[0.67357, 0.69900]	0.64063	[0.62431, 0.65824]
NSW Country	0.03480	[0.00385, 0.06724]	0.06060	[0.03891, 0.08185]
Newcastle	-0.03070	[-0.04501, -0.01626]	-0.06170	[-0.07832, -0.04669]
Northern Beaches	0.46586	[0.45269, 0.47970]	0.41884	[0.40089, 0.43764]
South	0.24065	[0.23108, 0.24925]	0.19254	[0.17957, 0.20490]
Upper North Shore	0.56097	[0.54831, 0.57318]	0.52338	[0.51090, 0.53692]
West	-0.14240	[-0.15812, -0.12931]	-0.10892	[-0.12509, -0.09147]
Wollongong	-0.01504	[-0.02608, -0.00510]	-0.02256	[-0.03426, -0.00920]
Variance				
Const.	0.03554	[0.02697, 0.04172]	0.02402	[0.01744, 0.03012]
Quality	0.12675	[0.12189, 0.13315]	0.08073	[0.07577, 0.08545]
In-room	-0.01055	[-0.01725, -0.00382]	-0.00658	[-0.01242, -0.00026]

Notes: Maximum likelihood estimates and 95 percent confidence intervals for buyer and seller value distribution parameters. "Quality" refers to unobserved housing quality, estimated following Roberts (2013). "Region" and "Year" are a set of geographic and time dummy variables; the left out categories are "Canterbury Bankstown" for regions and 2011 for years.

of prices and under-predicts the sales rate for all numbers of bidders, while the Weibull distribution performs better in predicting prices but over-predicts the sales rate for small numbers of bidders. In the Weibull case, the estimated shape parameters for both buyers and sellers fall in the 4.5 to 5.5 range, suggesting the data favor distributions with high symmetry, as is the case in our benchmark parameterization using the Normal distribution.

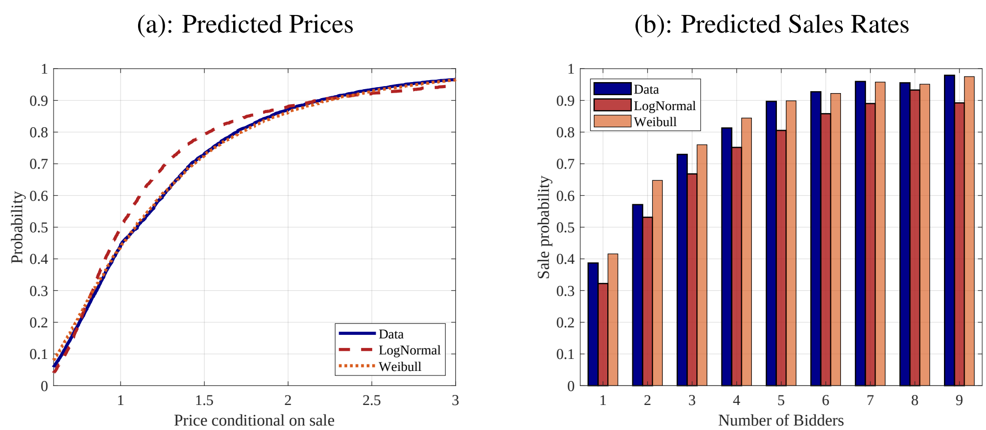
Unobserved heterogeneity: Our estimation follows Roberts (2013) to account for unobserved quality. For robustness, we also estimate the distribution of unobserved housing

Table D.2: Results: auction bidder arrival

	Coeff.	95 pct. CI
w_1	0.23535	[0.23488, 0.23582]
w_2	0.57869	[0.57835, 0.57902]
w_3	0.15579	[0.15562, 0.15597]
$\delta_1\theta^A$	1.15385	[1.15229, 1.15540]
$\delta_2\theta^A$	3.38894	[3.38695, 3.39094]
$\delta_3\theta^A$	8.17109	[8.16685, 8.17533]
$\delta_4\theta^A$	16.13255	[16.12682, 16.13828]

Notes: Estimates and 95 percent confidence intervals for the distribution of the number of buyers at auction. The weight for the Poisson distribution with parameter $\delta_i\theta^A$ is w_i, where $w_4 = 1 - \sum_{i=1}^{3} w_i$, $\sum_{i=1}^{4} w_i\delta_i = 1$, and $\theta^A = 3.992$ is the mean number of buyers per auction.

Figure D.1: Auction Model Fit with Alternative Specifications



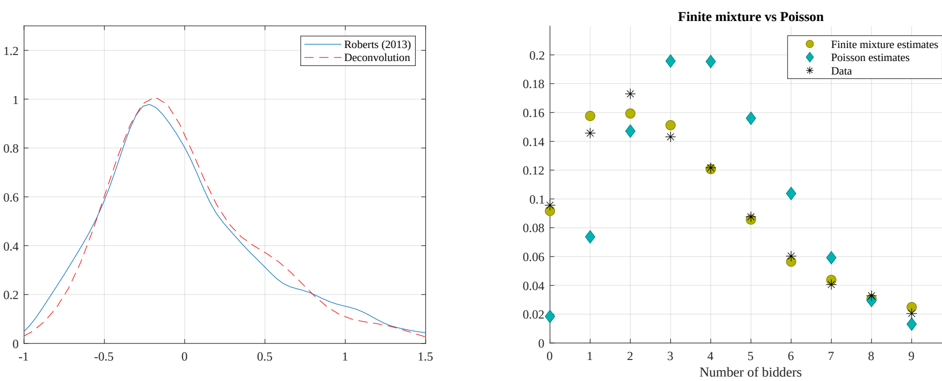
quality by deconvolution (e.g., Decarolis (2018)). We use the subset of auction observations containing data on the opening bid placed during the auction and the seller's commitment price to measure the distribution of unobserved housing quality. Specifically, we assume that the opening bid is $OB = W + Y$ and the commitment price is $CP = W + U$, where W, U, and Y are i.i.d across auctions and W represents the unobserved quality. For example, we might view Y as a function of the idiosyncratic component of a bidder's value and U as a function of the idiosyncratic component of the seller's value.

Panel (a) of Figure D.2 displays the unobserved housing quality distributions from both methods. They are clearly very similar. Our estimation uses the Roberts (2013) method as it generates point estimates of the unobserved quality for each auction, greatly reducing the computation burden of estimation.

Buyer arrivals: Panel (b) of Figure D.2 shows the estimated distribution of the number

Figure D.2: Other specification comparisons

(a) Unobserved heterogeneity **(b)** Auction bidders



of bidders at auction. Our finite mixture estimates closely approximate the empirical distribution, capturing the large portion of probability mass associated with low (either zero or one) and high (eight or more) bidder numbers. In contrast, the Poisson distribution fits the data poorly, with too much probability mass near the mean and too little near the tails.

Using the finite mixture rather than the Poisson has quantitatively meaningful impacts on implied auction outcomes and illustrates a key advantage of flexible estimation. The finite mixture estimates, in combination with our estimates of buyer and seller values, predict a 61% sales rate, very near the observed 60%. In contrast, the same estimation and simulation procedure but with the Poisson distribution estimates implies a 69% sales rate.[27]

Appendix E. Simulations and Polynomial Approximation

This appendix describes the output from the polynomial approximations using simulated outcomes for auctions and MS negotiations.

Appendix E.1. Estimating steady state negotiation tightness

First, we estimate the steady state negotiation tightness by simulated method of moments. Specifically, we fix the buyer and seller steady state mean values and the parame-

[27] This carries over to the surplus accruing to sellers under the Poisson by 13% higher than under the finite mixture. Seller surplus under each of the mechanisms described in Section 2.1 is a key feature determining tightness in each mechanism and agents' responses to dynamic shocks. Over-predicting seller surplus at auctions would imply seller auction search costs of search that are too high or too low an auction tightness; it will also influence how agents move across mechanisms in response to shocks.

ters determined by the auction data and estimate $\overline{\theta}^N$ by minimizing the squared difference between the simulated sale probability for the negotiation model as a function of negotiation tightness and the weekly sale rate of 0.1361 in the Sydney time-on-market data for negotiated sales. This generates an estimate of $\hat{\theta^E} = 0.25$ for the Nash bargaining case and $\hat{\theta}^N = 0.43$ for the MS case, which we use in the simulations for the negotiated model.

Appendix E.2. The grid

Both mechanisms are functions of the buyer's mean value, the seller's mean value, and the arrival rate. For the buyer's and seller's values, the grid extends from 0.15 (AUD$150,000) below the mean to 0.15 above. For the arrival rate, the grid is over a multiplier to the base arrival rate that ranges from 75% of the original value to 125% of the original value. To clarfiy, at a given point with multiplier $\xi \in [0.75, 1.25]$, the finite mixture maintains the same mixture probabilities w_k but distinct Poisson parameters $\xi\delta_k$ for $k = 1, 2, 3, 4$. We use 15 grid points per parameter in the simulations.

Appendix E.3. Auction polynomials

The polynomials are used to approximate the expected price conditional on sale, sale probability, buyer match probability, buyer surplus, buyer value conditional on trade, seller value conditional on no trade, and the probability that no buyers arrive at the auction.

Price conditional on sale: We provide a detailed description of how the grids for buyer and seller value means and buyer arrival rates map into the simulated outcomes auction prices; the main components of this approach carry over to the other endogenous variable simulations below. Let $\boldsymbol{\mu} \equiv [\mu_B, \mu_S]$ and $\boldsymbol{\sigma} \equiv [\sigma_B, \sigma_S]$ denote the vectors of means and standard deviations of buyer and seller values, and $H(r^A(\boldsymbol{\mu}, \boldsymbol{\sigma}))$ the distribution over the optimal reserve price $r^A(\boldsymbol{\mu}, \boldsymbol{\sigma})$. The expected price conditional on n buyers at auction is

$$P_n^A = \int_0^\infty \frac{\left[\int_{r^A}^{\overline{v}} vn\left[1 - F\left(v\right)\right] dF^{(n-1)}\left(v\right) + r^A n \left[1 - F\left(r^A\right)\right] F^{n-1}\left(r^A\right)\right]}{1 - F^n(r^A)} dH(r^A)$$

where $H(r^A)$ is the distribution over the seller's reserve r^A and depends on the seller's value realization c and the distribution of buyer values F_{μ_B}; for simplicity of notation we suppress the dependence of r^A on the distribution parameters.

Recall that the distribution of bidder numbers is estimated as a finite Poisson mixture with parameters $\{w_i, \delta_i\}_{i=1}^{4}$, where $w_i \equiv \Pr(\delta = \delta_i)$ and the δ_i are the Poisson parameters. To shorten notation, denote the probability a given buyer faces n total buyers at a seller by $\pi_n^{BA}(\delta_i, \xi) = \Pr(N = n | N \geq 1, \delta = \delta_i \xi \theta^A)$ and the probability of n total buyers arriving at a seller by $\pi_n^{SA}(\delta_i, \xi) = \frac{(\delta_i \xi \theta^A)^n e^{-\delta_i \xi \theta^A}}{n!}$. The expected auction price conditional on sale is

$$\tilde{\mathcal{P}}^A(\mu_B, \mu_S, \xi) = \sum_{n=1}^{\mathcal{N}} \sum_{i=1}^{4} w_i \pi_n^{SA}(\delta_i, \xi) P_n^A(\mu_b, \mu_s)$$

This object depends on three features of the auction model: the distribution of buyer values (which determines F), the distribution of seller values, which determines r_t^A, and the arrival rate of buyers, which determines n. The micro simulations treat the price as a function of (i) the mean of the buyer value distribution μ_B, (ii) the mean of the seller cost distribution μ_S, and (iii) tightness multiplier ξ as described above. For brevity, we do not indicate the dependence of π and P_n^A on these objects below. The simulations treat the standard deviations of buyer and seller distributions (governing idiosyncratic heterogeneity) as fixed and do not alter the distributions over the Poisson parameters in the mixture distribution. We simulate the expected price for each distinct vector for parameters (μ_B, μ_S, ξ) and fit these outcomes to polynomial approximations following the dynamic model solution description. The remaining simulated values are described below.

Seller Probability of sale: The simulated probability of sale for a given seller, $\mathcal{TP}^A$, for each grid point $(\boldsymbol{\mu}, \xi)$ is given by $\widetilde{\mathcal{TP}}^A = \sum_{n=0}^{\mathcal{N}} \sum_{i=1}^{4} w_i \pi_n^{SA}(\delta_i, \xi) \int_0^\infty \left(1 - F_{\mu_b}^n\left(r^A\right)\right) dH(r^A)$.

Buyer match probability: $\widetilde{\mathcal{BM}}^A = \sum_{n=1}^{\mathcal{N}} \sum_{i=1}^{4} w_i \pi_n^{BA}(\delta_i, \xi) \frac{1}{n} \mathbb{E}[1\{v^{(n)} \geq r^A\}]$, with expectation over the distribution of the highest value of n bidders $v^{(n)}$ and seller reserve r^A.

Expected buyer value conditional on trade: $\widetilde{\mathcal{BV}}^A(\mu_b, \mu_s, \xi) = \sum_{n=1}^{\mathcal{N}} \sum_{i=1}^{4} w_i \pi_n^{BA}(\delta_i, \xi) \mathbb{E}[v^{(n)} | v^{(n)} > r^A]$.

Expected seller value, given no trade: $\widetilde{\mathcal{SV}}^A = \sum_{n=1}^{\mathcal{N}} \sum_{i=1}^{4} w_i \pi_n^{BA}(\delta_i, \xi) \mathbb{E}[c | v^{(n)} < r^A]$.

Probability of zero buyers at auction: $\widetilde{\mathcal{ZB}}^A(\xi) = 1 - \sum_{i=1}^{I} w_i \pi_0^{SA}(\delta_i, \xi)$.

Appendix E.4. Myerson-Satterthwaite mechanism polynomials

As for auctions, we generate functional approximations for price conditional on trade, sale probability conditional on a buyer and seller meeting, probability of a seller meeting a buyer, buyer value conditional on trade, seller value conditional on no trade, and the probability that a buyer matches and trades with a seller.

Probability of sale conditional on meeting: This is given by $\widetilde{\mathcal{TP}}(\mu_B, \mu_S) = \mathbb{E}[1\{\Phi^{\tilde{a}(\mu_b,\mu_s)}(c) \geq \Gamma^{\tilde{a}(\mu_B,\mu_S)}(c)\}]$ where the expectation is taken over buyer values v and seller values c. As the mechanism allocation rule changes as the distribution means vary, for each pair μ_B, μ_S, we re-solve for the $\tilde{a}(\mu_B, \mu_S)$ that characterizes the optimal mechanism. Hereafter, we suppress the dependence on the means and simply write $\tilde{a}$.

Price conditional on trade: The expected payment to sellers, unconditional on trade, is $\mathbb{E}[\Gamma^0(c)Q^{\tilde{a}}(v,c)]$, with expectation taken over v, c. Conditioning on trade, the expected price is $\tilde{\mathcal{P}}^N(\mu_b, \mu_s) = \mathbb{E}[M^S_{\mu_s}(c)|\Phi^{\tilde{a}}(c) \geq \Gamma^{\tilde{a}}(c)]$.

Probability of a seller meeting a buyer: $\widetilde{\mathcal{MB}}(\xi) = 1 - \sum_{i=1}^{I} w_i \pi_n^{SN}(\delta_i, \xi)$ where $\pi_n^{kN}(\delta_i, \xi)$ is the negotiation analog to π_n^{kA} (i.e., using negotiation tightness θ^N in place of auction tightness) for $k = B, S$.

Probability of a buyer trading with a seller: $\widetilde{\mathcal{BM}}(\xi, \mu_b, \mu_s) = \sum_{n=1}^{\mathcal{N}} \sum_{i=1}^{4} w_i \pi_n^{BN}(\delta_i, \xi) \frac{1}{n} \widetilde{\mathcal{TP}}(\mu_b, \mu_s)$.

Expected seller value conditional on meeting a buyer and no trade: $\widetilde{\mathcal{SV}}(\mu_b, \mu_s) = \mathbb{E}[c|\Phi^{\tilde{a}}(v) < \Gamma^{\tilde{a}}(c)]$.

Expected buyer value conditional on trade: $\widetilde{\mathcal{BV}}(\mu_b, \mu_s) = \mathbb{E}[v \mid \Phi^{\tilde{a}}(v) \geq \Gamma^{\tilde{a}}(c)]$.

Table E.1: Comparing Simulation & Approximation Moments

	Simulation Mean	Approximation Mean	Steady State
Auction Price	1.331	1.331	1.327
Negotiation Price	1.174	1.174	1.174
Buyer Trade Prob. Auc.	0.153	0.153	0.154
Seller Trade Prob. Auc.	0.610	0.609	0.614
Buyer Trade Prob. Neg.	0.314	0.314	0.314
Seller Trade Prob. Neg.	0.133	0.133	0.136
Buyer Value Cond. Trade Auc.	1.447	1.447	1.444
Buyer Value Cond. Trade Neg.	1.344	1.344	1.339
Targeted Moments:			
Auction Tightness	3.992	3.992	3.992
Negotiation Tightness	0.432	0.432	0.432
Mean Uncond. Buyer Value	1.196	1.196	1.196
Mean Uncond. Seller Value	1.102	1.102	1.102

Notes: Moments not listed under *Target moment* are non-targeted. *Simulation mean* is the micro-simulation computed mean. *Approximation mean* is the mean approximated using 2nd-order polynomials. *Steady state* is the steady state mean for the dynamic MS-auction model with idiosyncratic shocks only.

Appendix E.5. Approximation accuracy

Table E.1 compares the: i) micro-simulation means computed in steps 1 and 2 (column 2); ii) means of the polynomial approximations from steps 3 and 4 (column 3); and iii) steady state of the full dynamic model featuring idiosyncratic but not aggregate uncertainty (column 4).[28] All three sets of means are very close. For example, in the MS-Auction model, the micro-simulation mean of the auction trade probabilities differ from that of the dynamic model's steady state by no more than 0.001 and 0.005 respectively, with similarly small differences for negotiation. Differences in tightness and price are also small.

Figure E.1 shows the micro-simulation values and the predicted values derived from the polynomial approximations used to parameterize expected price, trade probabilities for buyers and sellers, and conditional surpluses by mechanism, and where simulations are ordered in ascending value. The accuracy of the approximations is high: the maximum absolute error (MAE) for expected price and buyer value (conditional on trade) are less than 0.2% of the mean micro-simulation value with the root mean squared error (RMSE) about one third to one quarter of the MAE. The trade probabilities for buyers and sellers are also accurate with a RMSE no greater than 0.01 across all approximating polynomials.

Appendix E.6. Auctions-only compared with dual mechanisms

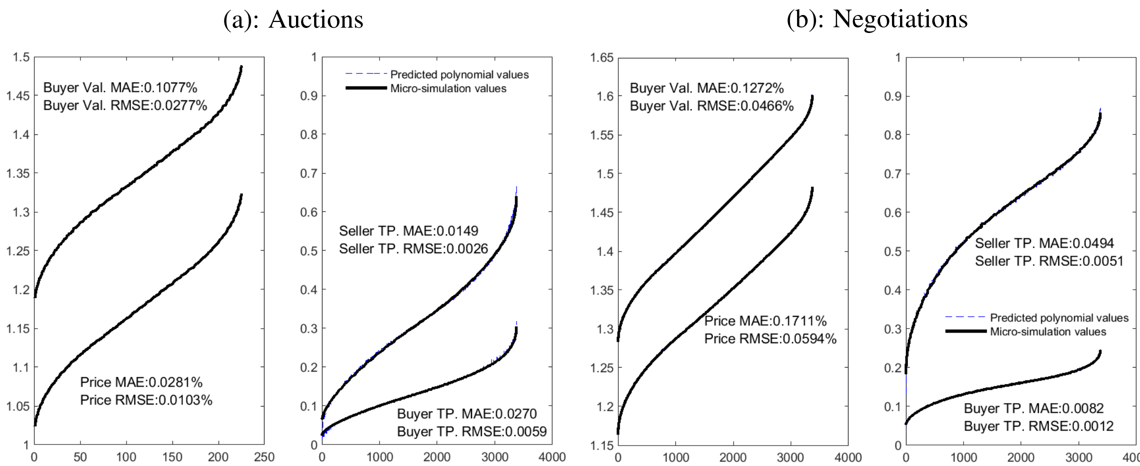
Figures E.2 and E.3 show impulse response functions comparing shock responses for the dual-mechanism model against a model with auctions as the sole mechanism. Figure E.2 shows responses to a shock to intra-city mobility, and Figure E.3 shows responses to a flow utility shock. These figures are the auction-only analog to Figures 5 and 6. That the shock responses are so similar to those figures comparing dual mechanisms with only MS negotiations despite the differences between MS negotiations and auctions as mechanisms indicates that it is the operation of both mechanisms that generates the shock responses we observe, rather than the features of any one mechanism.

Appendix F. Selection

In the benchmark model, buyers and sellers receive their private match quality and cost draws after choosing a mechanism. Thus, agents on each side of the market are ex-ante

[28]Experiments with different polynomial orders found second-order polynomials to be highly accurate, yet parsimonious. We use a second-order approximation (with pruning) when solving the full dynamic model.

Figure E.1: Polynomial Approximations



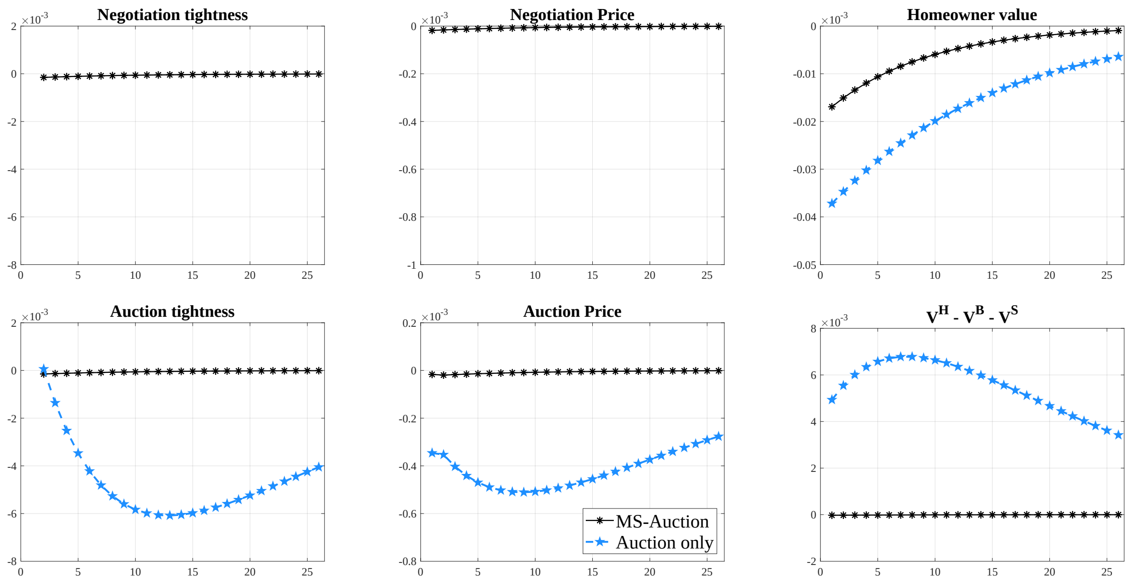
Note: Each point on the x-axis denotes a different grid point over the buyer value mean, seller value mean, and the arrival rate by mechanism. The x-axis is ordered so that y-values are ascending. *Buyer value* denotes the expected buyer value conditional on trade, *Price* denotes expected price, *Seller TP.* and *Buyer TP.* denote seller and buyer probabilities of trade. *MAE* is the maximum absolute error and *RMSE* the root mean squared error of the polynomial approximation used for each function, and are reported as a percentage of the mean micro-simulation value for *Price* and *Buyer value*.

identical until their private information is drawn after arriving at their chosen mechanism. Mechanism selection at the start of each period is determined by aggregate market conditions but not private information or per-period idiosyncratic preferences.

In this appendix, we investigate these modeling assumptions in two ways. We first empirically investigate whether property characteristics generate selection into transaction mechanisms for sellers that impact our estimates. One concern, for example, is that particularly attractive or desirable houses are sold via auction while other homes are sold using negotiations. Following Genesove and Hansen (2023), which uses similar data from the Sydney housing market, we match properties sold at auction to properties sold using negotiation on observed attributes and re-estimate the dynamic parameters on the matched sample. We find little difference in the estimates, suggesting that mechanism selection based on home characteristics or quality does not substantially alter the estimates we obtain.

Next, we examine whether idiosyncratic, mechanism-specific preferences of buyers and sellers generate selection into mechanisms. For instance, a buyer may find the idea of haggling with a seller unappealing in a given period and prefer going to an auction instead. To test whether this type of selection is quantitatively meaningful, we modify the benchmark

Figure E.2: Moving shock IRFs



Notes: Impulse response functions for a shock to intra-city moving rates. Values on the y-axis are percent deviations from steady state.

model to include idiosyncratic taste shocks for each mechanism for both buyers and sellers. We estimate versions of the model that account for these preferences in several ways.

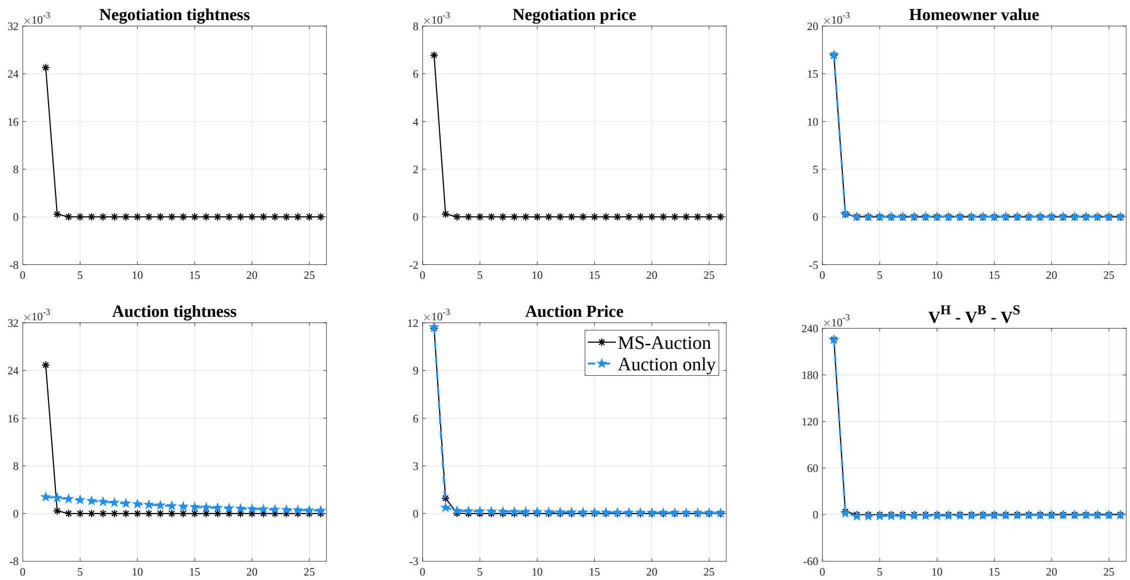
Finally, a third potential source of selection into mechanisms concerns agents who draw their private information *before* choosing a mechanism. A single-mechanism analog is the auction entry model of Samuelson (1985) in which auction participants learn their private valuation before deciding to pay the auction entry cost. Incorporating this type of selection would substantially complicate identification and estimation, and we leave further investigations of the timing of private information revelation to future work.

Appendix F.1. Selection on Home Attributes

We use a Nearest Neighbor (NN) matching algorithm that first identifies the auctions with overlap, and then, for each auction in this sample, identifies the closest NN match of a home sold through negotiation. See Genesove and Hansen (2023) for a full description of the algorithm implementation.

After constructing the matched samples, we estimate weekly log-hedonic price regressions on each matched sample, restricting attention to the 2010–2019 sub-sample, which corresponds to the sample period of the structural auction estimation; results of the match-

Figure E.3: Flow utility shock IRFs



Notes: Impulse response functions for a shock to flow utility. Values on the y-axis are percent deviations from steady state.

ing on price indices and covariate balance are available on request. Panel A of Table F.1 reports results after re-estimating the model using the NN matched prices. The estimates are similar to those of the benchmark model (Table 3).

Appendix F.2. Mechanism Preference Shocks

We use two approaches to understand whether idiosyncratic preference shocks are important. The first posits a model with a substantial degree of idiosyncratic selection but requires that model to have exactly the same steady state as the benchmark model. We then use the time series data to determine whether the benchmark model or the model with substantial idiosyncratic selection is preferred by estimating a weighting parameter on the two models' equilibrium conditions.

The second approach flips the hypothesis. Rather than imposing substantial selection through preferences and the same steady state, we estimate a model that allows for an arbitrary degree of preference selection (converging in the limit to the benchmark model) but relaxes the assumption that the steady state of the two models must be identical. We then examine how mechanism choices respond to moving shocks to investigate the importance of these mechanism preference shocks on mechanism choices and find qualitatively similar dynamic responses.

Consider transitory multiplicative preference shocks ε_t^{jk} to agents of type $k \in \{\text{B, S}\}$ for each mechanism $j \in \{\text{A, N}\}$. Agents on side of the market k now choose mechanism $j_t^k \in \arg\max_j \left\{\varepsilon_t^{jk}\mathcal{V}_t^{jk}\right\}$ for $j \in \{\text{A,N}\}$. Two restrictions, (i) assuming that $\varepsilon_t^{Nk}/\varepsilon_t^{Ak} \overset{i.i.d.}{\sim}$ LogNormal(μ^k, σ^k), and (ii) requiring the same steady state as the benchmark model, suffice to identify the preference shock distributions, i.e., μ^k and σ^k, given the mechanism propensities for buyers and sellers Ψ^{jk} in the benchmark model.[29]

We use this specification to examine whether the time series variation – in mechanism-specific prices, time-on-market, auction clearance rates, and the auction sales share – is more consistent with i.i.d preference shocks or the benchmark model by replacing each equilibrium indifference conditions of the benchmark model with a convex combination of it and the equilibrium mechanism selection condition for the above i.i.d preference shocks:

$$0 = \left(1 - \epsilon^k\right) \underbrace{\left(1 - \frac{\mathcal{V}_t^{Nk}}{\mathcal{V}_t^{Ak}}\right)}_{\text{Indifference equilibrium}} + \epsilon^k \underbrace{\left(\exp\left(\sigma^k \Phi^{-1}\left(\Psi_t^{Nk}\right) - \frac{\left(\sigma^k\right)^2}{2}\right) - \frac{\mathcal{V}_t^{Nk}}{\mathcal{V}_t^{Ak}}\right)}_{\text{Equilibrium with mechanism preference shocks}}$$

where Φ^{-1} is the inverse of the standard normal CDF. This allows us to estimate the model weight parameters $\epsilon^k \in [0, 1]$, one for buyers and one for sellers, noting that as $\epsilon^k \searrow 0$ the data support the model with the indifference equilibrium, and $\epsilon^k \nearrow 1$ they support the alternative model with selection. Beyond the boundary cases, however, there is no structural interpretation to the value of ϵ^k.

The first two columns in Panel B of Table F.1 show the results. The first column imposes an equal weight restriction on the buyer and seller preference shock equilibrium conditions ($\epsilon^s = \epsilon^b$). The second column is unrestricted, allowing for different weights ($\epsilon^s \neq \epsilon^b$). The restricted model finds a weight on the preference shock model of 0.076, implying a benchmark model weight of 0.924, while the unrestricted model places almost zero weight

[29]The time-varying probabilities of choosing negotiation are , for $k \in \{\text{B, S}\}$, $\Psi_t^{Nk} = \Pr\left(\log(V_t^{Ak}/V_t^{Nk}) \leq \sigma^k \log(\varepsilon_t^{Nk}/\varepsilon_t^{Ak})\right)$. Inverting, and imposing $\mu^k = -\frac{1}{2}\left(\sigma^k\right)^2$ to give the preference shock ratio a mean value of one to maintain the original steady state, we have $\frac{1}{\sigma^k}\log\left(V_t^{Nk}/V_t^{AS}\right) + \frac{1}{2}\left(\sigma^k\right)^2 = \Phi^{-1}\left(\Psi_t^{Nk}\right)$ and so we see σ^k is uniquely identified from the steady state $\overline{\Psi}^{Nk}$, since $\overline{V}^{Nk} = \overline{V}^{Ak}$. The mean restrictions uniquely identifies σ^k without re-parameterizing the model.

Table F.1: Estimates with NN Matching and Mechanism Preference Shocks

Panel A: Nearest neighbor matching estimation results

Parameter	Value	Parameter	Value
Persistence		*Standard Deviation*	
Flow utility shock	0.022	Flow utility shock	0.018
ρ_{r^H}	(7.372e-04)	σ_{r^H}	(7.000e-04)
Intracity moving shock	0.991	Intracity moving shock	6.365e-06
ρ_{α^b}	(0.028)	σ_{α^b}	(9.007e-06)
Discount factor shock	0.984	Discount factor shock	2.360e-04
ρ_β	(0.006)	σ_β	(9.029e-05)
		NP meas. error	0.019
		σ_N	(7.763e-04)
		AP meas. error	0.022
		σ_A	(8.625e-04)

Panel B: Mechanism preference shock models

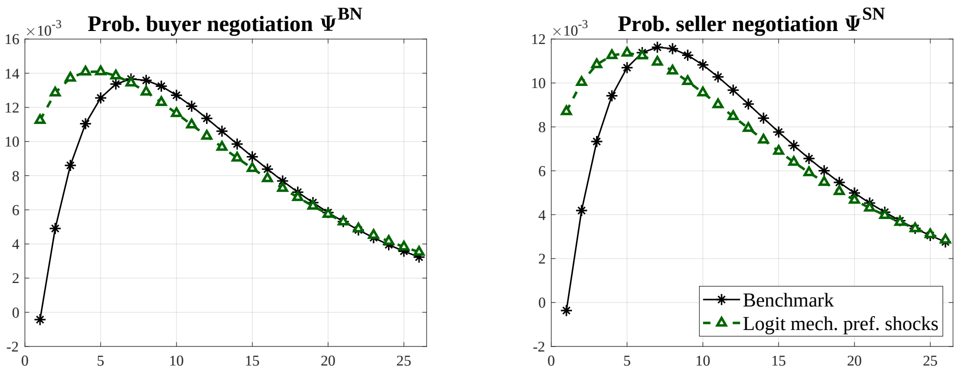
	Log-normal		Logit
	$\epsilon^b = \epsilon^s$	$\epsilon^b \neq \epsilon^s$	$\sigma^b_{\text{logit}} \neq \sigma^s_{\text{logit}}$
Buyer model weight ϵ^b	0.0749	0.0459	
	(0.0080)	(0.0030)	
Seller model weight ϵ^s	0.0749	0.0004	
	(0.0080)	(0.0008)	
Buyer logit σ^b_{logit}			0.0021
			(0.0001)
Seller logit σ^b_{logit}			0.0000
			(0.0005)

Notes: Panel A shows the results of re-estimating the dynamic shock parameters of Table 3 using nearest neighbor matching. Panel B displays estimated selection parameters for models that incorporate mechanism-specific preference shocks. The first two columns show the weight parameters for the restricted (same weight for buyers and sellers) and unrestricted model with multiplicative Log-normal shocks. The final column shows the dispersion parameter estimate for the model with additive Type I EV shocks.

on the preference shock model for sellers and a 0.046 weight for buyers. In both models, substantially greater weight is placed on the benchmark model than the preference shock specification.

The Log-normal specifications impose large dispersion in the mechanism preference shocks due to the distribution's shape. These specifications test whether the time series data is more consistent with our original specification or a specification in which preference shocks are substantial. As a final robustness check, we estimate a third model with random additive, Type I Extreme Value (EV) distribution mechanism preference shocks in which we use the time series data only to estimate the dispersion in mechanism preference shocks, but with the implication that the model's steady state may no longer be identical to that of the benchmark model. This replaces the equilibrium indifference condition with a logit specification for mechanism choice probabilities: $\sigma^k_{\text{logit}} \log(\Psi^{Ak}_t/1 - \Psi^{Ak}_t) = V^{Ak}_t - V^{Nk}_t$, where σ^k_{logit} governs the dispersion parameter associated with the additive Type I EV shocks. We estimate σ^k_{logit} by SMM.

Figure F.1: Moving shocks and mechanism choices with preference shocks



The final column in Panel B of Table F.1 shows the estimated logit dispersion parameters σ^k_{logit} for the model with additive Type I EV mechanism preference shocks. We estimate a seller parameter of less than 0.0001, which is similar to the unrestricted Log-normal model results in suggesting that mechanism preference shocks are unimportant for sellers. The estimated buyer parameter is 0.0021 and is statistically different from zero, suggesting that preference shocks may play some role for buyers. However, the coefficients on their own are relatively uninformative as to the importance of these shocks in determining mechanism choices. To better understand how mechanism choice response in the logit model compares to our benchmark specification, we re-simulate dynamic responses to a moving shock (as in Figure 5) for both the benchmark and the logit mechanism preference shock models. Figure F.1 plots the negotiation mechanism shares Ψ^{BN} and Ψ^{SN} in response to the shock. We find similar responses to the shocks, suggesting that mechanism choice responses to this shock remains similar even after allowing for mechanism preference shocks.

While many avenues remain for examining the effects of preference shocks or other mechanism selection models, a complete investigation of these issues is outside the scope of this paper for several reasons. Firstly, identification is an issue. The mechanism preference shock models above require additional assumptions for identification. While we achieve identification by anchoring these models around the benchmark steady state lacking these preference shocks, such a strategy is geared toward a comparison with our benchmark specification and not a holistic evaluation of these forces in general. Additionally, evaluating the importance of these preference shocks requires comparing their magnitudes to those of aggregate shocks that shift endogenous variables, such as search values. Settings where preference shocks are large relative to movement in values will differ from settings where these shocks are dwarfed by value responses. We leave individual evaluations of each of these effects for future work.

Appendix G. Surpluses are functions of V

We show that the MS-negotiation mechanism surpluses are functions only of $V \equiv V^H(0) - V^B - V^S$ and not of its component parts, where $V^H \equiv V^H(0)$. The proof for auctions is similar. Let $h^B \equiv \frac{1-F}{f}$ and $h^S \equiv \frac{1-G}{g}$. By equation (4) in the text, trade occurs iff $V^H - V^B + v - (1-a)h^B(v) - V^S - c - (1-a)h^S(c) \geq 0$. The increasing virtual utility condition implies $h^{B\prime} < 1$, and so allows us to summarize the trade condition as $v \geq v(c, V, a) \equiv c + (1-a)[h^B(v) + h^S(c)] - V$ and write the condition for a (appearing as the last equation in Appendix A.1 with equality) as

$$\int \int_{v(c,V,a)} (V^H - V^B + v - h^B(v) - V^S - c - h^S(c)) dF dG = V^S + \bar{c} - \int (V^S + c + h^S(c)) dG$$

that is, $\int \int_{v(c,V,a)} (V + v - h^B(v) - c - h^S(c)) dF(v) dG(c) = \bar{c} - Ec - \int G(c)) dc$.

Thus a and so the interim trade probabilities are functions only of V and not its constituent parts. Then by the 'envelope theorem'-like equations (4) and (5) of Myerson and Satterthwaite (1983), we have that the surpluses are likewise functions of V only.

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