# Haggle or Hammer? Dual-Mechanism Housing Search*

Aaron Barkley[a], David Genesove[b], James Hansen[c]

[a]*Department of Economics, The University of Melbourne, Faculty of Business and Economics, Melbourne, 3010, Victoria, Australia*
[b]*Department of Economics, The Hebrew University of Jerusalem, Mount Scopus, Jerusalem, 91905, , Israel*
[c]*Department of Economics, The University of Melbourne, Faculty of Business and Economics, Melbourne, 3010, Victoria, Australia*

**Abstract**

This paper investigates how dual trading mechanisms and incomplete information affect price formation and search. We pose a dynamic search model in which agents can trade by auction or negotiation, with both mechanisms featuring two-sided incomplete information. We apply the model to housing transaction data, using structural auction estimation to recover the distributions of buyer and seller values, primitives that are then used in solving for the equilibrium of the dynamic search model. Adding auctions as a second trading mechanism dampens the response of prices and values to mobility, but not to flow utility, shocks as agents optimally switch between mechanisms. Investigating the effects of information disclosure regulations on sellers, we find that greater information disclosure can benefit sellers and harm buyers in contrast to their intended purpose. Our estimates also highlight how information and efficiency assumptions influence estimated search costs, with estimated seller search costs at negotiation significantly lower under full information Nash bargaining than under incomplete information.

*Keywords:* Auctions, Housing search, Incomplete information bargaining, Price determination, Housing prices, Housing market dynamics, Information disclosure

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*Email addresses:* aaron.barkley@unimelb.edu.au (Aaron Barkley), david.genesove@mail.huji.ac.il (David Genesove), james.hansen@unimelb.edu.au (James Hansen)

## 1. Introduction

Buyers and sellers searching for a trading partner frequently face options over how to transact. A government agency can search for and negotiate with a supplier or organize a procurement auction to complete a project. A pedestrian searching for a driver may hail a passing taxi, or they can choose to be matched via a ride-hailing app. Suppliers face a similar choice to buyers in both of these cases, as well as in the many other settings in which multiple mechanisms operate.[1] Agents in such settings must consider how mechanisms differ when comparing expected surplus across them: How quickly will a counterparty arrive? If a counterparty arrives, what is their trade value, and how should any surplus be divided if trade occurs? And if trade does not occur, what is the continuation value of searching again? Characterizing agents' search behavior requires analyzing these questions for all available mechanisms.

We study how two key features of this environment – the co-existence of mechanisms and imperfect knowledge about the counterparty's trade value – affect search markets. Despite the prevalence of these features across many markets, their consequences on search behavior, price dynamics, and other market outcomes are poorly understood. We pose a dynamic equilibrium search model with two mechanisms – negotiation and auction – in which agents are free to choose the mechanism through which they meet and transact and rationally choose the mechanism with the highest expected payoff. In contrast to the previous equilibrium search literature, we do not assume that agents learn their counterparty's value before trade occurs. Thus, both mechanisms feature two-sided incomplete information. Our empirical application is housing search in Sydney, Australia, a large real estate market where auction and negotiation mechanisms co-exist. We use the estimated model to quantify how dual mechanisms affect pricing responses to shocks, show how incomplete information is informative of the empirical inference of search parameters, and evaluate the effects of information disclosure policies on search outcomes.

We provide three main contributions. First, we demonstrate that the co-existence of mechanisms is theoretically and quantitatively important for assessing price dynamics. In single-mechanism search models, increases in market tightness affect price by increasing sellers' outside option and reducing buyers'. The presence of a second mechanism breaks the identity between market tightness and mechanism tightness, or the buyer-to-seller ratio at each mechanism, thus severing these links between the overall ratio of buyers to sellers in a market and price. Shocks with straightforward effects on market tightness in a single-mechanism setting will be theoretically ambiguous with dual-mechanisms due to the re-sorting behavior of both

[1] The settings in which multiple trading mechanisms operate simultaneously extend beyond government procurement (Bajari et al. (2009)) and ride-hailing (Buchholz (2022), Buchholz et al. (2020)) and include housing (Genesove and Hansen (2023)), mineral rights leases (Covert and Sweeney (2022)), online consumer goods (Einav et al. (2018)), and financial assets (Hendershott and Madhavan (2015)), among others.

buyers and sellers. Our analytical results demonstrate that mechanism tightnesses can either co-move or diverge depending on the change in market conditions, and we characterize settings under which each will occur.

Our empirical results show that these re-sorting effects are quantitatively significant, as we find that mechanism co-existence generates strong dampening effects on price volatility. Compared to a negotiation-only model, allowing buyers and sellers to choose a second mechanism reduces volatility by 34%. This volatility reduction is a natural consequence of agents' movement across mechanisms in response to shocks; for example, when studying a shock to overall market tightness, we find that agents re-sort across mechanisms to reduce the shock's effect substantially. This re-sorting is impossible in a single-mechanism environment, and the market tightness shock has lasting consequences for prices and search values. Incomplete information also dampens price volatility, even without a second mechanism, as incomplete information bargaining exhibits 17% lower volatility than Nash bargaining when both are the sole mechanism.

Second, we show that modeling assumptions on information completeness have quantitatively significant effects on the measurement of key search parameters. Search costs and buyer-seller meeting rates are often estimated or parameterized in models where a single complete information trading mechanism is assumed, usually a Nash bargain. The meeting rate of buyers and sellers required to rationalize observed time-on-market is relatively low in this framework, as trade occurs whenever a positive trade surplus is possible. Incomplete information, in contrast, has trade occurring less often conditional on a buyer-seller meeting, as information frictions prevent some positive-surplus trades. This implies that more buyer-seller interactions are required, given the observed time-on-market. Replacing the incomplete information negotiation mechanism in our benchmark model with complete information Nash bargaining causes a 43% decline in inferred negotiation tightness.

Furthermore, the change in surplus conditional on trade in the presence of incomplete information shifts the search costs required to explain agents' participation. The payoff to a mechanism is the probability of trade times the payoff conditional on trade. The seller's trade probability at negotiations is fixed empirically by the observed time-on-market there; the negotiation payoff conditional on trade is greater under incomplete information than Nash since the trades lost to inefficiency in the former are the lowest surplus trades that occur under the latter. Thus, to explain observed seller participation at each mechanism, we find that the seller negotiation search cost under Nash must be lower by 21% than under incomplete information. Together, these results indicate that correct inference about search behavior and the measurement of search frictions, and so the evaluation of market distortions and welfare, relies on accurately modeling the information environment in which agents trade.

Our third result emphasizes how mechanism co-existence matters for policy. We consider a commonly proposed policy where one side of the market must disclose information that reduces uncertainty about their value from the counterparty's perspective. The goal of these policies is to generate an information advantage for one side of the market to aid them in the price determination process. In housing, disclosure policy commonly requires sellers to provide such information to buyers, such as by disclosing information about the property (Myers et al. (2022)) or by placing constraints on the range of values they can communicate to buyers (Gargano and Giacoletti (2020)).[2] The goal of these policies is to benefit buyers. By forcing a seller to disclose information to the buyer, the buyer can extract a greater share of the information rent available when information is incomplete. This policy works as intended in a single-mechanism setting: prices fall, and buyer search values improve.

When mechanisms co-exist, the results are not so straightforward. In response to the greater buyer information rent, both parties can switch mechanisms. Suppose the returns to buyers from switching to negotiation are sufficiently strong to cause many buyers to choose negotiation, as auctions are not similarly affected by the disclosure requirements. In that case, sellers too may switch to negotiation as there are many buyers, and the probability of trade is high. This re-allocation of buyers and sellers across the two mechanisms in response to the policy causes tightness to increase at both mechanisms if relatively more buyers switch in this way than sellers. The outcome is that buyer search values 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 can depend crucially on whether alternative trade mechanisms exist.

We begin by laying out negotiation and auction mechanisms (Section 2.1).[3] Motivated by growing empirical evidence that complete information fails to explain much real-world bargaining (Backus et al. (2020), Larsen (2021), Larsen and Freyberger (2021), Byrne et al. (2022)) and mechanism design theory that rules out ex-post efficient trade under incomplete information, we model incomplete information bargaining outcomes as generated 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 about their own value to extract rents from the other side, and designs the best direct mechanism that has no need to subsidize agents' participation from outside. The auction mechanism is a second-price sealed-bid auction with optimal seller reserve (Krishna (2009)).

These mechanisms are embedded in a Diamond-Mortensen-Pissarides (DMP) equilibrium search model of durable good transactions (Section 2.2). The model features buyers and sellers of a durable asset who each period choose either an incomplete information negotiation mechanism or an auction mechanism and search for a trade partner within that mechanism. The

[2]Information disclosure policies are common in many markets, including those for health care, education, and finance. See Loewenstein et al. (2014) for a review of this literature.

[3]While we focus on these mechanisms due to their prevalence in housing, the model is easily extendable to others, such as a posted price and auction combination popular in online markets (Einav et al. (2018)).

allocation of agents across mechanisms is determined by the market's ratio of buyers to sellers, mechanism-specific costs of search, flow utilities from asset ownership, and trade probabilities and payoffs from each mechanism. The frequency of transactions in each mechanism is endogenously determined by the evolution of these factors over time, thus shifting the proportion of agents in each mechanism as underlying economic conditions evolve.

Our application to the Greater Sydney metropolitan area residential housing market is described in Section 3. Housing is a large and important market, and its purchase is many households' most important financial decision. Australian real estate markets are particularly attractive for our application as they feature trade via formal, legally defined auctions and negotiations (Genesove and Hansen (2023)), and sellers must publicly choose a mechanism before receiving buyers' offers. While auctions are an institutional feature of Australian markets, auctions may appropriately model trade in other housing markets when multiple buyers arrive at a seller, coexisting alongside bilaterally negotiated sales (Han and Strange (2014)).[4] Finally, 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 (Section 4). The first stage uses structural estimation techniques from the auction literature 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 a seller.

The second stage solves the model with a perturbation-based approach. We embed polynomial-based approximations of simulations from the structural micro estimates into the dynamic equilibrium 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 moments characterizing the distributions of buyer and seller values and the arrival (matching) process of buyers to sellers. These moments are then linked using a standard DMP model of housing search, and we solve for the corresponding rational expectations equilibrium.

There are several advantages to this approach. Because the structural estimates are obtained from data on our population of interest, we directly estimate the decision-making process of individual buyers and sellers within the model and embed these model primitives in an equilibrium framework. This "ground up" approach synthesizes mechanism design theory and structural estimates of individual decisions with a macroeconomic-style equilibrium model, where each part of the model is fit to data from the same population. Also, fitting the simulations to polynomial approximations lets the data govern functional form choices for key distributions governing the transaction process, eschewing distributions chosen solely for analytical

[4] Nevertheless, a crucial aspect of the Australian market that is central to our analysis but missing elsewhere is that at listing time sellers choose whether or not to list their property as an auction, and if so, set an auction date several weeks in the future.

tractability.

The results are presented in Section 5. We first use comparative static simulations using the estimated mechanism models to illustrate the differences between the auction and negotiation mechanisms as values and mechanism tightness change. For example, the extra surplus created by increased buyer values is nearly entirely captured by sellers in the auction mechanism but slightly favors buyers at negotiation. We then give our benchmark steady state parameterization, describing the source of identification for steady state values and parameters, with an accompanying proof of steady state uniqueness in Appendix C. Using estimated parameters governing dynamic shocks, we compute impulse response functions for shocks to the overall buyer-to-seller ratio and the flow utility of homeownership separately for our benchmark dual-mechanism specification and a negotiation-only specification to evaluate the effect of a second mechanism on pricing and mechanism tightness dynamics.

Finally, Section 6 details our counterfactual investigation of information disclosure policies. Policy has increasingly turned to information disclosure in which, for example, sellers must reveal information that reduces buyers' uncertainty about the sellers' values. This policy requires sellers to indicate a "reasonable" price range in the housing market we study. For example, Australian residential real estate listings commonly require the seller to nominate an indicative price range supported by a minimum of three comparable, recently sold properties to justify the range. Information disclosure laws have been applied in other settings, most notably in labor markets, such as a 2022 New York City law requiring firms to provide "good faith" salary ranges for prospective employees.[5] Having incomplete information in our framework allows one to explore such policies in a dynamic search environment. Our findings indicate that such policies should be carefully scrutinized in settings where alternative trade mechanisms operate.

### *1.1. Related literature*

This paper contributes to the study of price determination in search models, empirical studies of markets with multiple mechanisms, and housing search models. It is related, firstly, to empirical studies of multiple trading mechanisms. This literature is partial equilibrium in nature, as it concerns one side of the market's choice between two simultaneously operating mechanisms (Salz (2022), Einav et al. (2018), Gentry and Stroup (2019)).[6] 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 move across mechanisms in response to changing market conditions or economic policy. We demonstrate that considering the cross-mechanism movement of both sides of the market is important for measuring market responses to shocks or policy changes. In our auctions-and-negotiations setting, we consider a policy change that improves negotiations for buyers while leaving auctions unaffected. If

[5]https://www.reuters.com/legal/government/nyc-pay-disclosure-law-aimed-closing-wage-gaps-takes-effect-2022-11-01/
[6]Larsen (2021) is essentially a single mechanism study, as auctions and bargaining are used sequentially.

only buyers can move across mechanisms in response, increasing tightness at negotiation must decrease tightness at auction. However, if both buyers and sellers can respond, the effects are ambiguous, as the resulting mechanism tightnesses could each increase, each decrease, or move in opposite directions, depending on buyers' and sellers' relative responses. Our results show that the movement of both sides of the market can flip the sign of the policy's effects on buyers and sellers relative to the case when only one side of the market can respond.

We also 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), Wheaton (1990), Head and Lloyd-Ellis (2012), Piazzesi et al. (2020), Ngai and Tenreyro (2014), and Ngai and Sheedy (2020). Such papers primarily adopt some version of 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.[7] Unlike these papers, we observe unaccepted offers.[8]

In contrast to the competing mechanism literature (Eeckhout and Kircher (2010)), the mechanisms we consider lack an instrument such as entry fees or posted prices that sellers can manipulate to direct buyers their way. Directed search is crucial to obtaining a single mechanism, or only equally efficient mechanisms, equilibrium outcome for ex-ante homogeneous agents in those models.[9] Not only are such outcomes at odds with observing two fundamentally different mechanisms, but the mechanisms used in this market lack the ability to fully direct buyers. There are no entry fees, and although list prices are used in negotiations, they are not always used, are not used for auctions, and even when used for negotiations, are a noisy 'directing' device given variations in quality (Wang (2011)), and are constrained by regulation of the real estate brokerage industry from deviating too much from expected prices.

Finally, we relate to empirical studies of incomplete information in bargaining environments. This literature primarily uses take-it-or-leave-it offers as the bargaining mechanism, as in Allen et al. (2019) and Silveira (2017). An exception is Larsen and Zhang (2021), which adopts a mechanism design approach to estimating bargaining outcomes. Our contribution to this literature is to include two-sided incomplete information within an equilibrium search model, which allows search costs and continuation (or 'search') values to determine the payoffs to agents when transactions do not occur.

[7] Anenberg (2016) studies sellers learning about the sale value of their homes. Arefeva (2023) studies an equilibrium model of housing search with prices determined by second-price auctions and micro-structure noise.

[8] We are aware of only two other housing research lines with unaccepted offers: Merlo and Ortalo-Magne (2004) and Merlo et al. (2015), who take advantage of the UK rule requiring all negotiation offers be made in writing, and Anundsen et al. (2023), which studies digital platform auctions in Norway.

[9] More than one equilibrium mechanism is possible with ex-ante heterogenous agents, although at least in those papers the mechanisms differ in a listed price, not in form.

## 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 one-period expected surplus for whatever mechanism the agent chooses plus the value of continued search, where the mechanism-specific surplus is relative to the continuation search value. In Section 2.1 we lay out these mechanism-specific expected surpluses, eschewing time subscripts for now to concentrate on the payoffs that are realized when transactions occur.

Once we incorporate these mechanisms into our dynamic search model in Section 2.2, draws of buyer values and seller costs will be interpreted as time-dependent transformations of more basic draws. For sellers, the cost will represent the continuation value of search given a current period realization for the seller's search cost. Buyer values will be determined by 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. The endogenous determination of these continuation values within the dynamic search model is, along with considering both sides of the market, our point of departure from previous studies of dual-mechanism trade (Salz (2022), Gentry and Stroup (2019)).

### *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 buyer bargaining weight $\phi \in [0, 1]$, so that if trade occurs, the buyer pays the seller $\mathcal{P}^E(v, c) = \phi v + (1 - \phi)c$, and 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 payoff for buyers, $\mathcal{W}_n^{EB}$, is thus

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

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 payoff. The expected payoff for sellers, $\mathcal{W}_n^{ES}$, is expressed similarly as

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

*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 both sides of the market have an incentive to use their private information to extract rents from the other party. Specifically, Myerson and Satterthwaite (1983) show that any mechanism with *ex-post* efficient outcomes requires agents' participation 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 allocation rule (e.g., the 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 proscribes 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 $n \geq 2$ buyers to meet with the seller before value realization, a buyer's expected payoff, $\mathcal{W}_n^{NB}$, is

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

and the expected seller payoff, $\mathcal{W}^{NS}$, is

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

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

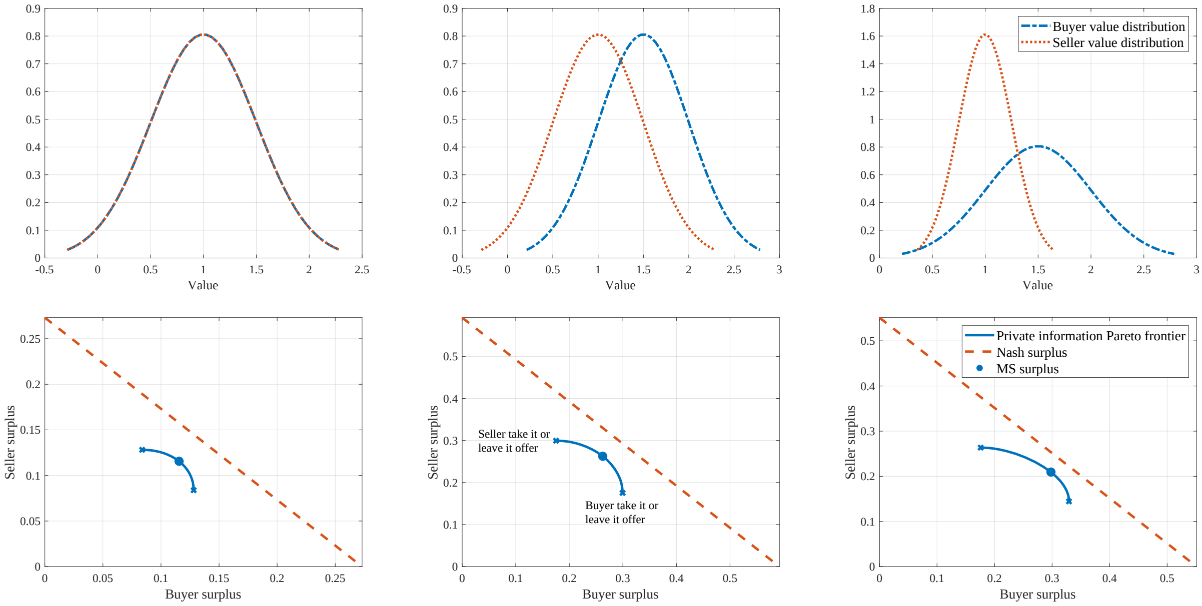
Figure 1 shows how the surplus generated by the MS mechanism compares to Nash bargaining. In panel (a), buyers and sellers have the same distribution. The Nash surplus, represented by the dashed line in the lower half of the panel, can be divided between buyers and sellers based on the Nash bargaining parameter $\phi$ without changing the total surplus. The impossibility result of Myerson and Satterthwaite (1983) implies that this surplus level is unobtainable by an IC and IR mechanism not running a budget deficit, under two-sided incomplete information.

The set of outcomes that maximize the weighted sum of buyer and seller expected surplus subject to, IC, IR and not running a budget deficit is the private information Pareto frontier (Williams (1987)). This frontier extends from the buyer to seller take-it-or-leave-it offers, i.e., from maximum to zero buyer weight. Points above this frontier are inaccessible to any bargaining mechanism when agents have private information, while points below it are Pareto-dominated. In contrast to Nash bargaining, which admits a continuum of first-best outcomes by varying the bargaining parameter, the MS mechanism that equalizes buyer and seller weights is the unique second-best outcome that maximizes expected total surplus.

Panels (b) and (c) show how surplus moves with the distributions. Panel (b) shifts the buyer value distribution to the right. This increases surplus, but does not affect the MS Pareto frontier's symmetry around the 45-degree line, and the MS mechanism continues to generates equal surplus for buyers and sellers. Panel (c) decreases the variance of the seller distribution. This generates a relative information advantage for buyers, who now face less uncertainty about sellers' values than sellers about buyers', tilting the Pareto frontier in their favor. This last case captures the qualitative features of the buyer and seller distributions that we estimate.

**Figure 1:** Buyer and seller surplus in the MS mechanism

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




*Auction*

At each 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

$$\mathcal{R} = c + \frac{1 - F(\mathcal{R})}{f(\mathcal{R})}. \tag{7}$$

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:

$$\mathcal{Q}_n^A(v^{(n)}, c) = \begin{cases} 1 & \text{if } v^{(n)} \geq \mathcal{R}(c), \\ 0 & \text{otherwise.} \end{cases} \tag{8}$$

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, receiving its surplus from the auction plus the outside option value. The expected buyer payoff in an auction with $n$ buyers is

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

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

$$\mathcal{W}_n^{AS} = \underbrace{\Pr(\mathcal{Q}^A(v^{(n)}, c) = 1)}_{\text{Trade prob.}} \times \underbrace{\mathbb{E}\left[\mathcal{P}^A(\mathbf{v}, \mathcal{R}(c)) - c \mid \mathcal{Q}_n^A(v^{(n)}, c) = 1\right]}_{\text{Seller's trade-conditional payoff}} \tag{10}$$

*2.2. Search and Competing Mechanisms with Dynamics*

We embed these mechanisms in a DMP model, allowing for competing mechanisms. This entails interpreting buyer and seller values as reflecting dynamic opportunities, so that $v := \mathcal{V}_t^H(z) - \mathcal{V}_t^B$ and $c := \mathcal{V}_t^{jS}(c^{jS})$, where $\mathcal{V}_t^H(z)$ is the value of a home with quality $z$ to a buyer, $\mathcal{V}_t^B$ is the forgone value of continuing as a buyer when a home is purchased, and $\mathcal{V}_t^{jS}(c^{jS})$ is the seller value with realized (mechanism-specific) search cost $c^{jS}$. The subscript $t$ indexes 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 the beginning of the interval, then draws a mechanism-specific search cost, $c^{jS}$. The probability that $n$ buyers visit a seller at mechanism $j$ is $\gamma_{t,n}^j(\theta_t^j)$ – a function of mechanism tightness[10] and the interval's duration. Stacking these probabilities in vector $\boldsymbol{\gamma}_t^j$, the value of a seller who chooses mechanism $j$ at $t$ and draws search cost $c^{jS}$ is:

$$\mathcal{V}_t^{jS}(c^{jS}) = \beta_t \mathbb{E}_t \left[\boldsymbol{\gamma}_t^j \cdot \mathcal{W}_{t+1}^{jS} + \max_j \left\{\mathcal{V}_{t+1}^{jS}\left(C^{jS}\right)\right\}\right] - c^{jS} \tag{11}$$

where $\beta_t$ is the discount factor (which may be subject to shocks), and $\max_j \left\{\mathcal{V}_{t+1}^{jS}\left(C^{jS}\right)\right\}$ is the maximal value of search at the beginning of the next interval, when a seller is free to re-optimise their mechanism choice, and $C^{jS}$ is the random variable corresponding to the cost of search drawn in the next interval. $\mathcal{W}_{t+1}^{jS}$ is the vector of expected payoffs from trade realised at $t+1$ with $n^{th}$ element, $\mathcal{W}_{t+1,n}^{jS}$, the mechanism-specific payoffs when $n$ buyers visit the seller at mechanism $j$, as defined in Equations (6) and (10). $\mathbb{E}_t[.]$ denotes the rational expectation formed conditional on the aggregate state at the beginning of $t$, and is 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. Stacking these probabilities in vector

[10]This is sometimes called 'queue length' in the competing markets literature (Eeckhout and Kircher (2010)).

$\boldsymbol{\lambda}_t^j$, the value from searching as a buyer through mechanism $j$ is:[11]

$$\mathcal{V}_t^{jB} = \beta_t \mathbb{E}_t \left[ \boldsymbol{\lambda}_t^j \cdot \mathcal{W}_{t+1}^{jB} + \max_j \left\{ \mathcal{V}_{t+1}^{jB} \right\} \right] - c^{jB} \tag{12}$$

where $\max_j \left\{ \mathcal{V}_{t+1}^{jB} \right\}$ 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 payoffs for the buyer with $n^{th}$ element, $\mathcal{W}_{t+1,n}^{jB}$, the expected payoff to the buyer given that $n-1$ other buyers also visit that seller from Equations (5) and (9). $c^{jB}$ is the cost of buyer search through mechanism $j$.

We complete the description of values by identifying the payoffs from home-ownership that accrue to a successfully matched buyer (a homeowner). Homeowners can receive a match-quality shock, with probability $\varphi_t^m$, that dissolves the value of the match with their current home. On receiving this shock, with probability $p^m$ the homeowner becomes a seller only and receives a fixed exogenous payoff (e.g., from exiting the market altogether), and searches to sell their existing home; with probability $1-p^m$, the homeowner becomes both a seller and a buyer, with zero demand for their current home, and unit demand for another home in the market (e.g., moving homes within the same market). The flow utility from homeownership is an affine function of match quality $z$, that is idiosyncratic and drawn at the start of the match and constant for its duration, and thus the value for a matched homeowner is:

$$\begin{aligned} \mathcal{V}_t^H(z) \; = \; & \underbrace{r_t^H + z}_{\text{Ownership flow utility}} + \beta_t \mathbb{E}_t \Big[ \underbrace{\varphi_t^m (1-p^m) \left( \mathcal{V}_{t+1}^S + \mathcal{V}_{t+1}^B \right)}_{\text{Pr(Within-city move)} \times \text{(Buyer + seller value)}} \\ & + \underbrace{\varphi_t^m p^m (\mathcal{V}_{t+1}^S + \Upsilon)}_{\text{Pr(Leave city)} \times \text{Leaving seller value}} + \underbrace{(1-\varphi_t^m)\, \mathcal{V}_{t+1}^H(z)}_{\text{Pr(Remain matched)} \times \text{Homeowner value}} \Big] \end{aligned} \tag{13}$$

where $r_t^H$ denotes the common component of flow utility (potentially subject to aggregate shocks). $\Upsilon$ is the exogenous payoff when exiting the market, and $\mathcal{V}_{t+1}^S := \max_j \left\{ \mathcal{V}_{t+1}^{jS} \right\}$ and $\mathcal{V}_{t+1}^B := \max_j \left\{ \mathcal{V}_{t+1}^{jB} \right\}$ 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,

[11] We place the usual restrictions on the mechanism-specific arrival probabilities with $\lambda_{t,n}^j : \mathbb{R}^+ \to [0,1]$, $\gamma_{t,n}^j : \mathbb{R}^+ \to [0,1]$ 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 $\boldsymbol{\gamma}_t^j$.

we have equilibrium indifference conditions for each side of the market:

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

$$\mathbb{E}\left[\mathcal{V}_t^{NS}\right] = \mathbb{E}\left[\mathcal{V}_t^{AS}\right] \tag{15}$$

that hold $\forall t$. We next account for how the measures of homeowners, buyers and sellers (and thus overall tightness) evolve over time. The measure of homeowners ($\mathcal{H}_t$) evolves as:

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

where $\mathbf{Q}_{t+1}^j$ is the vector of ex-ante probabilities that the buyer acquires the home when visiting the seller at mechanism $j$.[12] The measure of total buyers on the market $B_t$ evolves as:

$$\mathcal{B}_{t+1} = \varphi_t^m (1-p^m)\mathcal{H}_t + I_t + \sum_{j\in A,N} \left(1 - \boldsymbol{\lambda}_t^j \cdot \mathbf{Q}_{t+1}^j\right)\mathcal{B}_t^j \tag{17}$$

$$\mathcal{B}_t := \mathcal{B}_t^A + \mathcal{B}_t^N \tag{18}$$

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

$$\mathcal{S}_{t+1} = \varphi_t^m \mathcal{H}_t + \sum_{j\in A,N} \left(1 - \boldsymbol{\gamma}_t^j \cdot \mathbf{Q}_{t+1}^j\right)\mathcal{S}_t^j \tag{19}$$

$$\mathcal{S}_t := \mathcal{S}_t^A + \mathcal{S}_t^N \tag{20}$$

This completes the model description.

*2.3. Rational Expectations Equilibrium*

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

i. Probabilities $\Psi_t^{jk}$ with which sellers and buyers choose a given trading mechanism $j$ at time $t$ such that they are indifferent to trading through either mechanism in equilibrium (14) and (15);

ii. Allocation rules $\mathbf{Q}_t^j := \mathbf{Q}^j(\mathcal{V}_t^H(z) - \mathcal{V}_t^{jB}, \mathcal{V}_t^{jS}(c^{jS}))$, given the distributions $F_t$ of net homeowner values $(\mathcal{V}_t^H(z) - \mathcal{V}_t^{jB})$ and $G_t$ of seller values, that satisfy (4) and (8) given

[12]Define $x_{t+1} := \{v_{t+1}, c_{t+1}\}$, with joint distribution $J_{t+1}(x_{t+1}) := F_{t+1}(v_{t+1})\,G_{t+1}(c_{t+1})$ defined over $\mathcal{X}_{t+1} := [\underline{v}_{t+1}, \overline{v}_{t+1}] \times [\underline{c}_{t+1}, \overline{c}_{t+1}]$. The $n^{th}$ element of $\mathbf{Q}_{t+1}^j$ is the probability that a buyer successfully trades given $n-1$ other buyers also visited the seller, and is given by $\mathbf{Q}_{t+1,n}^j := \frac{1}{n}\int_{\mathcal{X}_{t+1}} Q^j(x_{t+1})\,dJ_{n,t+1}^j(x_{t+1})$, noting that $Q^j(x_{t+1})$ is the mechanism $j$ trading rule, and that it is integrated over the joint distribution of values for negotiation, $J_{n,t+1}^N = J_{t+1}$. For auctions, the integration is over the CDF of the $nth$-order statistic (given $n$ buyers arrive) and seller values $J_{n,t+1}^A = F_{t+1}^n G_{t+1}$.

the optimal seller reserve at auction (7);

iii. Distributions of values for homeowners, sellers and buyers, $\mathcal{V}_t^H(z), \mathcal{V}_t^{jB}, \mathcal{V}_t^{jS}(c^{jS})$, that satisfy (11) to (13) given the vector-valued payoff functions $\mathcal{W}_t^{jS}, \mathcal{W}_t^{jB}$ and the probabilities of trade , $\boldsymbol{\gamma}_t^j, \boldsymbol{\lambda}_t^j$ ; and

iv. Measures of homeowners, sellers and buyers, $\mathcal{H}_t, \mathcal{S}_t^j, \mathcal{B}_t^j$ that satisfy the laws of motion (16) to (20);

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. Some Intuition on the Model (PRELIMINARY)*

We have written $n$-conditional payoffs and offer arrival rates as arbitrary functions of time in order to emphasize the flexibility of our polynomial smoothing approach. The underlying model at the mechanism level, however, restricts $n$-conditional payoffs to depend on time solely through the *net value* $\mathcal{V} \equiv \mathcal{V}^H(0) - \mathcal{V}^B - \mathcal{V}^S$, so that, so long as 'within mechanism' parameters remain unchanged, we can write, e.g., $\mathcal{W}_t^{AS} = \mathcal{W}^{AS}(\mathcal{V}_t)$. Similarly, a mechanism's offer-arrival rates depends on time solely through mechanism tightness, so that $\gamma_{t,n}^j = \gamma_n^j(\theta_t^j)$ and $\lambda_{t,n}^j = \lambda_n^j(\theta_t^j) = \gamma_n^j(\theta_t^j)/(\theta_t^j/n)$. The cross-mechanism arbitrage conditions (14) and (15) then imply that the equilibrium tightness values $(\theta_t^A, \theta_t^N)$ depend on $\mathcal{V}_{t+1}$ only.[13]

Totally differentiating the buyer and seller arbitrage conditions provides intuition on how the market responds to shocks in the model. For negligible differences in search costs across mechanisms, and considering shocks other than to the buyer arrival rate function, we get

$$\begin{pmatrix} dln\theta^A \\ dln\theta^N \end{pmatrix} = DET^{-1} \begin{pmatrix} -E^{NB} & E^{NS} \\ -E^{AB} & E^{AS} \end{pmatrix} \begin{pmatrix} \Delta W^{S(N-A)} \\ \Delta W^{B(N-A)} \end{pmatrix}$$

where $E^{jk}$ is the elasticity of the payoff from mechanism $j$ for the $k$ side of the market with respect to $\theta^j$, $\Delta W^{k(N-A)}$ the excess of the percentage change in side $k$'s payoffs at negotiation over the auction, and $DET = -E^{AS}E^{NB} + E^{NS}E^{AB}$. Since only one buyer bargains with the seller in negotiation, $E^{NS}$ and $E^{NB}$ are functions of $\theta^N$ only (and not the value functions).[14] Constant returns in the matching function implies that $E^{NS} \in (0,1)$; the relationship between $\gamma$ and $\lambda$ (see footnote 7) implies that $E^{NB} = E^{NS} - 1$, so that $E^{BS} \in (-1,0)$. That in turn implies that auction tightness will be more (less) responsive to buyer betterment at negotiation relative to auction if $E^{NS}$ is greater (less) than one-half.

[13] In the special case of intracity-only mobility shocks, we can subtract equations 11 and 12 for auction (although for negotiation would be just as well) from equation 13 to get a non-linear relationship between $\mathcal{V}_t$ and $\mathcal{V}_{t+1}$

$$\mathcal{V}_t = r_t^H + z + c^{NS} + c^{NB} + \beta_t \mathbb{E}_t \Big[ (1 - \varphi_t^m)\, \mathcal{V}_{t+1}(z) - \boldsymbol{\gamma}_t^A \cdot \mathcal{W}^{AS}(\mathcal{V}_{t+1}) - \boldsymbol{\lambda}_t^A \cdot \mathcal{W}^{AB}(\mathcal{V}_{t+1}) \Big] \qquad (21)$$

[14] $E^{NS} = dln(1 - \gamma_0(\theta^N))/dln\theta$.

So long as sellers benefit from a higher buyer arrival rate at auction and buyers harmed, $E^{AS} > 0$ and $E^{AB} < 0$, so that the 2 by 2 matrix is positive. That in turn implies, for example, that a shock that improves payoffs from the same mechanism relative to the other for both sides of the market will lead to both tightness rates moving in the same direction; which direction depends on $DET$ and so on the exact values of the elasticities. For $\theta^A > \theta^N$ and $E^{NS}(\theta)$ a decreasing function of $\theta$ (the case for the mixed Poisson distribution that fits our data best), and were sellers at auction, like at negotiation, to earn the same with multiple buyers attending as with one only, then $E^{AS} < E^{NS}$. However, since the elasticity of the probability of $N$ buyers arriving increases in $N$, and sellers at auction do earn more with more buyers, the ranking of $E^{AS}$ and $E^{NS}$ is an empirical matter, even given $\theta^A > \theta^N$ and a declining elasticity. As for $E^{AB}$, the relationship between the buyer arrival rate for sellers and buyers suggests that its value is likely to be about 1 less than $E^{AS}$, although how the highest valuing buyer's auction surplus varies with the number of bidders will also have an effect.

## 3. Institutional Background and Data

We apply the model to data from the New South Wales (NSW) housing market, which accounts for one-third of Australian real estate transactions. Recent estimates place the total value of NSW residential real estate at about \$4 trillion Australian dollars with roughly 6% of the stock sold in any given year.[15] Housing is the single largest asset held on household balance sheets, making up just over one-half (54%) of all household assets. As well as being a large market of macroeconomic significance, this market is ideal for studying price formation and search through alternative trading mechanisms, given the substantial use of formal auctions alongside the usual negotiations seen elsewhere.

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

Residential property auctions are regulated under NSW law, which requires that sellers 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 is retained by nearly all sellers. Bidders are required to register before the auction commences. During the auction, the auctioneer solicits increasing bids from bidders 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 by the auctioneer as such, 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

[15] See ABS release "Total Value of Dwellings: Mar 22.

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 sell 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, prior to the auction.[16] If the seller decides to sell to the highest bidder, that bidder wins the auction and pays the winning bid. If the seller decides not to sell, the auction is termed to be passed in. The home may then be listed for sale again through negotiation or auction.[17]

This institutional setting is ideal for studying the dynamic equilibrium effects of incomplete information and multiple mechanisms for several reasons. Negotiation and auction mechanisms operate simultaneously in the market, with each seller selecting a sales mechanism. There is also strong evidence for two-sided incomplete information. Buyers in the market have private information about their preferences for housing and their borrowing capacity, among other factors. Sellers also have private information about their willingness to sell at a particular price.[18] The very use of ascending, open outcry auctions indicates incomplete information, as such English auctions are specifically designed to force bidders to reveal their private values via the drop-out prices. Each sales mechanism has separate procedures, suggesting mechanism-specific costs of search for buyers and sellers.[19] Finally, the market is inherently dynamic, with prices and sales rates responding to economic changes over time.

Several institutional features of the auction market are especially useful: i) before the auction, sellers are required to *privately* commit to a price at which they are willing to sell the home;[20] ii) buyers' offers are publicly disclosed to the seller and other buyers; iii) both the winning bid and the number of bidders are recorded; and iv) the requirement to publicize information about failed auctions implies that we observe data on both successful and unsuccessful auctions. These features, together with standard results from the structural auctions literature, imply that we can identify and directly estimate the distributions of both buyer and seller values for homes, and arrival rates by mechanism.[21]

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

[17]A subsequent successful negotiation may occur on the same day or days or weeks after the auction is held. Our data do not separately record post-auction sales via negotiation. Successful sales, whether via negotiation or auction, require that the buyer provide a deposit, typically 10 percent of the purchase price.

[18]For example, a seller moving to a new home may need to sell before buying a new home. Such a seller will have a higher search cost than a similar seller who has no such sales requirement for moving.

[19]For example, sellers at auction must typically pay an additional fee for the services of the auctioneer.

[20]This must be communicated to the seller's agent or the auctioneer before the auction. As elaborated on below, a seller may lower the price at which they are willing to sell before or during the auction, but may not raise it.

[21]Relatively little is known about the shapes of distributions in buyer and seller values in general. The most common approach is to assume tractable functional forms for these distributions (e.g. uniform or exponential), and then calibrate them to match implied aggregate moments from data.

### 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,[22] and contain records for approximately 47,000 scheduled auctions for Sydney and the broader NSW region between January 2009 and October 2019.[23] 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.[24]

Panel A of Table 1 reports summary statistics on the auction estimation sample; see Appendix B for a full description of its construction. The mean sale price is \$1.31 million AUD and the average sales rate is 73 percent, conditional on at least one bid placed. The mean commitment price is \$1.32 million AUD. On average, auctions with at least one bidder participating have an average 4.41 bidders. Including scheduled auctions in which no bidders participated lowers the average number of bidders to 3.99 and the sale rate to about 65 percent. The data also indicate that sellers' use of the vendor bid frequently results in no sale being made.

**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 |
| $\Delta$log auction price | 0.001 | 0.026 | -0.030 | 0.033 |
| $\Delta$log 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: $\Delta$ log auction (negotiation) price* denotes the weekly change in the estimated log auction (negotiation) price. *Auction sales rate* is the probability with which a home put to auction is successfully sold (the probability of trade for the seller), *Auction sales share* is the share of auction sales in all home sales (auctions plus negotiations), and *Neg. Seller TOM (weeks)* is time on market from first listing to sale for a seller using negotiation measured in weeks.

We combine the auction data with transaction-level data for the universe of sales in the

[22] The data are sourced from Cooley Auctions. See the copyright and disclaimer notices in the Online Appendix.

[23] 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)).

[24] Appendix B discusses sample construction. We exclude (i) withdrawn and postponed auctions and (ii) auctions missing variables used in the estimation, principally the seller's commitment price and the number of bidders.

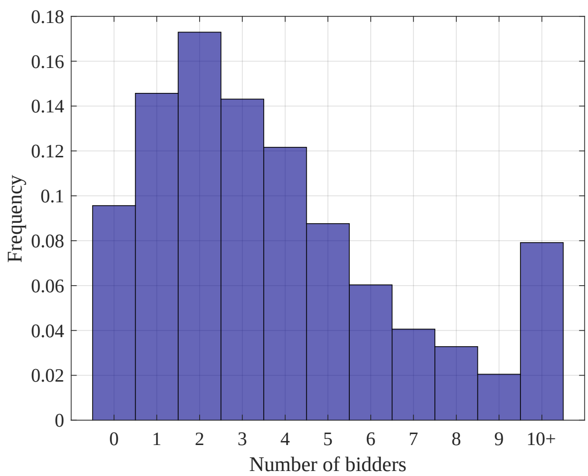
greater Sydney metro area. Summary statistics for this data are given in Panel B of Table 1. These data are sourced from state administrative data merged to listings information that record the sale mechanism, the listing date and the sale date.[25] From this data we compute a weekly distribution of 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 at auction are also common, with slightly under 10% of auctions drawing no bidders and over 14% drawing 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%.

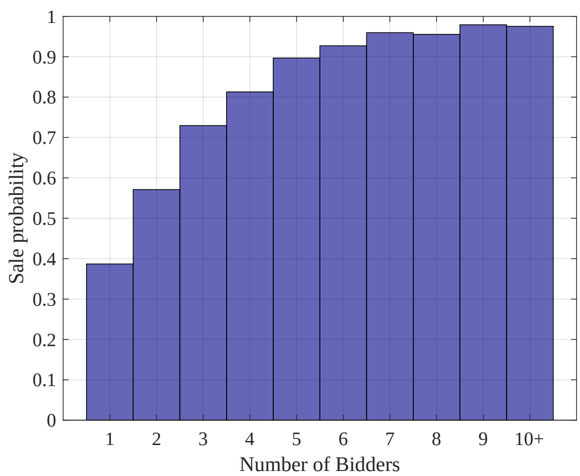
Figure 3 reports the CDF of the high bid divided by the commitment price for all auctions and the sale price divided by the commitment price for successful auctions. Panel (a) shows that the distribution of the high bid over the commitment price in all auctions is close to symmetrically distributed around one, with approximately 7% of the mass at exactly one. A similar jump in the distribution can be seen in panel (b), suggesting that the commitment price serves as an upper bound in some auctions. However, panel (b) also shows that the commitment price is not a binding lower bound, with sales occurring below it in 35% of successful auctions. As noted earlier, if the highest bid meets or exceeds the commitment price, the home always sells.

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

(a): Bidder frequency




(b): Sales rate by $N$




## 4. Parameterizing and Solving the Model

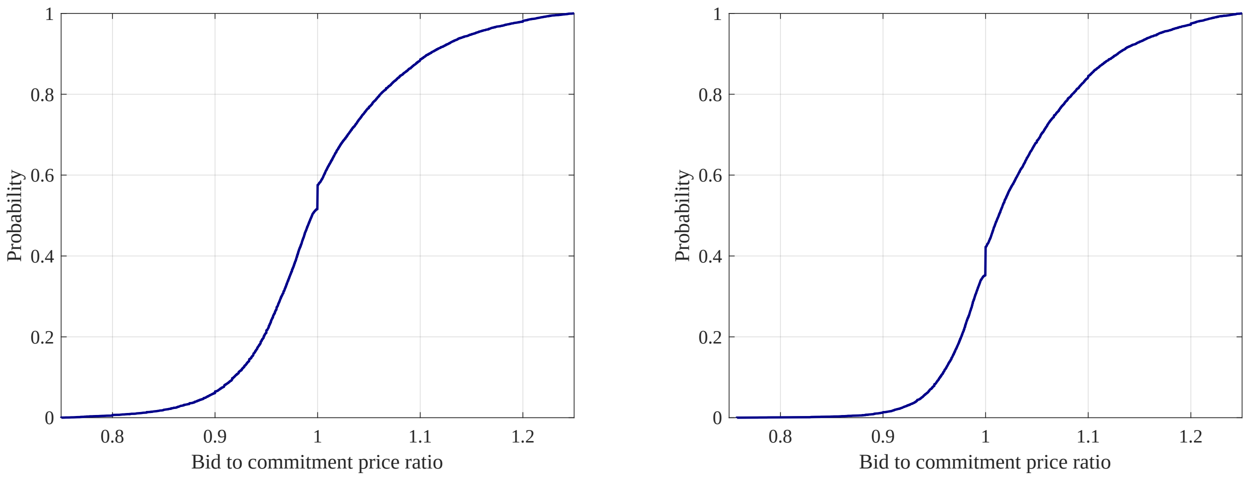
### *4.1. Methodology*

There are two challenges to parameterizing and solving the model. The first is that buyers, sellers and homeowners values comove in response to aggregate shocks. Without unit record

[25] The last is the date that contracts are signed (exchanged) as opposed to the settlement date.

**Figure 3:** CDF of highest bid over commitment price

(a): All auctions (b): Successful auctions




data on either values or offers (or a subset of these data), in general the shape of these distributions and how they might shift over time is unknown.[26] The second is that the functions that characterise expected prices, trade probabilities and payoffs conditional on trade are functions of the distributions of types and, in many cases, require approximation even if the distribution of types were known and there were no aggregate shocks present in the model.

We proceed with a 'ground-up' approach that estimates the model in stages. *Step 1* uses standard structural auctions identification methods to directly estimate the distributions of buyer and seller values, 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, and frees us from conventional simplifying assumptions of tractable parametric distribution shapes (e.g. uniform or exponential). We also estimate the meeting function and steady state tightness at auction. Combining seller time on the market for negotiation then yields steady state negotiation tightness. Finally, mobility rate estimates and setting a discount rate and a flow utility allows us to break apart the mean buyer value $\overline{\mathcal{V}}^H(0) - \overline{\mathcal{V}}^B$ into the mean homeowner value $\overline{\mathcal{V}}^H(0)$ and the buyer search value $\overline{\mathcal{V}}^B$, all at steady state.

*Step 2* uses the models of Section 2.1 to solve for expected (i) price, (ii) trade probabilities and (iii) surpluses conditional on trade, by mechanism, over a grid of values for (a) mechanism tightness rates, (b) mean buyer value, and (c) mean seller value, centred around their steady state values.[27] The grid is chosen to cover empirically plausible ranges of prices, trade probabilities, and surplus, as shown below. Solving the four Bellman equations with these estimates

[26] Athey and Haile (2002) provide an in-depth discussion of data requirements for auctions.

[27] For Auctions and Nash bargaining under negotiation we use (pseudo-) Monte Carlo integration. For MS negotiation, we use numerical (Gauss-Hermite) integration. See Appendix E, for further detail.

at steady state values yields the buyer and mean seller search cost parameters.

*Step 3* uses polynomials to approximate the computed outcomes (i)-(iii) as smooth functions of the grid values of (a)-(c), for each mechanism. We find a simple low-order polynomial regression to be highly accurate.

*Step 4* combines these polynomials with the indifference conditions governing tightness (and so the arrival rate of buyers) by mechanism, the Bellman equations for the value of search, 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 Value Distributions and Buyer Arrival Rates by Mechanism*

To estimate the distributions of buyer and seller values $v := V^H(z) - \mathcal{V}^B$ and $c := V^S(c^S)$ we specify a structural auction model, and estimate it using the auction data and institutional features described in Section 3. The distribution of buyer values is identified using standard auction approaches (Athey and Haile (2002)). The distribution of seller values is identified from vendor bids placed by the seller and the final auction outcome of whether or not sale occurred. Our estimation allows for unobserved home quality using the Roberts (2013) method.

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.[28] 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 components of the likelihood function used in estimation below, where, for clarity, we omit the conditioning on observable characteristics and unobserved home quality; full details of the estimation implementation appear in Appendix D.

Recall that vendor bids are recorded in the data only when it is bid first or last.[29] We observe four types of auction outcomes in the data 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) or above

[28]An English auction, followed in some cases by a take-it-or-leave-it vendor bid offer to the high bidder, is used in practice. This variant of the English auction is analogous to the optimal mechanism in Bulow and Klemperer (1996). As with conditionally independent private values, this is observationally equivalent to a second-price sealed-bid auction with a public reserve price, we can estimate the sealed bid model without loss of generality.

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

the commitment price (case 4).[30] Let $\bar{b}$ be the highest submitted bid in the auction. The log-likelihood for an observation from each of the four cases is represented as

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

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

*Buyer arrivals*

Data on the number of buyers at each auction allows us to estimate the arrival process for auction buyers directly.[31] A Poisson mixture accurately approximates the probability of observing $n$ buyers:

$$\gamma_n\left(\theta^A\right) = \sum_{i=1}^{I} w_i \frac{(\delta_i\theta^A)^n e^{-\delta_i\theta^A}}{n!} \tag{22}$$

where $\sum_i w_i = \sum_i w_i\delta_i = 1$, $w_i \geq 0$, $\delta_i \geq 0$ $\forall i$ and $n \geq 0$. We assume that auction and negotiation buyer arrivals have the same functional form and omit the mechanism superscript in the definition of $\gamma$. This specification generalizes the standard urn-drawing process by adding heterogeneous (e.g., weather) shocks $\delta_i$ 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. Requiring an assumption on the interval length on which buyers and sellers are committed to a mechanism, we assume it to be one week. Appendix D shows how we estimate $\{w_i, \delta_i\}_i$ using an Expectation-Maximization algorithm (Aitkin and Rubin (1985)) with $I = 4$.

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 the auction buyer arrival process. To estimate negotiation market tightness $\theta^N$, we minimize the squared distance between the model-implied per-week 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 take $\hat{F}$ and $\hat{G}$ estimated from the auctions as given. The nonlinear least squares estimator for negotiation tightness is

$$\hat{\theta}^N = \arg\min_{\theta} \| \, \boldsymbol{\gamma}(\theta) \cdot \tilde{\mathbf{Q}} - \widehat{\boldsymbol{\gamma} \cdot \mathbf{Q}} \|$$

[30]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 which was accepted by the buyer.

[31]We assume that arrival depends only on tightness and not on the buyer or seller values.

We again set the period used in estimation to be one week.

*Step 2: Computing price, conditional payoffs and trade probabilities*

With estimates for buyer and seller value distributions, and mechanism arrival rates, the next step is to compute price, conditional payoffs, 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 endogenous variables of which it is a function, the approximating polynomial of $\mathcal{F}$ of order $l$ is $\widehat{\mathcal{F}}_l\left(\mathbf{v}_l;\mathbf{y}\right) := \sum_{|\alpha_{\mathbf{y}}|=0}^{l} \mathbf{v}_{\alpha_{\mathbf{y}}} \mathbf{y}^{\alpha_{\mathbf{y}}}$, 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 $|\alpha_{\mathbf{y}}| = \alpha_1 + ... + \alpha_Y$, $\alpha_s$ the $s^{th}$ element of $\alpha_{\mathbf{y}}$, (ii) multi-index power $\mathbf{y}^{\alpha_{\mathbf{y}}} := \prod_{s=1}^{Y} y_s^{\alpha_s}$, $y_s$ the $s^{th}$ element of $\mathbf{y}$, (iii) $\mathbf{v}_{\alpha_{\mathbf{y}}}$ is the parameter coefficient on polynomial term $\mathbf{y}^{\alpha_{\mathbf{y}}}$ of polynomial approximation $i$, (iv) $\boldsymbol{\nu}_l$ is the stacked vector of polynomial coefficients $\mathbf{v}_{\alpha_{\mathbf{y}}}$, 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. We experimented with different orders of approximation $l$, and found $l = 2$ to be a parsimonious but accurate approximation as shown below and in Appendix E.

Replacing the true functions with their polynomial approximations,[32] 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 model's solution around the steady state with idiosyncratic but not aggregate shocks.

*Step 5: Parameterizing the Dynamic Model*

Let $\zeta$ 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 $\|\mathbf{m}(\zeta|X)\|_{\boldsymbol{\Omega}}$, where $\mathbf{m}(\zeta|X) := \frac{1}{sT-b}\sum_{t=1+b}^{sT} m_t(\zeta) - \frac{1}{T}\sum_{t=1}^{T} m_t(X)$ is the vector difference of the model-implied simulated moments $m_t(\zeta)$ and their sample counterparts $m_t(X)$, $\boldsymbol{\Omega}$ is a symmetric positive definite weighting matrix, $s$ a multiple of the data length used in the simulations used to compute each model-implied moment, 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 $b = 1000$, with simulations that assume independent AR1 dynamic shocks perturbed by Gaussian white noise, and Gaussian white noise measurement errors in auction and negotiation log-prices.[33] For the weighting martix $\boldsymbol{\Omega}$,

[32]This is a required step in general. Unless specific functional forms are assumed for the buyer and seller value distributions (e.g., uniform or exponential), in general these functions have no known analytical representation.

[33]This implies 20 times the sample length simulations, less the first 1000, are used to compute the moments.

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.[34]

## 5. Results

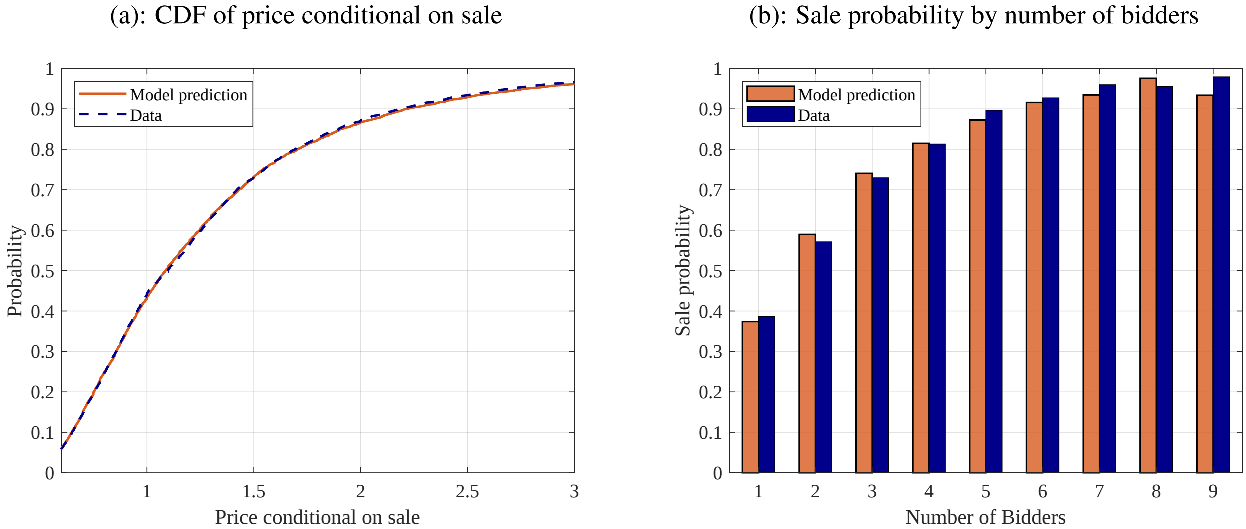
This section describes the results of the model, beginning with the fit of the estimated structural auction model component, with the full table of parameter estimates in Appendix D.

### *5.1. Mechanism Models Results*

#### *5.1.1. Model fit*

Figure 4 shows the 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.

**Figure 4:** Auction model fit – prices and sale probability

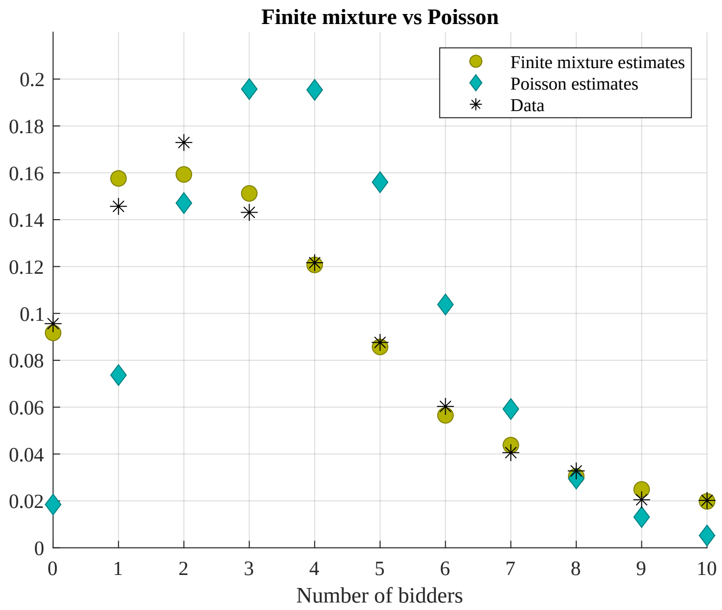



The estimated distribution of the number of bidders at auction is shown in Figure 5. Our finite mixture estimates closely approximate the empirical distribution, capturing the large portion of probability mass associated with low (either zero or one) and high (eight or more) bidder numbers. In contrast, the Poisson distribution fits the data poorly, with too much probability mass near the mean and too little near the tails.

[34]Following Ruge-Murcia (2012) and Newey and West (1994), 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 and consistency when assessing model identification.

Using the finite mixture rather than the Poisson has quantitatively meaningful impacts on implied auction outcomes and illustrates a key advantage of flexibly estimating the micro-level distributions. 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 exact same estimation and simulation procedure but with Poisson distribution estimates implies a 69% sales rate. 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.

**Figure 5:** Distribution estimates for number of auction bidders




*5.1.2. Comparative Static Simulations*

Before demonstrating the empirical results of integrating the two mechanisms into the dynamic equilibrium search model of Section 2.2, we first use the estimated results from the auction estimation, combined with the implied time-on-market in negotiation estimated from the transaction data, to illustrate how the two mechanisms differ in surplus allocation and trade probabilities and values and mechanism tightness change. How buyers and sellers sort across mechanisms in equilibrium is governed by the relative surplus obtained through each mechanism, which responds to the difference between seller values and buyers' net ownership values, which governs the amount of total surplus available, and the mechanism tightness, which determines the rate at which a seller is matched to buyers. In our setting, the mechanisms differ in how the total surplus is divided between buyers and sellers and the rate at which increasing mechanism tightness affects trade probabilities for buyers and sellers. This section demonstrates these differences empirically, and the results of the dynamic search model in Section 5.2 reveal how these differences are balanced across mechanisms and sides of the market in equilibrium to remove any mechanism-specific arbitrage.

Panels (a) and (b) of Figure 6 shows how surplus division and trade probabilities change as the net ownership value for buyers, or $\mathcal{V}^H(0) - \mathcal{V}^B$, increases from the benchmark estimates. Panel (a) shows trade-conditional surplus for MS bargaining and auctions. At auction, use of reserve prices and competition among buyers allows sellers to receive most of the surplus gains that result from increasing buyer net ownership values. MS negotiations, in contrast have a more even division of the extra surplus generated by increasing buyer values, with buyers benefiting slightly more due to the dispersion in their values being higher than that of sellers, giving them an information advantage similar to that shown in Panel (c) of Figure 1.

Panel (b) of Figure 6 shows how trade probabilities, conditional on at least one buyer arrival, change as buyer net ownership values increase. Unsurprisingly, trade probabilities at auction are high for sellers at the benchmark estimates and increase further with higher buyer values. Buyer trade probabilities at auction are reported per-buyer, and so rising buyer values only marginally increase per-buyer trade probabilities at auction holding market tightness fixed. At negotiation, trade probabilities for sellers are slightly higher than that for buyers due to buyer congestion: when multiple buyers arrive at a negotiation seller, the seller choses one at random with whom to negotiate, and the other buyers search again next period. For fixed market tightness, this generates a proportional gap between seller and buyer trade probabilities as buyers' net owernship values rise.

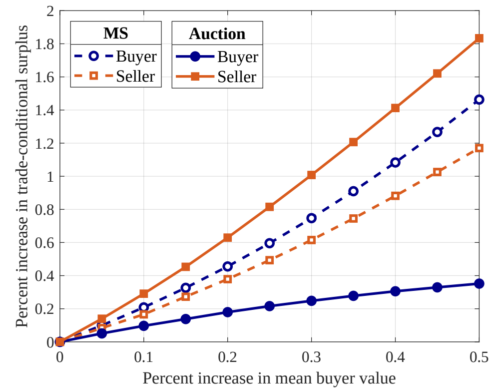
Panels (c) and (d) of Figure 6 investigate how the impact of changing mechanism tightness affects trade-conditional surplus and trade probability at each mechanism. Panel (c) shows trade-conditional surplus as mechanism tightness increases by up to 50% from the estimated steady state levels. Surplus is not affected at negotiation, as the MS allocation rule and payments are determined only by the distribution of buyer and seller values. At auction, sellers benefit from additional competition among buyers induced by greater auction tightness, while buyers surplus goes down as winning buyers pay higher prices. Finally, Panel (d) shows how trade probability at each mechanism changes with increases to market tightness.

### *5.2. Dynamic Search Model Steady State*

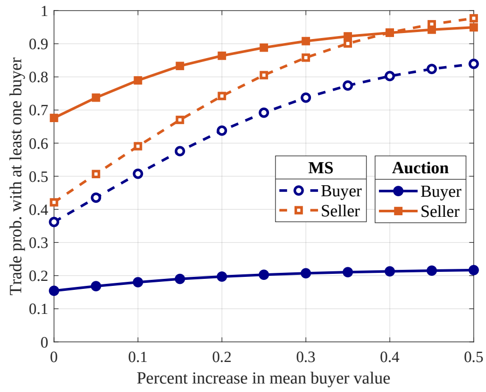
Table 2 reports steady state values for the benchmark MS-Auction model. After calibrating mobility rates and the weekly auction holding probability to match housing transaction or population census data and the weekly buyer search probability to match buyer time on market reported in Gargano et al. (2020), the remaining parameters and values of the model are identified up to a choice for the discount factor and the homeownership flow utility. Appendix C proves this result.

**Figure 6:** Effects of mean buyer value increase

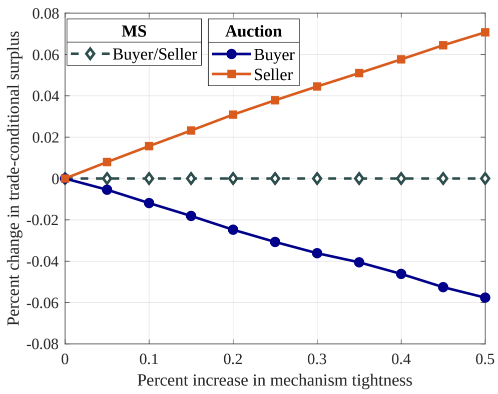
**(a)** Buyer values and surplus



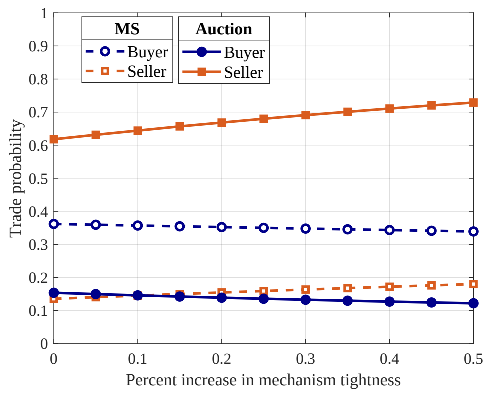

**(b)** Buyer values and trade probability




**(c)** Market tightness and surplus




**(d)** Market tightness and trade probability




Parameters (denoted in the table by P) and steady state values (denoted by S) are reported in Table 2 in the order in which they are estimated or calibrated. Step (i) gives the results for the steady state net ownership value for buyers, the seller search value, and dispersion in match quality and seller search costs, respectively. Step (ii) estimates meeting function parameters and auction tightness. These values are estimated from the auction data following the model of 2.1 and the auction data. Step (iii) combines the meeting function parameters with the transaction data on homes sold by negotiation, along with the MS negotiation model of 2.1, to estimate negotiation tightness.[35] With the seller auction share and the mechanism tightness rates ($\overline{\theta}^A$ and $\overline{\theta}^N$), we obtain a steady-state market tightness of $\overline{\theta} = \overline{\Psi}^{NS}\overline{\theta}^N + (1 - \overline{\Psi}^{NS}) \times \overline{\theta}^A = 1.315$; that it exceeds one will be important for the dynamics.

Step (iv) lists parameters estimated from transaction or census data or assigned. Mobility rates for intracity moves and intercity moves are calibrated to match population census data for NSW. The weekly probability that an auction is held is set to match the time-on-market for

[35]Given the estimated mixed Poisson, the buyer arrival rate for MS-negotiation of 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).

auction sales in the transaction data. Weekly buyer search probabilities are set to match the buyer time-on-market reported in Gargano et al. (2020) for the Australian real estate market. We set a weekly discount factor of 0.9988, which corresponds to an annual housing interest rate of 6% from 2011 to 2019.[36] Flow utility for homeownership is set to 0.0016.[37] Finally, the intercity buyer payoff is set to the buyer search value, and the inflow of new entrants is set to match the intercity mobility rate, as required by the steady state conditions of the model.

Steps (v-vi) report the steady state homeownership 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.

Alongside our main results for the baseline MS-auction model, for comparison, we also present results for an equal bargaining weight Nash-auction model. The results highlight the importance of assumptions on the efficiency of transaction mechanisms for empirical inference about search processes. Search frictions are a crucial determinant of the value from trade, net surplus for participants, and the deviation from competitive outcomes (Satterthwaite and Shneyerov (2007)). The mismeasurement of these search frictions may lead to incorrect assessments of market performance, implying that 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 in our benchmark specification has two main implications. First, implied negotiation tightness is substantially lower, by 43%, under Nash bargaining. Lower negotiation tightness is a natural implication of reducing mechanism inefficiency. Because negotiation tightness is estimated using the transaction data to match the time-on-market for negotiated sales and the fully efficient bargaining mechanism results in trade more often than inefficient bargaining conditional on a buyer-seller meeting, fewer such meetings are required to match the observed time-on-market, and the implied buyer to seller ratio is correspondingly lower.

Second, implied seller search costs at negotiation are lower under the Nash bargaining assumption. This is driven by low-surplus trades that occur with Nash bargaining but would not occur due to information frictions in the MS mechanism. The loss of these trades raises the trade-conditional surplus for MS compared to Nash. The auction remains unchanged, and this, combined with the mechanism indifference condition, implies that all seller value terms in equation (11) 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

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

[37]Flow utility is not separately identified from the costs of buyer search. We set flow utility consistent with an imputed rent of 3.8% per annum plus an occupier premium of 2.5% per annum measured relative to price. Results are robust to alternative calibrations. For example, estimates of the user cost of housing for Australia (that exclude any local match-specific benefit of owning a home), imply an annual user cost of about 5% per annum (Fox and Tulip, 2014).

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 $\beta_t$, and match dissolution (becoming both a buyer and seller) probability $\alpha_t^b := \varphi_t^m(1-p)$, where we assume all shocks independent AR1 processes with Gaussian innovations, and two for the standard deviations of Gaussian white noise measurement errors in the 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.[38]

The SMM estimation sample is 505 weekly observations from 2010W8:2019W44 on 5 observables: the log auction price less the log negotiation price, the change in the log negotiation price, the auction sales rate, time on market for homes sold through negotiation, and the auction sales share.[39] All observables are detrended using a constant and linear time trend prior to estimation, with the exception of negotiation price growth which is simply demeaned. Descriptive statistics for the data underlying these variables (prior to detrending) are reported in Table 1 and graphed in Appendix Figure B.1. Simulated and empirical moments are calculated for all variances, covariances, and autocovariances up to a four-week lag (75 moments in total). The results using the SMM estimator are reported in Table 3.

*5.4. Results from Dynamic Simulations*

We use the dynamic model to examine the importance of dual mechanisms in determining dynamic responses to shocks. Comparing dynamic responses under the benchmark model and a negotiation-only model, which is solved for the same parameters but with auctions removed, shows how a second mechanism opens up an additional margin of response to shocks by allowing participants to move across mechanisms. We find that the presence of a second mechanism dampens price and value responses for mobility shocks, which directly affects the overall ratio of buyers to sellers in the market, but not for shocks for home ownership flow utility.

[38]The controls used in the hedonic regressions (that are fit separately for the auction and negotiation samples) include dummies for week of sale, home type (detached home, cottage, semi-detached, terrace, villa townhouse, apartment, flat, duplex or studio), postcode, and the number of bedrooms and bathrooms both interacted with home type. Weekly fixed effects provide the mechanism-specific prices used in the model estimation.

[39]Time on market via negotiation is measured as time in weeks between the sale date, using the contract of exchange, and the first listing date. The auction sales share is defined as weekly auction sales divided by the sum of weekly auction and negotiation sales. For all observables outliers are removed. Missing observations are imputed using the R package "tsclean" before estimation. Weekly seasonal dummies are included for the public holiday period spanning the last two and first six weeks of the year, with very similar results if not included.

**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 | $\sigma_B$ | 0.1962 | P | Auction Data |
| i | Seller Search Cost Dispersion | $\sigma_S$ | 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 | $\beta$ | 0.9988 | P | Yearly interest of 6% |
| iv | Flow Utility | $r^H$ | 0.0016 | P | 7.2% annual R/P |
| iv | Intracity Mobility Rate | $\alpha^b$ | 0.0011 | P | Population Census |
| iv | Intercity Mobility Rate | $\alpha^s$ | 0.0003 | P | Population Census |
| iv | Holding Auction Probability | $\rho^A$ | 0.1556 | P | Transaction Data |
| iv | Buyer Search Probability | $\rho^B$ | 0.1053 | P | Gargano et al. (2020) |
| iv | New Entrants | $I$ | 0.0003 | P | Steady State Condition |
| iv | Intercity Buyer Payoff | $\Upsilon$ | 0.0729 | P | Steady State Condition |
| v | Homeownership Value | $\overline{\mathcal{V}}^H(0)$ | 1.2685 | S | i-iv, Eqn (13) |
| v | Buyer Search Value | $\overline{\mathcal{V}}^B$ | 0.0729 | S | i-iv, Eqn (13) |
| vi | Mean Seller Auc. Search Cost | $c^{AS}$ | 0.0188 | P | i-iv, Eqn (11) |
| vi | Mean Seller Neg. Search Cost | $c^{NS}$ | 0.0142 | P | i-iv, Eqn (11) |
| vi | Buyer Auc. Search Cost | $c^{AB}$ | 0.0015 | P | i-v, Eqn (12) |
| vi | Buyer Neg. Search Cost | $c^{NB}$ | 0.0045 | P | i-v, Eqn (12) |
| | Nash-Auction Model Estimates | | | | |
| iii | Negotiation tightness | $\theta^N$ | 0.2483 | S | i, Transaction Data |
| v | Mean Seller Auc. Search Cost | $c^{AS}$ | 0.0187 | P | i-iv, Eqn (11) |
| v | Mean Seller Neg. Search Cost | $c^{NS}$ | 0.0113 | P | i-iv, Eqn (11) |
| vi | Buyer Auc. Search Cost | $c^{AB}$ | 0.0014 | P | i-v, Eqn (12) |
| vi | Buyer Neg. Search Cost | $c^{NB}$ | 0.0048 | P | i-v, Eqn (12) |

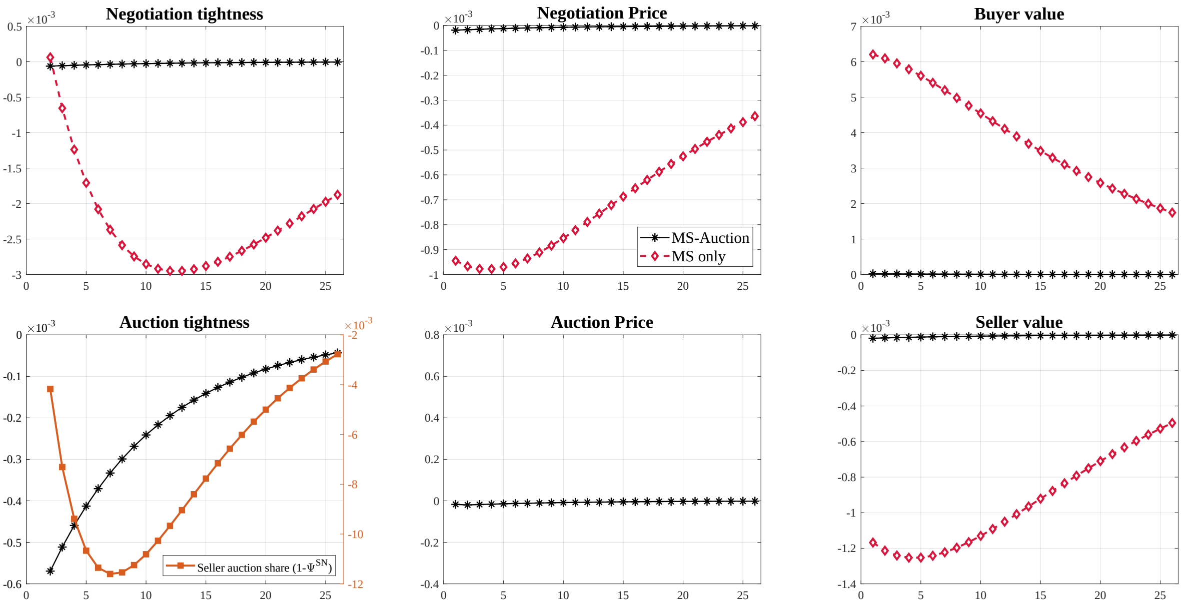
Notes: All parameters are estimated at a weekly search frequency. Type denotes whether the value is a steady state value (S) or a parameter (P). Search costs are reported as a percentage of the overall mean price. The intracity (intercity) mobility rate is defined as $\alpha^b := \varphi^m(1-p^m)$ ($\alpha^s := \varphi^m p^m$). 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.

**Table 3: Estimated Dynamic Shocks**

| Parameter | Value | t-stat | Parameter | Value | t-stat |
|---|---|---|---|---|---|
| *Persistence* | | | *Standard Deviation* | | |
| Flow utility shock | 0.017 | 46.525 | Flow utility shock | 0.021 | 34.062 |
| $\rho_{r^H}$ | (0.000) | | $\sigma_{r^H}$ | (6.241e-04) | |
| Intracity moving shock | 0.898 | 16.859 | Intracity moving shock | 2.418e-05 | 2.817 |
| $\rho_{\alpha^b}$ | (0.053) | | $\sigma_{\alpha^b}$ | (8.584e-06) | |
| Discount factor shock | 0.998 | 965.277 | Discount factor shock | 8.388e-06 | 2.032 |
| $\rho_{\beta}$ | (0.001) | | $\sigma_{\beta}$ | (4.128e-06) | |
| | | | NP meas. error | 0.007 | 18.563 |
| | | | $\sigma_N$ | (3.558e-04) | |
| | | | AP meas. error | 0.021 | 40.180 |
| | | | $\sigma_A$ | (5.135e-04) | |
| | | | J-test statistic of over-identifying restrictions: | 64.486 | |
| | | | p-value of J-test statistic: | 0.564 | |

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 New 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.

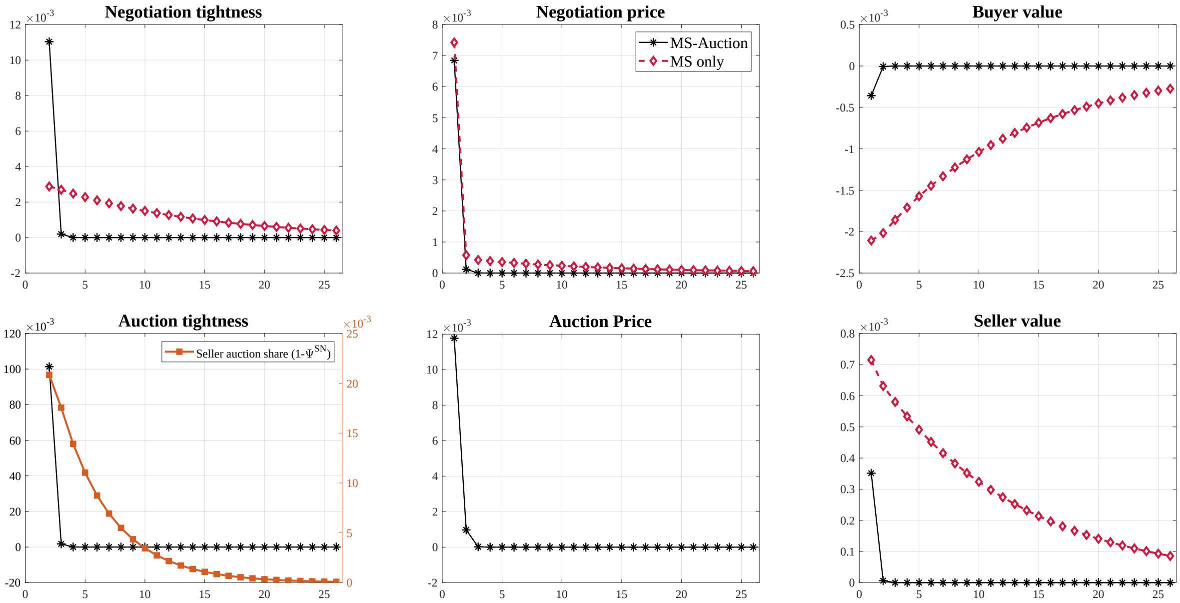
**Figure 7:** Effects of moving shock with and without auction mechanism




### 5.4.1. *Dynamic effects of multiple mechanisms*

Figure 7 shows the effects of a shock that increases the probability of a within-market homeowner move, $\alpha^b$, plotting the percentage deviation from steady-state against the weeks since the shock's onset. The shock increases the measures of buyers and sellers by the same amount, 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 worsen sellers', a deterioration

**Figure 8:** Effects of flow utility shock with and without auction mechanism




in seller's relative bargaining position that lowers price, as is standard.

In contrast, in the dual-mechanism case, the fall in market tightness is accommodated mostly by a shift of both buyers and sellers from auctions to negotiations while keeping the mechanism tightness rates nearly unchanged. (Note the order-of-magnitude greater scale of the seller auction share deviation than for the auction tightness deviation in the 'Auction tightness' figure.) The result is that prices in both mechanisms are nearly completely unaffected by the moving rate shock. Only the extensive persistence in the shock, whose higher future values portend a shorter stay in homeowner status and so reduces its value, prevents the price effect from being fully eliminated by the mechanism shifts of market participants.

The price response to an **ownership flow utility** $r^H$ shock is, by contrast, common to the two models (Figure 8). This shock increases the value of homeownership, but has limited effects on buyer and seller search values, given the shock's small persistence and the forward looking nature of these latter two values. With the increased value to homeownership dominating the change to search values (by two ordrs 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 shift to the less tight mechanism to ensure a constant *market* tightness, which only responds, through the laws of motion, in the subsequent period.

The subsequent dynamics in response to an increase in $r^H$ vary between the models and follow from the higher transactions engendered by the increased value of home ownership during the shock. Higher transactions deplete buyer and seller stocks equally, implying higher

**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 | 0.061 | 0.088 | 0.105 |
| Buyer search value | 0.006 | 0.008 | 0.004 |
| Seller search value | 0.056 | 0.086 | 0.105 |
| Homeownership value | 0.066 | 0.096 | 0.102 |
| Negotiation price | 0.057 | 0.087 | 0.105 |
| Average price | 0.057 | 0.087 | 0.105 |
| Negotiation tightness | 0.011 | 0.016 | 0.016 |
| Seller trade probability | 0.009 | 0.009 | 0.010 |
| Buyer trade probability | 0.021 | 0.021 | 0.025 |
| Auction price | 0.059 | | |
| Auction tightness | 0.101 | | |

than steady state market tightness after the initial shock, given that steady state market tightness exceeds one. For the dual mechanism model, the quick dissipation of the shock quickly returns homeownership and search values back to near steady state values, 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. Thus the seller auction share is abnormally low in the period of the initial shock to accommodate higher mechanism tightness rates and an unchanged market tightness, then abnormally high to accommodate near-steady state mechanism tightness rates but unusual high market tightness, and then converges back to steady state along with market tightness.

When negotiation is the only available mechanism, mechanism tightness is market tightness, and so can only evolve back to steady state relatively slowly with the gradual inflow and outflow of market participants, depressing buyers' search values and elevates sellers'. This explains why these values respond more under the negotiation-only than the dual-mechanism model, and converge more slowly back to steady state.

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 estimated parameters of the model to investigate 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, the NYC law on wage disclosure requires employers to reveal a good faith range of wages an employee could expect to receive, and some housing markets require sellers to reveal an expected price range.[40] These policies' stated purpose is often to help the other side of the market: job searchers in the case of the NYC wage disclosure law and home buyers in that of housing price range requirements.

Sellers providing a more precise signal of their value will certainly benefit negotiating buyers in a static, single-mechanism environment. However, its effect on buyer and seller welfare in a dynamic 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 surplus for sellers, auction sellers may also find switching to negotiation worthwhile. These switches across mechanisms may increase or decrease tightness at either mechanism.

To study the effects of information disclosure policies, we assume that negotiating sellers must reveal additional information about their private value; we leave auctions unchanged. Specifically, each time a negotiation seller draws a private value, the value distribution used in the MS mechanism is a trimmed version of the original distribution. A $\Delta\%$ information disclosure policy trims the supports of the distribution until the remaining support has a total probability of $1 - \Delta$ and truncates the original distribution to these trimmed supports.[41] We assume that the resulting supports depend linearly on the quantile of the seller's value draw. For example, in a 10% information disclosure policy, a seller with a value equal to the median will trim equally from the top and bottom supports, while a seller with a 25th percentile value draw will trim at the 0.025 and 0.925 quantiles of the original distribution; examples of the implementation of the disclosure policy on the seller value distribution used in the MS mechanism are shown below in Figure 9

This information disclosure implementation mimics the stated goals of many such policies, such as providing salary ranges in the case of job search or home price ranges in the case of housing, while allowing us to abstract from the theoretical design of information disclosure mechanisms that are outside the scope of this paper. Importantly, in our model, buyers need not be aware of the specific seller value distribution used by the MS mechanism, provided

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[40]In a related setup regarding worker pay transparency, Cullen and Pakzad-Hurson (2021) study a theoretical model of information disclosure and pay transparency using $k$-double auctions as the transaction mechanism.

[41]Specifically, we define a $\Delta\%$ information disclosure policy as an interval $[\underline{c}^{\Delta}(c), \overline{c}^{\Delta}(c)] \subset [\underline{c}, \overline{c}]$ and distribution $\tilde{G}^{\Delta}$ such that for all seller values $c$ we have $c \in [\underline{c}^{\Delta}(c), \overline{c}^{\Delta}(c)]$, $G(\overline{c}^{\Delta}(c)) - G(\underline{c}^{\Delta}(c)) = \Delta$, and $\tilde{G}^{\Delta}$ is the distribution resulting from the truncation of $G$ to the interval $[\underline{c}^{\Delta}(c), \overline{c}^{\Delta}(c)]$.

**Figure 9:** Implementation of 5% Information Disclosure on Seller Value Distribution

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

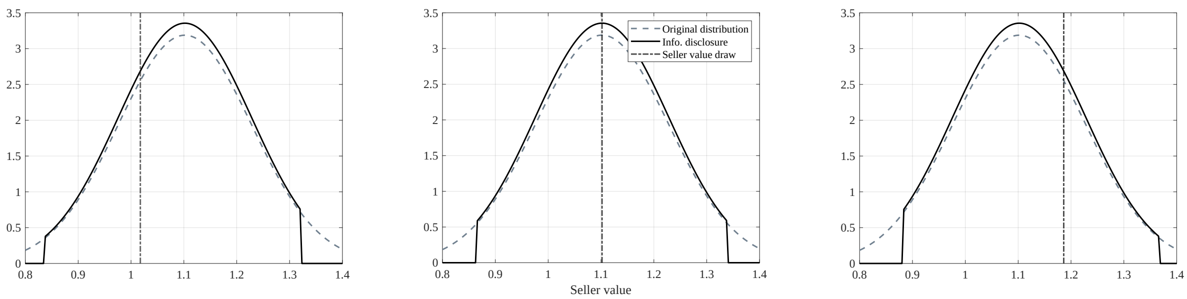


**Table 5:** Information disclosure before and after mechanism re-sorting

| | | 5% Information Disclosure | |
|---|---|---|---|
| | Benchmark Steady State | Fixed Market Tightness | After Re-sorting |
| 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 column imposes information disclosure at negotiation but fixes tightness at each mechanism to the original steady state levels; this shows the effects of information disclosure absent cross-mechanism movement. The last column shows the steady state equilibrium with information disclosure, allowing adjustment to tightness at mechanisms to equilibrate search values across mechanisms.

they 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 the steady state with re-simulated functional approximations of the endogenous variables but unchanged parameters.[42] The steady state solution assigns values for $\{\tilde{V}^H, \tilde{V}^S, \tilde{V}^B, \tilde{\theta}^A, \tilde{\theta}^N, \tilde{B}, \tilde{S}, \tilde{H}, \tilde{\Psi}^{BN}, \tilde{\Psi}^{SN}\}$, the endogenous variables that solve the model equations using the simulated payoffs at negotiation $\tilde{\mathcal{W}}^{Nk}$ after incorporating the information disclosure. To close the model in the counterfactual, we assume a constant total housing supply, or that $\tilde{H} + \tilde{S} = H + S$, and an unchanged inflow of new buyers $I/H$.

The results of a 5% information disclosure policy on negotiation sellers are displayed in

[42]The parameters from the benchmark solution used in the counterfactual policy analysis are the mechanism-specific search costs $c^{jk}$, buyer search probability $\rho$, probability that an auction is held $\gamma_A$, discount factor $\beta$, ownership flow utility $r^H$, intracity mobility rate $\alpha^b$, intercity mobility rate $\alpha^s$, and inflow of new buyers $X/H$.

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 movement across mechanisms. The second column fixes tightness in each mechanism at the benchmark steady state levels and does not allow buyers and sellers to change mechanisms.[43] 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 buyers and sellers to move across mechanisms, as shown in the third column of Table 5. Agent movement causes tightness at both mechanisms to increase relative to the benchmark levels, benefiting sellers, and harming buyers.

**Figure 10:** Equilibrium mechanism indifference with information disclosure

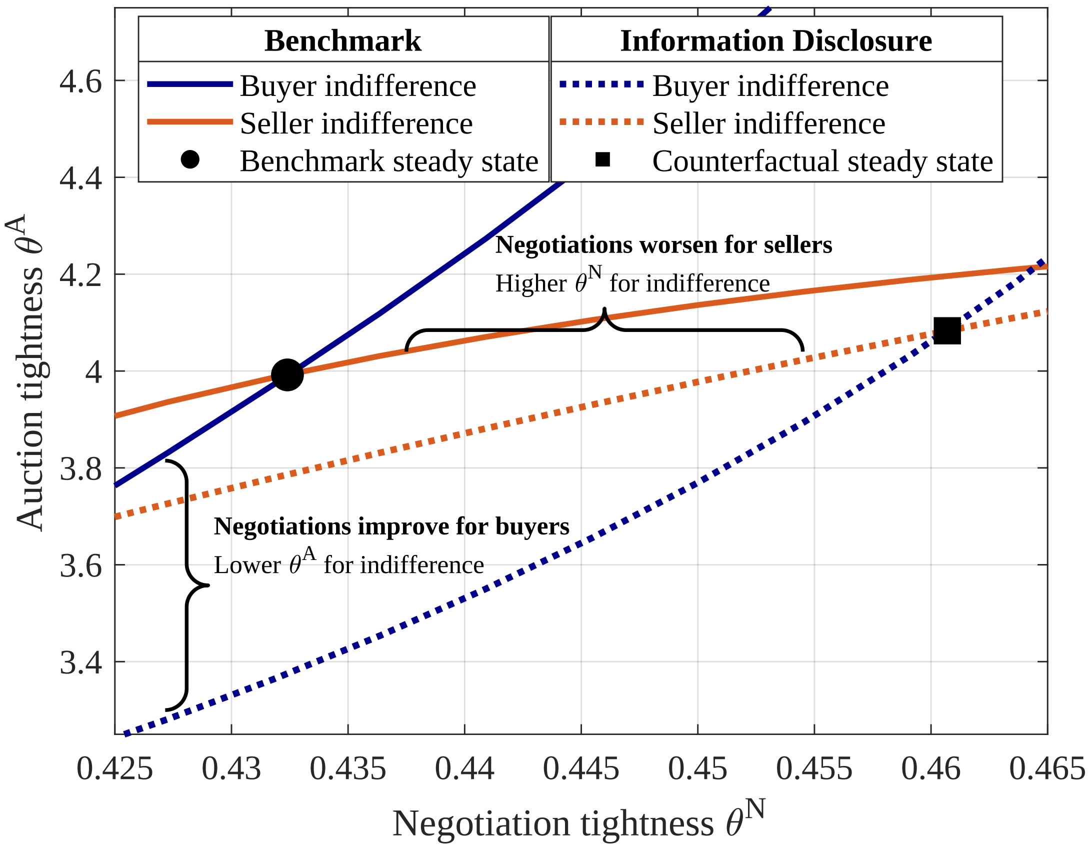


Figure 10 provides intuition by plotting the locuses of the mechanism tightness pairs $(\theta^N, \theta^A)$ that make each side of the market indifferent between the two mechanisms. These indifference curves for the benchmark model show, for each value of $\theta^N$, the $\theta^A$ that ensures mechanism

[43] 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 (13 - 12).

indifference for buyers and that which ensures it for sellers, which we generate by first jointly solving for $V^{NB}$ and $V^{NS}$ using the negotiation value equations (11 - 12), fixing $V^H$ to its steady state level. Both curves are upward sloping, as buyer and seller values are strictly monotonic in mechanism tightness. The intersection of these two curves is a steady state equilibrium.

The information disclosure policy counterfactual shifts the indifference curves for both buyers and sellers down. For buyers, information disclosure at negotiation increases surplus for any given level of tightness. Because higher auction tightness decreases the attractiveness of auctions for them, buyers require a lower auction tightness relative to the benchmark to be indifferent between the two mechanisms. For sellers, the policy reduces negotiation surplus; however, as higher tightness benefits sellers, lower auction tightness is needed to match the reduction in negotiation value, which also shifts the seller mechanism indifference curve down.

The relative magnitudes of these shifts determine the overall change in tightness at each mechanism. Because the downward shift of the buyer curve exceeds that of the seller curve and both curves slope upward, the resulting equilibrium necessarily has higher tightness at each mechanism. For intuition, suppose buyers respond first and sellers adjust after. The large gap between the mechanism indifference curves means many buyers will shift to negotiations to re-equilibrate the buyer value functions. As that will raise negotiation tightness, seller mechanism indifference will also require sellers to move to negotiations. However, the smaller vertical gap between the two seller mechanism indifference curves in Figure 10 implies that relatively fewer sellers move to negotiations than will buyers. This causes tightness at both mechanisms to increase.[44] Table 6 shows that these effects increase steadily with the extent of the policy, as we consider disclosure rates of 5% and 10%, and that mechanism intensity changes with the extent of information disclosure, with auctions accounting 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 markets with frictional search requires one to take into account agents' response by moving across mechanisms. Although the stated goal of these policies is often increased buyer welfare (employee welfare in the case of labor markets), cross mechanism movements may have the unintended consequence of benefiting the information-divulging side at the expense of the intended beneficiaries.

## 7. Conclusion (INCOMPLETE)

This paper formulated 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

[44] To further fix ideas, suppose that overall buyer-to-seller ratio $B/S$ is held constant in the policy. Let $\Delta^B$ denote the measure of buyers that move from auction to negotiation, and $\Delta^S$ that of sellers that move from auction to negotiation. For any $\Delta^B, \Delta^S > 0$ such that $\theta^N < \frac{\Delta^B}{\Delta^S} < \theta^A$, market tightness increases at both mechanisms.

**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 $\Psi^{BN}$ | 0.678 | 0.546 | 0.495 |
| Seller negotiation share $\Psi^{SN}$ | 0.752 | 0.624 | 0.573 |
| Fraction of sales via auction | 0.188 | 0.287 | 0.329 |

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.

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 trade mechanism models may *overstate* the responsiveness of prices to shocks, as agents' movements between mechanisms act as a price dampening device for certain shocks. In single mechanism search models, increases in market tightness affects price by reducing sellers' outside option, and increasing buyers', as well as directly increasing competition for auctions. The presence of a second mechanism breaks the identity between market tightness and mechanism tightness, thus severing these links between the overall ratio of buyers to sellers in a market and price. With a second mechanism, mechanism tightness rates equilibriate to ensure buyer and seller indifference between the two mechanisms, and so are impervious to shocks to the overall market tightness. This leaves price unchanged and leaves sellers' share of auctions to accommodate the change in the buyer to seller ratio. (Indeed, one might have thought that adding auctions, and so the direct competitive effect, might lead to a greater price response, but with auction tightness impervious to such shocks, that is not so.) Demand changes that work through the flow utility of housing do not have this characteristic, and price reacts to such shocks in the manner we would expect from simple demand-supply logic. Overall we find mobility shocks, which directly affect market tightness, of sufficient importance that a second mechanism substantially reduces price volatility.

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

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# Online Supplementary Appendix

## Appendix A. Mechanism description

In this appendix we provide additional description of the mechanisms used in the model, with a focus on the second-best mechanism of Myerson and Satterthwaite (1983). Much of our discussion is adopted from Appendix A of Loertscher and Marx (2022), and we refer readers to their treatment or to Section 5 of Krishna (2009) for a more complete discussion of the mechanism design principles underlying these results.

A direct mechanism takes as inputs each agent's type and outputs an allocation that determines whether trade occurs and payments that determine the amount 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 $Q : [\underline{v}, \overline{v}] \times [\underline{c}, \overline{c}] \rightarrow \{0, 1\}$ and payment functions by $M^j : [\underline{v}, \overline{v}] \times [\underline{c}, \overline{c}] \rightarrow \mathbb{R}$ for each agent $j \in \{B, S\}$. Before continuing, it is useful to define the $a$-weighted virtual type function for each agent type:

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

for some $a \in [0, 1]$.

The payments can be represented by the 0-weighted virtual type functions (Krishna (2009), Section 5.1), so that

$$M^B(v) = v - \frac{1-F(v)}{f(v)}, \qquad M^S(c) = c + \frac{G(c)}{g(c)}.$$

The allocation rule that maximizes surplus without requiring external subsidies to the agents remains to be determined. Intuitively, the solution procedure searches over all rules that do not run a deficit and selects the one that generates the highest expected surplus. The problem is to maximize the equally-weighted expected surplus from buyers and sellers,

$$\int_{\underline{v}}^{\overline{v}} \int_{\underline{c}}^{\overline{c}} \left[\left(v - M^B(v)\right) + \left(M^S(c) - c\right)\right] Q(v, c) dF dG,$$

subject to the no-deficit constraint,

$$\int_{\underline{v}}^{\overline{v}} \int_{\underline{c}}^{\overline{c}} (M^B(v) - M^S(c)) Q(v, c) dF dG \geq 0.$$

The impossibility of obtaining the first-best solution means that the budget constraint always binds – i.e., the Lagrange multiplier $\rho$ on the no-deficit constraint must exceed one.[45] For

[45]Intuitively, if $\rho < 1$, the shadow price of running a deficit is lower than the benefit of transferring money

any given $\rho > 1$, the allocation rule that maximizes expected surplus is given by

$$Q^{\rho}(v,c) = \begin{cases} 1 & \text{if } \Gamma^{1/\rho}(c) \leq \Phi^{1/\rho}(v) \\ 0 & \text{otherwise.} \end{cases}$$

The degree of distortion away from the first best mechanism is captured by $\rho$. If $\rho$ is equal to one, then the $1/\rho$-weighted virtual type functions are equal to the types themselves, and we have the first-best outcome of trade whenever $v \geq c$. As $\rho$ increases above one, the probability that trade does not occur when $v \geq c$ increases. Hence, $\rho$ determines how many positive-surplus transactions do not occur due to information frictions. The optimal allocation rule selects the smallest possible $\rho$ such that the no-deficit constraint is satisfied.[46] Let $\rho^*$ denote this optimal multiplier. Then the allocation rule for the second-best mechanism is defined as

$$Q^{N}(v,c) = \begin{cases} 1 & \text{if } \Gamma^{1/\rho^*}(c) \leq \Phi^{1/\rho^*}(v) \\ 0 & \text{otherwise.} \end{cases} \tag{A.1}$$

Payoff equivalence implies that the expected payoff for an agent is determined by the allocation rule and IC up to a constant term that is the interim expected payoff of the worst-off type for that agent; this is $\overline{c}$ for sellers and $\underline{v}$ for buyers. Let $\hat{u}^B(\underline{v})$ be the interim expected payoff for the worst-off buyer and $\hat{u}^S(\overline{c})$ the payoff for sellers. The second-best mechanism maximizes the equally-weighted surplus for buyers and sellers given by

$$\mathbb{E}_{v,c}\left[(v - \Phi(v) + \Gamma(c) - c)Q(v,c)\right] + \hat{u}^B(\underline{v}) + \hat{u}^S(\overline{c})$$

subject to the no-deficit constraint

$$\mathbb{E}_{v,c}\left[(\Phi(v) - \Gamma(c))Q(v,c)\right] - \hat{u}^B(\underline{v}) - \hat{u}^S(\overline{c}) \geq 0$$

and IR constraints $\hat{u}^B(\underline{v}) \geq 0,\ \hat{u}^S(\overline{c}) \geq 0$. The Lagrangian can be expressed as

$$\rho\mathbb{E}_{v,c}\left[\Phi^{1/\rho}(v) - \Gamma^{1/\rho}(c)Q(v,c)\right] + (1 - \rho + \mu^B)\hat{u}^B(\underline{v}) + (1 - \rho + \mu^s)\hat{u}^S(\overline{c})$$

where $\mu^B$ and $\mu^S$ are the Lagrange multipliers on the IR constraints and as before $\rho$ is the multiplier on the no-deficit condition.

Maximizing with respect to the constant payoffs $\hat{u}^B(\underline{v})$ and $\hat{u}^S(\overline{c})$ implies that $(1 - \rho + \mu^B)$ and $(1 - \rho + \mu^S)$ are equal to zero. Because all Lagrange multipliers must be non-negative,

directly to the market participants via fixed payments, so that surplus is maximized by running an infinite deficit and paying this out directly to buyers and sellers.

[46] I.e., the optimal mechanism selects the smallest $\rho$ such that $\int_{\underline{v}}^{\overline{v}}\int_{\underline{c}}^{\overline{c}}(M^B(v) - M^S(c))Q^{\rho}(v,c)dF_V dF_C \geq 0$.

we require that $\rho \geq 1$ as discussed in Section 2.1. As our focus is on settings in which the impossibility result holds, $\rho > 1$, and, so that the IR constraints bind, $\mu^B, \mu^S > 0$, we can set fixed payoff terms equal to zero. Intuitively, $\rho = 1$ would imply slack in the budget condition, and so the mechanism generated profit, which could be distributed back to agents via fixed payments. When $\rho > 1$ there is no such slack, and guaranteeing positive expected payments to either agent type makes the no-deficit condition even harder to satisfy, lowering efficiency.

*Appendix A.1. Payoffs are functions of V*

We show below that the buyer and seller payoffs for each mechanism are functions only of $V \equiv V^H(0) - V^B - V^S$ and not of its component parts. We use $E^+[X|Y]$ to signify $E[X|X \geq Y]$.

*Appendix A.1.1. Auctions*

As a preliminary step, we show that the deviation of the optimal reserve price at an auction, equivalently, the seller-take-it-or-leave-it offer, from $V^S$ is a function of $V$ only. First note that the reserve price for a seller with search value $V^S + c^S$ is characterized by

$$R = V^S + c^s + h(R - (V^H(0) - V^B))$$

where

$$h \equiv \frac{1-F}{f}$$

is the inverse hazard of $F$, the mean zero buyer quality match distribution. Defining

$$r = R - V^S$$

we get

$$r = c^S + h(r - V)$$

The assumption that buyers' virtual utility is increasing implies $h' < 1$, which in turn implies that $r$ is uniquely defined by this equation, so we can write $r(c; V)$ as the reserve price deviation. To simplify the notation, further define

$$r^+(c, V) = r(c; V) - V$$

Let $v^{(n)}$ is the maximum value and $v^{(n-1)}$ is the second highest. We now show that the probabilities of sale above the reserve ($l_1$) and at the reserve ($l_2$) are functions of $V$. The first case obtains when the second highest buyer's net value (i.e., net of the value of search) exceeds the reserve price, which occurs with the following probability

$$\Pr\{V^H(0) - V^B + v^{(n-1)} \geq V^S + r(c; V)\} = \Pr\{v^{(n-1)} \geq r(c; V) - V\} \equiv l_1^n(V)$$

The second occurs when the second highest value falls below the reserve price but the highest value falls above

$$\begin{aligned}\Pr\{V^H(0) - V^B + v^{(n)} &\geq V^S + r(c;V) \geq V^H(0) - V^B + v^{(n-1)}\} \\ &= \Pr\{v^{(n)} \geq r^+(c,V) \geq v^{(n-1)}\} \equiv l_2^n(V)\end{aligned}$$

so that in expectation the seller facing $n$ bidders is paid (unconditional on sale)

$$l_1^n(V) \times (V^H(0) - V^B + E^+[v^{(n-1)}|r^+(c,V)]) + l_2^n(V) \times (V^S + E[r(c;V)|v^{(n)} \geq r^+(c,V) \geq v^{(n-1)}])$$

The seller does not transact with probability $(1 - \sum \gamma_n(\theta^A)(l_1^n(V)) + l_2^n(V)))$, in which case the seller obtains their search value $V^S$. Combining the event of sale and the event of no-sale, the seller's expected value from going to the auction is

$$\begin{aligned}\sum \gamma_n(\theta^A)\{l_1^n(V)) \times (V^H(0) - V^B + E[v^{(n-1)}|r^+(c,V)] \\ +l_2^n(V)) \times (V^S + E[r(c;V)|v^{(n)} \geq r^+(c,V) \geq v^{(n-1)}])\} \\ +(1 - \sum \gamma_n(\theta^A)(l_1^n(V)) + l_2^n(V))) \times V^S \\ = \\ \sum \gamma_n(\theta^A)\{l_1^n(V)) \times (V + E^+[v^{(n-1)}|r^+(c,V)] \\ +l_2^n(V)) \times (V + E[r(c;V)|v^{(n)} \geq r^+(c,V) \geq v^{(n-1)}]\} + V^S &\equiv W^{AS}(V) + V^S\end{aligned}$$

We now turn to buyers. The chosen buyer's walk-away utility, gross of price and conditional on a sale, at auction is

$$E[V^H(0) + v^{(n)}|V^H(0) - V^B + v^{(n)} \geq V^S + r(\varepsilon^S;V)] = V^H(0) + E^+[v^{(n)}|r^+(c;V)]$$

so that the buyer gets, net of price and conditional on a sale,

$$\sum_n \lambda_n(\theta^A)\frac{1}{n}\times$$

$$\{(V^H(0)+E[v^{(n)}|v^{(n)}\geq r^+(c,V)])\times(l_1^n(V)+l_2^n(V))$$

$$-l_1^n(V)\times(V^H(0)-V^B+E^+[v^{(n-1)}|r^+(c,V)]-l_2^n(V)\times E[V^S+r(c;V)|v^{(n)}\geq r^+(c,V)\geq v^{(n-1)}]\}$$

$$+(1-\sum_n \lambda_n(\theta^A)\frac{1}{n}(l_1^n(V)+l_2^n(V))\times V^B$$

$$=\sum_n \lambda_n(\theta^A)\frac{1}{n}\{(E^+[v^{(n)}|r^+(c,V)])\times(l_1^n(V)+l_2^n(V))$$

$$-l_1^n(V)\times E^+[v^{(n-1)}|r^+(c,V)]-l_2^n(V)\times E[r^+(c,V)|v^{(n)}\geq r^+(c,V)\geq v^{(n-1)}]\}+V^B$$

*Appendix A.2. Negotiation (Myerson-Satterthewaite)*

The transaction condition is

$$V^H(0)-V^B+v-(1-a)h^B(v)-V^S-c-(1-a)h^S(c)\geq 0$$

for some $a$. This can be written as

$$V+v-(1-a)h^B(v)-c-(1-a)h^S(c)\geq 0$$

We can write the condition as

$$v\geq v(c,V,a)$$

To see that $a$ is itself a function only of $V$, note that it is determined by

$$\int\int_{v(c,V,a)}(V^H(0)-V^B+v-h^B(v)-V^S-c-h^S(c))dG=V^S+\overline{c}-\int(V^S+c+h^S(c))dG$$

that is,

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

Thus the interim trade probabilities are functions only of $V$ and not its constituent parts. Then from the 'envelope theorem'-like equations (4) and (5) of Myerson and Satterthewaite, we have that the payoffs are likewise functions of $V$ only.

## Appendix B. Data and Sample Construction

### *Appendix B.1. Auctions microdata*

The auction microdata consists of 50,378 entries in total, sourced from a large real estate auction company headquartered in Sydney, Australia. The data consist of auctions run by this company starting in 2008 until September 2019. After removing properties classified as commercial listings, we are left with a sample of 46,939 total listings.

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 full auction sample, we require complete information on the highest bid, number of bidders, seller's commitment price, auction outcome, date, and region. For the number of bidders sample, we require all of this except the commitment price and highest bid. We also remove the approximately 0.1% of observed auctions with more than 25 bidders. Third, we remove listings with low (<\$500,000) or very high (>\$5 million) highest bids, which correspond to a small percentage of the overall sample. Fourth, we remove any auctions outside of New South Wales. Finally, we trim outliers by removing observations for which the highest bid-to-commitment price ratio falls below 0.75 or exceeds 1.25 – these typically correspond to typos in the price or commitment price entry in the raw data. We are left with 14,482 observations for the full auction sample and 18,203 observations for the number of bidders sample.

We supplement the auction data with a census of all property transactions in the greater Sydney area between 2011 and 2016. The data contains price, location, date first listed, the date a sale was agreed, and sales mechanism type (auction or negotiation). From this data we obtain seller time-on-market by mechanism type.

Steady state weekly moving rates are calibrated to match Sydney and NSW 3-year mobility data published in ABS Catalogue: 3240.0 - Residential and Workplace Mobility, and Implications for Travel: NSW and Vic., October 2008. We fit split (mutually independent) Poisson processes for the arrival of intracity shocks (defined as the sum of Moved within suburb, Moved to different suburb: less than 5km, Moved to different suburb: 5km to less than 20km, Moved to different suburb: 20km to less than 50km) and intercity shocks, (defined as all other moves to the state, i.e. from interstate or from overseas). The latter pins down not only the inflow of new buyers, but the exit rate of sellers as well, as these must be the same in steady state.

### *Appendix B.2. Auctions and Negotiations Sales Data*

We also use an overlapping census of sales transactions for Sydney covering 2010:W8 to 2019:W44 inclusive. These data are sourced from Australian Property Monitors (APM) (see the Copyright and Disclaimer Notics at the end of this Appendix) and cover the same Sydney metropolitan area (i.e., the same postal codes) as the auctions microdata. The transactions data include the sale price, listing date, sales (contract) date, the mechanism of sale, 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. Details of their construction follow.

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

$$\ln P_{hzt}^{j} = \kappa_z^j + \vartheta_t^j + \sum_r H_{hrt}\chi_r^j + \sum_s X_{hst}\delta_s^j + \sum_r \sum_s H_{hrt}X_{hst}\omega_{rs}^j + \nu_{hzt}^j \tag{B.1}$$

where home $h$ is sold in postal code $z$ in week $t$ via mechanism $j \in \{\text{Negotiation}, \text{Auction}\}$. The weekly log hedonic price by mechanism is constructed using the estimates of the $(\vartheta_t^j)$ coefficients. In addition to them, we control for postal (Zip) code $(\kappa_z^j)$ 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 computed using all homes sold at auction divided by the sum of all homes sold via auction plus homes that are passed in at auction (either on a public (buyer) bid, vendor (seller) bid, or where no bids were offered). The auction sales share is computed using the number of homes sold at auction divided by the sum of all homes sold through auction and negotiation. Negotiation seller time on market is computed as the number of weeks from when a home is first listed to it when it is sold (i.e., when a contract of sale is signed). We measure all variables, including prices, on a contract date basis as opposed to settlement dates.

Figure B.1 reports the original source data after outliers are removed using the R-package ”tsclean”.[47] All data are measured a weekly frequency. There are clear seasonal patterns in the data with the auctions sale share dropping sharply in the last weeks of December and the early weeks of January where few, if any auctions, are held. This increases the volatility of log prices (where available) in those periods as well. Negotiations, however, take place throughout the year including in late December and early January holiday period. Prior to 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.

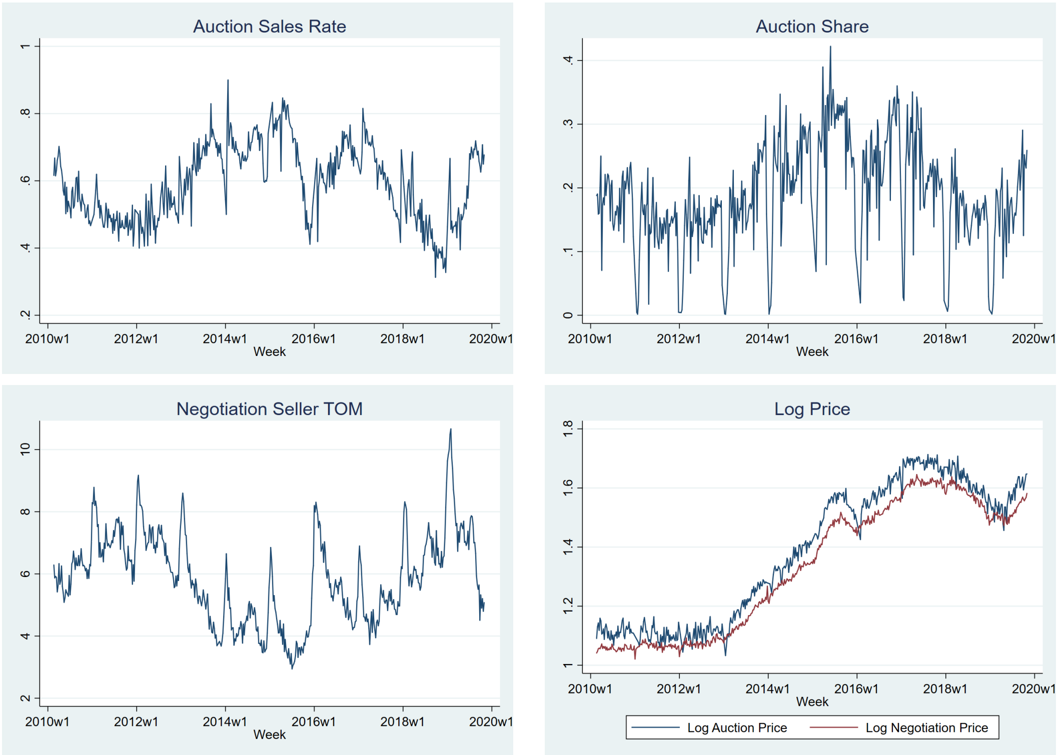
**Appendix C. Identification**

This appendix discusses the identification of the steady-state model parameters. Our main result, Theorem 1, shows that the model is identified up to a choice for the time discount factor $\beta$ and the flow utility from ownership $r^H$.[48] This result is similar to identification results of other dynamic models, such as Arcidiacono and Miller (2020), that show that identification

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

[48] While we assume that other parameters are known in the proof of Theorem 1, we later generalize this result to allow for other data sources to identify these parameters without impacting the main result.

**Figure B.1:** Observables used in SMM Estimation (before detrending)




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

depends upon a choice for the 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 mechanism-specific payoffs, trade probabilities, and market tightness.

**Assumption 1 (Auction mechanism).** *The auction mechanism is an independent private values second-price sealed bid 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 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 $\theta^A$ is auction market 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 market 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 $\beta$, owner match dissolution probability $\alpha^m$, probability of leaving the market $p^m$, ownership flow utility $r^H$, seller auction arrival rate $\rho^A$, and buyer search probability $\rho^B$ are known.*

**Theorem 1.** *The steady-state equilibrium model primitives $B, S$, 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 up to a choice of ownership flow utility $r^H$ by the joint set of bidders at each auction, highest auction bid, and 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 Theorem 1 proceeds in three steps. First, we show that the buyer and seller trade probabilities, auction market tightness, and the distributions of values for buyers and sellers at auction are identified from the data on auction outcomes, the 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 and that the MS mechanism determines negotiation outcomes. Together, these results imply the identification of steady-state mechanism-specific payoffs $\mathcal{W}^{jk}$. Finally, we show that the remaining model steady-state equilibrium parameters, which are the measures of buyers and sellers, the probability that buyers and sellers choose to search in the negotiation mechanism, and the mechanism-specific costs of search for buyers and sellers, 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).** *$\lambda_n^A(\cdot)$, $\gamma_n^A(\cdot)$, $\theta^A$, $F(\cdot)$, 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 assumes that bidders in the auction participate in an ascending English auction until a single bidder remains and that the seller makes a binding take-it-or-leave-it offer equal to the optimal reserve price to the remaining bidder. 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, and adding this data improves the precision of the estimates but does not affect the primary 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 the number of bidders at each auction $n_t$ non-parametrically identifies the probability mass function for bidder numbers at auction. Separately identifying $\theta^A$ and the buyer arrival function $\lambda_n^A(\cdot)$, a necessary first step to determining $\theta^A$ in counterfactuals and outside of steady state, and inferring $\theta^N$, requires a parameterization, however. We use a flexible parametric representation, a finite Poisson mixture distribution. Auction market tightness is identified from the average number of buyers at each auction. Identification of the remaining parameters of the auction buyer arrival distribution function follows from the non-parametric identification of this distribution. Finally, $\gamma^A$ is the pmf associated with $\lambda^A$ conditional on $n_t \geq 1$. ■

**Lemma 2 (Negotiation identification).** *$\theta^N$ 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 of buyers to sellers is determined by the multiplier $\delta^{neg}$ in the negotiation buyer arrival distribution $\gamma_n^N(\theta^N) \equiv \gamma_n^A(\delta^{neg}\theta^A)$. Per-week sale probability is known from the seller time-on-market data, and per-period sale probability is a strictly increasing function of $\delta^{neg}$, holding all other model parameters fixed. This implies identification of $\delta^{neg}$ whenever the per-period seller sale probability implied by the data lies in the interval $[0, \overline{p}^{neg}]$, where $\overline{p}^{neg}$ is the probability of trade at negotiation conditional on a buyer-seller meeting (i.e., when $\gamma_0^N = 0$). The parameter $\delta^{neg}$ determines both negotiation market tightness, $\theta^N = \delta^{neg}\theta^A$, and the matching of a given buyer to a seller $\lambda_n^N(\theta^N)$, which is the pmf associated with $\gamma^N$ conditional on buyer at the set of sellers where $n \geq 1$. ■

**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 $B$, $S$, $\Psi^{Nk}$, and $c^{jk}$ for $j \in \{A, N\}, k \in \{B, S\}$ are identified from the steady-state equilibrium of equations (13-20).*

**Proof.** For simplicity, we assume that $\rho^A = \rho^B = 1$ 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 (11) 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 (12) we have

$$\begin{aligned} V^B &= \beta\lambda^j(\theta^j)\mathcal{W}^{jB} + \beta V^B - c^{jB} \\ \Rightarrow \quad (1-\beta)V^B &= \beta\lambda^j(\theta^j)\mathcal{W}^{jB} - c^{jB}, \end{aligned}$$

and from the ownership value equation (13) we have

$$\begin{aligned} V^H &= r^H + \varphi^m\beta(V^S + V^B) + (1-\varphi^m)\beta V^H \\ \Rightarrow \quad (1-\beta)V^H &= r^H + \varphi^m\beta V^S - \varphi^m\beta(V^H - V^B). \end{aligned}$$

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 the mechanism-specific buyer search costs $c^{jB}$ are identified up to the ownership flow utility $r^H$.

The seller negotiation choice probability $\Psi^{NS}$, buyer negotiation choice probability $\Psi^{NB}$, buyer mass $B$ and seller mass $S$ 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 $\Psi^{NS}$.

By definition, the market tightnesses at each mechanism are

$$\theta^N = \frac{\Psi^{NB}B}{\Psi^{NS}S}, \qquad \theta^A = \frac{(1-\Psi^{NB})B}{(1-\Psi^{NS})S}$$

which, given that we now know $\Psi^{NS}$, can be solved for $\Psi^{NB}$ and the overall market tightness $B/S$. To complete the proof, the steady-state mass of buyers and sellers are then identified from the laws of motion (17) and (19), respectively:

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

■

## Appendix D. Structural Auction Model Estimation

This appendix 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.

From Section 4.1, we parameterize buyer and seller values as Normal distributions with mean and variance determined by auction $k$ covariates and the quality term $\eta_k$:

$$V_k^i \sim \mathcal{N}\left(\zeta_\mu^i X_k^\mu + \alpha_\mu^i \eta_k,\ \zeta_\sigma^i X_k^\sigma + \alpha_\sigma^i \eta_k\right)$$

We assume that home quality $\eta_k$ is observed by all buyers and seller but unobserved by the econometrician. The set of variables determining the mean is $X_k^\mu = [\ell_k, \tau_k, D_k]$ where $\ell_k$ indicates whether the auction took place at the property or in a separate auction room, and $\tau_k$ and $D_k$ are a set of year and region dummy variables, respectively. To economize on the number of estimated parameters, we assume that the variance is time- and space-invariant, so that $X_k^\sigma = [1, \ell_k]$, with unobserved quality $\eta_k$ 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 using the seller's reserve, we use the commitment price as the variable determining the house quality. Specifically, we assume that $\underline{R} = m(\eta_k; X_k)$ for some known function $m(\cdot)$ that is strictly increasing in $\eta$. In estimation, we assume that $m$ is a linear function with the set of variables are $X_k^\mu$ defined above. In making this assumption, we assume 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.[49] Our estimates for the distribution of home quality are not sensitive to this assumption, as we discuss below in Appendix D.1.4. We prefer the method of Roberts (2013) as it has the advantage of generating a point-estimate for the unobserved quality term for each auction. Deconvolution approaches, which are the main alternative to accounting for unobserved heterogeneity, require numerical integration over the distribution of unobserved quality, greatly increasing the computational burden in estimation.

After obtaining estimates $\hat{\eta}_k$, we estimate the parameters $\{\zeta_\mu^i, \zeta_\sigma^i, \alpha_\mu^i, \alpha_\sigma^i\}$ for $i \in \{B, S\}$ using maximum likelihood according to the four likelihood components detailed in Section 4.1. The estimation procedure first establishes an initial guess for all parameters except time dummies $\tau$ and region dummies $D_k$ and the uses the output as the initial guess in estimating all parameters. We find the initial guess and estimate the parameters using the Nelder-Mead

[49] We believe this assumption to be reasonable, as there is no reason for sellers to reveal information about their private value when the commitment price is set – the commitment price is jointly determined 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. Because the commitment price is never revealed to buyers, the seller's incentive is to set the commitment price as high as possible regardless of their private value.

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.

*Appendix D.1. Results and model fit*

*Appendix D.1.1. Parameter estimates*

The estimated parameters are listed in Table D.1.

**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.

*Appendix D.1.2. Buyer arrival parameters*

We estimate the distribution over the number of buyers $N$ at auction $n$ using a finite Poisson mixture with four groups. Our estimation procedure follows the standard EM algorithm applied to finite mixture models (e.g., Aitkin and Rubin (1985)). For a given set of parameters $\delta, w$, where $\delta$ is the vector of Poisson parameters and $w$ is a vector of mixture weights, we compute the type expectation $Z_{ti}$ for each observation $t = 1, ..., T$ and type $i = 1, .., 4$ as

$$\mathbb{E}[Z_{ti}|N, \delta, w) = \frac{w_i f(N_t|\delta_i)}{\sum_{k=1}^{4} w_k f(N_t|\delta_k)}$$

We then maximize the expected log likelihood with respect to parameters $\delta, w$, i.e., maximize

$$\sum_{t=1}^{T}\sum_{i=1}^{4} \ln(f(N_{ti}|\delta_i)\mathbb{E}[Z_{ti}|N, \delta, w] + \sum_{t=1}^{T}\sum_{i=1}^{4} \ln(w_i)\mathbb{E}[Z_{ti}|N, \delta, w].$$

We then re-compute the expectation using the updated values for the $\delta, w$ parameters. We iterate until the difference in the likelihood between steps is smaller than $10^{-5}$.

**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.

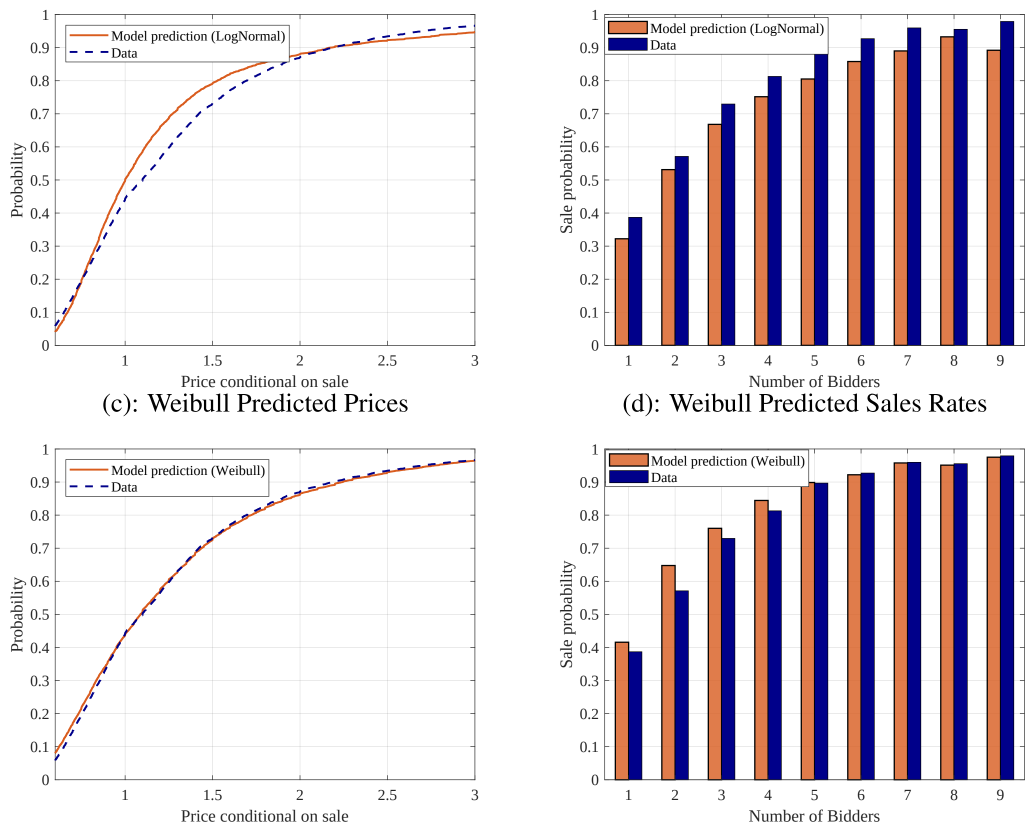
The results are presented in Table D.2, with confidence intervals generated by the asymptotic distribution for the maximum likelihood estimator.

*Appendix D.1.3. Alternative parametric specifications*

Figure D.1 shows the same fit measures of Figure 4 applied to estimated results using the Lognormal distribution (Panels (a) and (b)) and the Weibull distribution (Panels (c) and (d)) for buyer and seller value distributions. The Lognormal specification incorrectly generates the predicted distribution 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.

**Figure D.1:** Auction Model Fit with Alternative Specifications

(a): Lognormal Predicted Prices (b): Lognormal Predicted Sales Rates



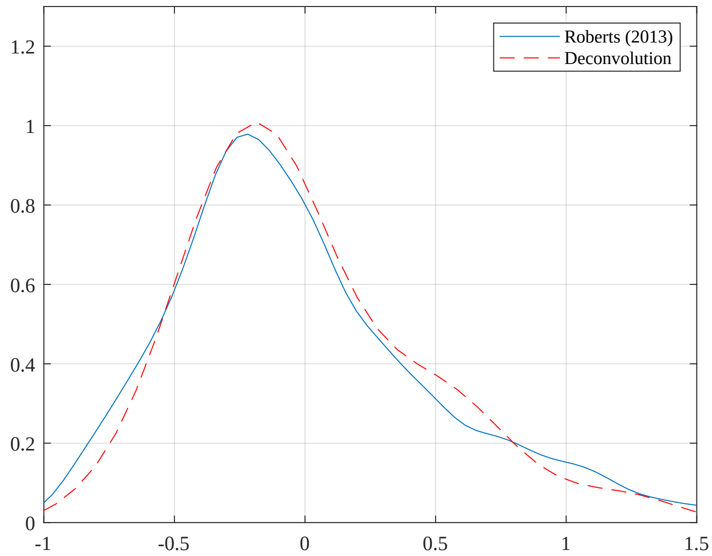

(c): Weibull Predicted Prices (d): Weibull Predicted Sales Rates

*Appendix D.1.4. Estimating unobserved housing quality*

Our estimation procedure uses the approach of Roberts (2013) to account for unobserved housing quality. For a robustness check, we also estimate the distribution of unobserved housing quality using deconvolution methods following Freyberger and Larsen (2020) and 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 house 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.

Results for the two methods are displayed in Figure D.2. Both methods generate a similar distribution of unobserved housing quality. In estimation we use the Roberts (2013) method as it generates point estimates of the unobserved quality component for each auction, greatly reducing the computation burden of estimation. This compares to the distributional estimates for deconvolution, which one would need to integrate over for each observation.

**Figure D.2:** Comparing unobserved housing quality distributions




## Appendix E. Simulations and Polynomial Approximation

This appendix describes the output from the polynomial approximations using simulated outcomes for auctions and negotiations, with the latter described for both complete information Nash bargaining and incomplete information via the MS 2nd best mechanism.

### *Appendix E.1. Estimating offer arrival rate for negotiation*

First, we estimate the offer arrival rate for homes listed for sale by the negotiation mechanism using the output from data on Sydney time-on-market for negotiated sales to infer the meeting rate, which gives a per-week sale probability of 0.1361. Specifically, we use the simulated sale probability to perform a method of simulated moments estimation which chooses the multiplier $\xi_{neg}$ affecting all Poisson arrival rate parameters $\lambda$ from equation (22) to minimize the squared distance between the monthly sales rate implied by the model and the weekly sales rate. 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. Parameters and function arguments*

Both mechanisms use parameters for the buyer's mean value, the seller's mean value, and a shock to the arrival rate.

For the buyer's and seller's values, the grid space takes the mean (for any given reserve) and adds between -0.15 (minus AUD$150,000) and 0.15 (plus AUD$150,000).

For the arrival rate, the grid consists of a multiplier to the base arrival rate that ranges from 75% of the original value to 125% of the original value. In all cases the multiplier applies to each of the Poisson parameters but *not* to the associated probabilities. That is, if we have a finite Poisson mixture with mixture probabilities $w_k$ for $k = 1, 2, 3, 4$ and Poisson parameters $\delta_k$ for $k = 1, 2, 3, 4$, then the multiplier term $\xi \in [0.75, 1.25]$ generates a new finite mixture with the same mixture probabilities $w_k$ but distinct Poisson parameters $\xi\delta_k$ for $k = 1, 2, 3, 4$.

Finally, the negotiation mechanism also uses the bargaining power term $\psi$ as a parameter. While we estimate polynomials over a grid for $\psi$, in using the simulation output we assume $\psi = 0.5$ to mirror the equal weights for buyer and seller surplus in the MS mechanism.

*Auction polynomials*

*I. Link to the dynamic model*

The equations approximated by the polynomials are 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 zero buyers arrive at the auction.

*Price conditional on sale:* Let $\boldsymbol{\mu} := [\mu_B, \mu_S]$ and $\boldsymbol{\sigma} := [\sigma_B, \sigma_S]$ denote the vectors of means and standard deviations of buyer and seller values, and $H(r^A(\boldsymbol{\mu}, \boldsymbol{\sigma}))$ denote the distribution over the optimal reserve price $r^A(\boldsymbol{\mu}, \boldsymbol{\sigma})$. The expected price conditional on $n$ buyers at auction is

$$P^A(n) = \int_0^\infty \frac{\left[\int_{r^A}^{\overline{v}} vn(n-1)[1-F(v)]F^{n-2}(v)\,dF(v) + r^A n\left[1-F\left(r_t^A\right)\right]F^{n-1}\left(r^A\right)\right]}{1-F^n(r^A)} dH(r^A) \tag{E.1}$$

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 $F_{\mu_B}$; 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 determined by parameters $\{w_i, \delta_i\}_{i=1}^4$, where $w_i \equiv \text{Pr}(\delta = \delta_i)$ and the $\delta_i$ are the Poisson parameters.

$$\mathbb{E}[P^A] = \sum_{n=1}^{\mathcal{N}} \sum_{i=1}^{4} w_i \text{Pr}(N = n | N \geq 1, \delta = \delta_i \theta^A) P^A(n) \tag{E.2}$$

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 $\mu_B$, (ii) the mean of the seller cost distribution $\mu_S$, and (iii) market tightness $\theta^A$ as described above. It treats the standard deviations of buyer and seller distributions (governing idiosyncratic heterogeneity) as fixed and does not alter the distributions over the Poisson parameters in the mixture distribution.

*Probability of sale:* The probability of sale for a given seller, $\mathcal{TP}^A$, is given by

$$\mathcal{TP}^A = \sum_{n=0}^{\mathcal{N}} \sum_{i=1}^{4} w_i \frac{(\delta_i \xi \theta^A)^n e^{-\delta_i \xi \theta^A}}{n!} \int_0^\infty \left(1 - F_{\mu_b}^n \left(r^A\right)\right) dH(r^A(\mu_s; \mu_b)) \tag{E.3}$$

Again, this object depends on the distribution of buyer values (which determines $F$), the distribution of seller values, which determines $r_t^A$, and the arrival rate of buyers. We simulate values for the sale probability $\widetilde{\mathcal{TP}}^A$ by varying the distribution means and arrival rate multiplier

$$\widetilde{\mathcal{TP}}^A(\boldsymbol{\mu}, \xi; \mathbf{c}, \mathbf{w}, \boldsymbol{\theta}, \boldsymbol{\sigma}) := \sum_{n=0}^{\mathcal{N}} \sum_{i=1}^{4} w_i \frac{(\delta_i \xi \theta^A)^n e^{-\delta_i \xi \theta^A}}{n!} \int_0^\infty \left(1 - F_{\mu_b}^n \left(r^A\right)\right) dH(r^A(\mu_s; \mu_b)) \tag{E.4}$$

*Buyer match probability:* The probability that a negotiated buyer trades with a seller $\frac{1}{n}\text{Pr}(N = n|N \geq 1) \times \text{Pr}(v^{(n)} \geq r_t^A)$, that is, the probability that a given buyer has the highest value out of $n$ buyers conditional on $N \geq 1$, which with independent values is $1/n$, times the probability that the highest value exceeds the seller's reserve.

$$\sum_{n=1}^{\mathcal{N}} \sum_{i=1}^{4} w_i \text{Pr}\left(N = n|N \geq 1, \theta = \delta_i \xi \theta^A\right) \frac{1}{n} \int_0^\infty \int_{\underline{v}}^{\overline{v}} 1\{v^{(n)} \geq r^A\} dF_{\mu_b}^n(v) dH_{\mu_s}(r^A)$$

*Buyer value conditional on trade:* For a given number of bidders $n$, the expected auction buyer value conditional on trade in the auction is given by

$$E[v \mid N = n, v \geq \max\{v^{(n)}, r^A\}]$$

where the expectation is taken over the seller's reserve price and the joint distribution of the $n$ buyer value order statistics. Integrating over the number of bidders gives the unconditional expected auction buyer value conditional on trade $\widetilde{\mathcal{BV}}^A$ as

$$\widetilde{\mathcal{BV}}^A(\mu_b, \mu_s, \xi) = \sum_{n=1}^{\mathcal{N}} \sum_{i=1}^{4} w_i \text{Pr}\left(N = n|N \geq 1, \theta = \delta_i \xi \theta^A\right) \frac{\int_0^\infty \int_{\underline{v}}^{\overline{v}} v^{(n)} 1\{v^{(n)} \geq r^A\} dF_{\mu_b}^n(v) dH(r^A)}{\int_0^\infty \int_{\underline{v}}^{\overline{v}} 1\{v^{(n)} \geq r^A\} dF_{\mu_b}^n(v) dH(r^A)}$$

*Seller value conditional on no trade:* The expected auction seller value conditional on no trade, $\widetilde{\mathcal{SV}}^A$ is given by

$$\widetilde{\mathcal{SV}}^A(\mu_b, \mu_s, \xi) = \sum_{n=1}^{\mathcal{N}} \sum_{i=1}^{4} w_i \text{Pr}\left(N = n|N \geq 1, \theta = \delta_i \xi \theta^A\right) \frac{\int_{\underline{c}}^{\overline{c}} \int_{\underline{v}}^{\overline{v}} c 1\{v^{(n)} < r^A(c)\} dF_{\mu_b}^n(v) dG_{\mu_s}(c)}{\int_{\underline{c}}^{\overline{c}} \int_{\underline{v}}^{\overline{v}} 1\{v^{(n)} < r^A(c)\} dF_{\mu_b}^n(v) dG_{\mu_s}(c)}$$

*Probability of zero buyers:* Finally, the probability that zero buyers, $\widetilde{\mathcal{ZB}}^A$ arrive at a seller is

$$\widetilde{\mathcal{ZB}}^A(\xi) = 1 - \sum_{i=1}^{I} w_i \frac{(\delta_i \xi \theta^A \epsilon)^0 e^{-\delta_i \xi \theta^N \epsilon}}{0!}$$

*Myerson-Satterthwaite mechanism polynomials*

As in the case of the auction mechanism, 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:* Recall that the probability of sale conditional on matching with a buyer is the probability that the $a^*$-weighted virtual type for the buyer exceeds that of the seller, or

$$E[Q^N(v,c)] = \text{Pr}(\Phi^{a^*}(v) \geq \Gamma^{a^*}(c))$$

This depends on the distribution of buyer and seller values but not on the arrival distribution. We assume fixed values for the variances of the distributions $\sigma_v, \sigma_c$ and simulate the sale probability $\widetilde{\mathcal{TP}}(\mu_b, \mu_s; \sigma_b, \sigma_s)$ for a grid of values for the mean buyer and seller values.

$$\widetilde{\mathcal{TP}}(\mu_b, \mu_s; \sigma_b, \sigma_s) = \int_{\underline{v}}^{\overline{v}} \int_{\underline{c}}^{\overline{c}} 1\{\Phi^{\tilde{a}(\mu_b,\mu_s)}(c) \geq \Gamma^{\tilde{a}(\mu_b,\mu_s)}(c) f_{\mu_b}(v) g_{\mu_s}(c) dvdc$$

where $f_{\mu_b}$ and $g_{\mu_s}$ are the pdfs of the buyer and seller distributions with means shifted to $\mu_b$ and $\mu_s$, respectively. The mechanism allocation rule changes as the means of the distributions change; therefore, for each pair $\mu_b, \mu_s$ we resolve for the weight $\tilde{a}(\mu_b, \mu_s)$ that characterizes the optimal mechanism. In the remainder of this section we suppress the dependence on the value means and refer to this parameter as $\tilde{a}$.

*Price conditional on trade:* The expected price received by sellers, not conditional on trade, is

$$M^S_{\mu_s}(c) = c + \frac{G_{\mu_s}(c)}{g_{\mu_s}(c)}$$

After conditioning on trade, the expected price is

$$\tilde{\mathcal{P}}^N(\mu_b, \mu_s; \sigma_b, \sigma_s \mid Q^N(v,c) = 1) = \frac{\int_{\underline{v}}^{\overline{v}} \int_{\underline{c}}^{\overline{c}} M^S_{\mu_s}(c) 1\{\Phi^{\tilde{a}}(c) \geq \Gamma^{\tilde{a}}(c) f_{\mu_b}(v) g_{\mu_s}(c) dvdc}{\int_{\underline{v}}^{\overline{v}} \int_{\underline{c}}^{\overline{c}} 1\{\Phi^{\tilde{a}}(c) \geq \Gamma^{\tilde{a}}(c) f_{\mu_b}(v) g_{\mu_s}(c) dvdc}$$

*Probability of a seller meeting a buyer:* The probability that a seller meets a buyer $\widetilde{\mathcal{MB}}$ is

$$\widetilde{\mathcal{MB}}(\xi; \mathbf{w}.\mathbf{c}, \theta^N) = 1 - \sum_{i=1}^{I} w_i \frac{(\delta_i \xi \theta^N \epsilon)^0 e^{-\delta_i \xi \theta^N \epsilon}}{0!}$$

*Probability of a buyer trading with a seller:* The ex-ante probability that a buyer trades with a seller is

$$\widetilde{\mathcal{BM}}(\xi, \mu_b, \mu_s; \mathbf{w}, \mathbf{c}, \theta^N, \sigma_b, \sigma_s) = \sum_{n=1}^{\mathcal{N}} \sum_{i=1}^{4} w_i \text{Pr}(N = n | N \geq 1, \theta = \delta_i \xi \theta^N) \frac{1}{n} \widetilde{\mathcal{TP}}(\mu_b, \mu_s; \sigma_b, \sigma_s)$$

*Seller value conditional on meeting a buyer and no trade:*

$$\widetilde{\mathcal{SV}}(\mu_b, \mu_s; \sigma_b, \sigma_s) = \frac{\int_{\underline{v}}^{\overline{v}} \int_{\underline{c}}^{\overline{c}} v 1\{\Phi^{\tilde{a}}(c) < \Gamma^{\tilde{a}}(c) f_{\mu_b}(v) g_{\mu_s}(c) dv dc}{\int_{\underline{v}}^{\overline{v}} \int_{\underline{c}}^{\overline{c}} 1\{\Phi^{\tilde{a}}(c) < \Gamma^{\tilde{a}}(c) f_{\mu_b}(v) g_{\mu_s}(c) dv dc}$$

*Buyer value conditional on trade:* The expected buyer value conditional on trade $\widetilde{\mathcal{BV}}$ is

$$\widetilde{\mathcal{BV}}(\mu_b, \mu_s; \sigma_b, \sigma_s) = \frac{\int_{\underline{v}}^{\overline{v}} \int_{\underline{c}}^{\overline{c}} v 1\{\Phi^{\tilde{a}}(c) \geq \Gamma^{\tilde{a}}(c) f_{\mu_b}(v) g_{\mu_s}(c) dv dc}{\int_{\underline{v}}^{\overline{v}} \int_{\underline{c}}^{\overline{c}} 1\{\Phi^{\tilde{a}}(c) \geq \Gamma^{\tilde{a}}(c) f_{\mu_b}(v) g_{\mu_s}(c) dv dc}$$

*Appendix E.3. Approximation accuracy*

Table E.1 compares: i) the micro-simulation means computed in steps 1 and 2 (column 2); ii) the means of the polynomial approximations for expected price, probabilities of trade and expected payoffs by mechanism in steps 3 and 4 (column 3); and the steady state of the full dynamic model featuring idiosyncratic but not aggregate uncertainty (column 4).[50] All three sets of means are very close to each other. For example, in the MS-Auction model, the micro-simulation mean of the probability of trade through auctions for buyers and sellers 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.

**Table E.1: Comparing Simulation & Approximation Moments**

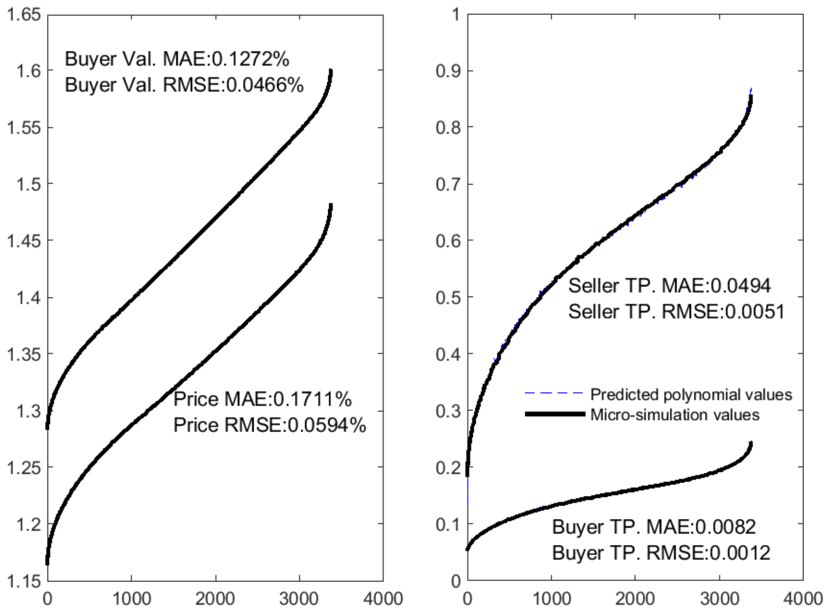
| | Simulation Mean | Approximation Mean | Steady State Mean |
|---|---|---|---|
| *Model-implied Moments:* | | | |
| Auction Price | 1.331 | 1.331 | 1.327 |
| Negotiation Price | 1.174 | 1.174 | 1.174 |
| Buyer Trade Prob. Auc. | 0.150 | 0.150 | 0.154 |
| Seller Trade Prob. Auc. | 0.591 | 0.591 | 0.614 |
| Buyer Trade Prob. Neg. | 0.318 | 0.318 | 0.314 |
| Seller Trade Prob. Neg. | 0.137 | 0.137 | 0.136 |
| Buyer Value Cond. Trade Auc. | 1.447 | 1.447 | 1.444 |
| Buyer Value Cond. Trade Neg. | 1.343 | 1.343 | 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 (see Appendix E). *Steady state mean* is the steady state mean from the dynamic MS-auction model with idiosyncratic shocks only.

[50]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.

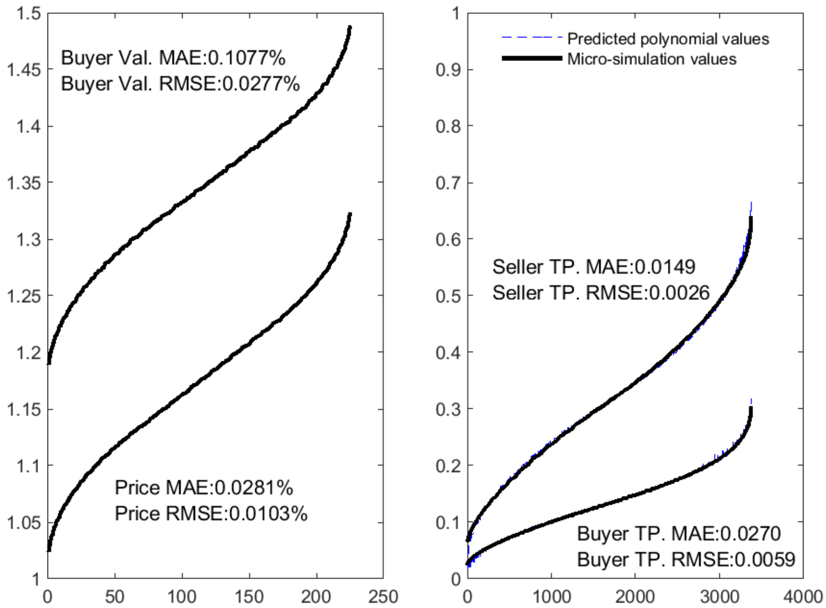
Figures E.1 to E.2 show the micro-simulation values and the predicted values derived from the polynomial approximations used to parameterize expected price, trade probabilities for buyers and sellers, and conditional payoffs by mechanism, and where simulations are ordered in ascending value. The accuracy 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.

**Figure E.1:** Auctions 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*.

**Figure E.2:** Negotiations (MS) 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*.

## Appendix F. Selection

In the benchmark model, buyers and sellers choose the mechanism with the highest expected payoff. Here we consider whether certain types of selection are important. We first consider selection on home attributes, and then randomness in the choice of mechanism by a seller or buyer.

### *Appendix F.1. Selection on Home Attributes*

The concern here is that certain homes, based on their location, size and type (house or apartment), may be more likely to be auctioned than they are negotiated. While controlling for the attributes of home sold through log-hedonic price regressions can help to control for changes in the composition of homes sold each week, unobserved differences in home attributes could remain and drive differences in mechanism propensities. One approach to addressing this is to use matching. By matching the auction and negotiation samples prior to the model's solution and estimation, the two samples – auctions and negotiations – should exhibit greater covariate balance and thus be more comparable.

Following Genesove and Hansen (2023), we use a Nearest Neighbor (NN) matching algorithm that first identifies the sample of auctions with overlap, and for each auction within this sample we identify the closest NN match of a home sold through negotiation. By quarter, $q$, we:

1. Estimate a logit-based propensity score of the transaction being an auction.[51]
2. Remove observations with estimated propensity score $\widehat{e}_{iq}$ outside interval $[0.05, 0.95]$ (i.e., remove sales very likely or unlikely to have been auctioned).
3. Remove any auction (negotiation) lacking a corresponding negotiation (auction) with estimated propensity score within 0.1 caliper.
4. Denote the remaining set of auctions (negotiations) in quarter $q$ as $\mathcal{A}_q$ ($\mathcal{P}_q$). Identify the single closest negotiated sale within the set $\mathcal{P}_q$ for auction sale $i \in \mathcal{A}_q$, matching on all home attributes including the type of home sold, bedroom number, bathroom number, log lot size and longitude and latitude. Call this $j\left(i\right)$. Denoting the covariate vector for observation $k$ as $\mathbf{x}_k$, $j(i)$ satisfies:

$$\mathbf{x}_{j(i)} \in \arg\min_{k \in \mathcal{P}_q} \left(\mathbf{x}_k - \mathbf{x}_i\right)' W_q^{-1} \left(\mathbf{x}_k - \mathbf{x}_i\right)$$

where $W_q$ is the inverse of the sample variance-covariance matrix. Matching is under-

[51]The covariates are: home type (house or apartment), bedroom number, bathroom number, log lot size interacted with property type, longitude, latitude, and distance to the Central Business District General Post Office (city core). Distances are calculated using Robert Picard, 2010. "GEODIST: Stata module to compute geodetic distances," Statistical Software Components S457147, Boston College Department of Economics, revised 22 Feb 2012.

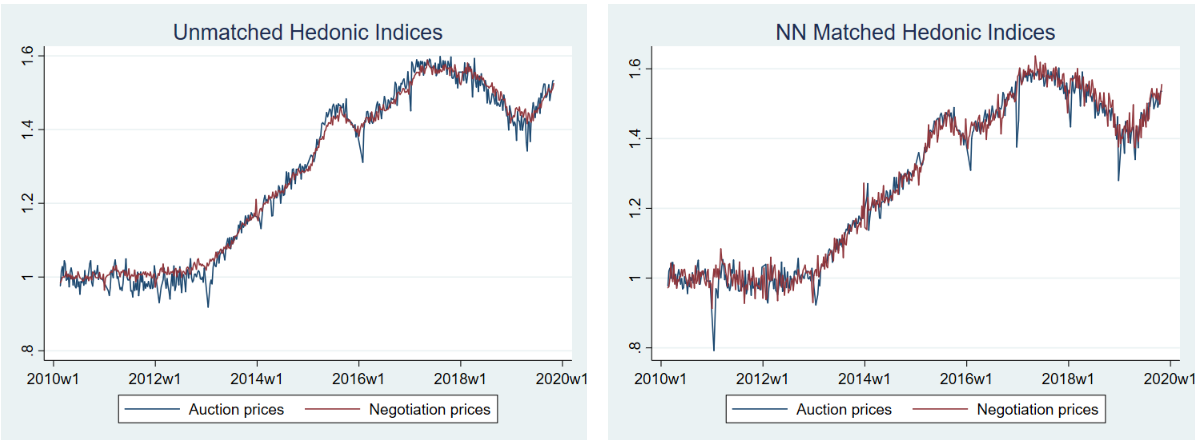
taken with replacement and ties are broken randomly.

5. Construct a matched negotiations sample for quarter $q$ collating the set of pairwise matches (one for each auction in quarter $q$) identified in Step (4). Denote it $\mathcal{P}_q^M$.
6. Append the quarterly samples of matched negotiated sales to form a single matched negotiated sales sample $\mathcal{P}^M = \bigcup_{q\in 1996:\text{I}-2019:\text{IV}} \mathcal{P}_q^M$. Do the same for the quarterly samples of auction sales used in matching: $\mathcal{A}^M = \bigcup_{q\in 1996:\text{I}-2016:\text{IV}} \mathcal{A}_q$.

After constructing the matched samples, we estimate weekly log-hedonic price regressions on each matched sample ($\mathcal{P}^M$ and $\mathcal{A}^M$), and the restrict attention the 2010–2019 sub-sample that matches that used in the structural auction estimation. Figure F.1 shows the estimated price indices with and without matching (differences in covariate balance after matching are small and full results are available on request). The comovement and volatility in price is more similar after matching, consistent with improved balance and that the auctions and negotiations matched samples now have identical size.

Table F.1 reports results after re-estimating the model using the NN matched prices (Model II). Compared with the benchmark model (Model I), we see estimates of the persistence and standard deviation shocks that are close to those of the benchmark model, with the exception being the persistence of the discount factor shock, which is now estimated at zero. Interestingly, the lack of the estimated persistence in the discount factor shock after matching, is also found when introducing random mechanism preference shocks in the model.

**Figure F.1: Prices: Unmatched & NN Matched**




*Appendix F.2. Random Shocks to Mechanism Choices*

A second concern is that buyers or sellers may simply prefer to haggle rather than hammer. Moreover, the preference to choose a given mechanism may change over time. A seller may initially choose to sell via negotiation for example, but then decide to hold an auction. Or a seller might schedule an auction, but then decide they are willing to consider offers and negotiate before the auction is held.[52] To allow for selection due to changing preferences, we introduce a random preference shock to buyers' and sellers' mechanism choices.

Consider a preference shock received by the agent of type $k \in \{\text{Buyer, Seller}\}$ at the beginning of the interval when the agent chooses their mechanism. Agents now choose mechanism $j_t^{k^*} \in \arg\max_j \left\{ \left(\varepsilon_t^{jk}\right)^{\sigma^k} V_t^{jk} \right\}$ for $j \in \{\text{Auction,Negotiation}\}$[53]. $\varepsilon_t^{jk}$ is the random mechanism and buyer (or seller) specific shock received when choosing a mechanism at time $t$, and $\sigma^k$ is a scale parameter that governs the dispersion of the shock received. Requiring a shock distribution that admits the same steady state as that of the benchmark model, we assume $\log \frac{\varepsilon_t^{Nk}}{\varepsilon_t^{Ak}}$ is i.i.d Gaussian with mean $\mu^k$ and unit variance for all $j$ and $k$.[54] An advantage of this assumption is that by restricting the mean difference in the log-preference shocks, $\mu^k$, to be a function of the dispersion parameters $\sigma^k$, the latter are uniquely identified from the steady state mechanism propensity shares $\left(\Psi^{jk}\right)$.

We use this specification to test whether the time series data – mechanism-specific prices, time on market, the auction clearance and and auction sales share – prefer the model with i.i.d preference shocks or the benchmark model. Specifically, we replace the equilibrium indifference conditions of the benchmark model with a convex combination of themselves and the equilibrium mechanism selection condition with i.i.d preference shocks as modelled above:

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

where $\Phi^{-1}$ is the inverse of the standard normal CDF. This allows us to estimate the 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 $\epsilon^k$.[55]

Table F.1 shows the results again using SMM. Model I is the benchmark model, imposing the equilibrium indifference condition for both buyers and sellers ($\epsilon^s = \epsilon^b = 0$). Model III

[52]We emphasis these are *random* changes in mechanism choice. Choices that are made due to changes in expected payoffs, for example due to changes in expected buyer demand, are already covered in the benchmark model.

[53]Note we do not place any restrictions on preference shocks for agents who are on both sides of the market. An agent who is buying and selling may receive a preference shock inducing them to buy via negotiation while at the same time selling their home on through auction.

[54]Note only the ratio of shocks identified. With this formulation preference shocks are interpeted as percentage deviations in values obtained from selling through auction or through negotiation.

[55]Note with i.i.d preference shocks, the time varying probabilities that a buyer or seller will choose auction or negotiation:

$$\Pr\left(\log \frac{V_t^{Ak}}{V_t^{Nk}} \leq \sigma^k \log \frac{\varepsilon_t^{Nk}}{\varepsilon_t^{Ak}}\right) = \Psi_t^{Nk} \quad \text{for } k \in \{\text{Buyer, Seller}\}$$

relaxes this allowing for a non-zero weight on the equilibrium condition with preference shocks, but imposes that the weighting on the preference shock equilibrium condition is the same for buyers as it is for sellers ($\epsilon^s = \epsilon^b \neq 0$). Model IV allows for differential weights on the equilibrium conditions preference shocks for buyers and sellers ($\epsilon^s \neq \epsilon^b$).

The results in Table F.1 show that the estimated weights on the equilibrium conditions with random preference shocks are small. Rejecting the null that estimated weights on the equilibrium condition with i.i.d preference shocks are the same for buyers and sellers (comparing Models III and IV), Model IV implies an estimated weight on the random shocks equilibrium condition of 0.0003 only, implying little evidence that preference shocks of this nature matter for their mechanism choice. For buyers, the estimated weight still favours the benchmark model at 0.0463, but there is statistically significant evidence that preference shocks play a role in their mechanism choices.

As noted earlier, the most significant effect of allowing for random shocks to mechanism choices is on the estimated persistence of the discount factor shock. As with the NN-matching, this shocks is now estimated to have zero persistence. For other shocks, however, the estimated parameters are similar.

As a final robustness check, we estimate a third model with random mechanism preference shocks (Model V). Rather than assume preference shocks are multiplicative and log-normally distributed, Model V assumes they are additive and drawn from a Type I Extreme Value Distribution. This model is commonly used in the empirical literature estimating dynamic discrete choice models. Here, we replace the equilibrium indifference condition with a logit-model $\sigma^k_{\text{logit}} \log \frac{\Psi^{Ak}_t}{1-\Psi^{Ak}_t} = V^{Ak}_t - V^{Nk}_t$, where $\sigma^k_{\text{logit}}$ governs the dispersion parameter associated with the additive Type I EVD shocks. We estimate the dispersion parameters $\sigma^k_{\text{logit}}$ via SMM.

Table F.1 Model V shows the results where the final rows now report the point estiamates and standard deviations of the dispersion parameters $\sigma^b_{\text{logit}}$ and $\sigma^s_{\text{logit}}$, and the standard deviation of the Type I EVD shocks are $\pi\sigma^b_{\text{logit}}/\sqrt{6}$ for buyers and $\pi\sigma^s_{\text{logit}}/\sqrt{6}$ for sellers. The estimates imply a weekly standard deviation equivalent to $0.0038$ per week for buyers, that is statistically significant, and $0.0002$ per week for sellers, which is not statistically different from zero. Thus, similar to the findings for Model IV, we see evidence of random shocks to the mechanism choices made by buyers, but not for sellers. Finally, in terms of the models parameters estimates, they again quite similar to Models II to IV, with only exception being that in the

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Inverting the selection conditions imposing $\mu^k = -\frac{(\sigma^k)^2}{2}$ we have

$$\frac{\log\left(\frac{V^{Nk}_t}{V^{AS}_t}\right) + \frac{(\sigma^k)^2}{2}}{\sigma^k} = \Phi^{-1}\left(\Psi^{Nk}_t\right)$$

and so we see $\sigma^k$ is uniquely identified from the steady state $\overline{\Psi}^{Nk}$, since $\overline{V}^{Nk} = \overline{V}^{Ak}$. Note the restrictions on the means are important, they allows us to uniquely identify $\sigma^k$ without reparameterizing the model.

**Table F.1: Estimates with NN-matching and Mechanism-preference Shocks**

| Parameter estimates | Model I: Benchmark indifference model | Model II: Nearest neighbor matching | Model III: Mech. pref symmetric $\epsilon^s = \epsilon^b$ | Model IV: Mech. pref asymmetric $\epsilon^s \neq \epsilon^b$ | Model V Mec. pref logit $\sigma^b_{\text{logit}} \neq \sigma^s_{\text{logit}}$ |
|---|---|---|---|---|---|
| Persistence | | | | | |
| $\rho_{r^H}$ | 0.017 | 0.013 | 0.00 | 0.00 | 0.283 |
| | (0.000) | (0.001) | (.) | (.) | (0.81) |
| $\rho_{\alpha^b}$ | 0.898 | 0.994 | 0.756 | 0.790 | 0.772 |
| | (0.053) | (0.004) | (0.032) | (0.0267) | (0.020) |
| $\rho_\beta$ | 0.998 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.001) | (.) | (.) | (.) | (.) |
| Std. Dev. | | | | | |
| $\sigma_{r^H}$ | 0.021 | 0.034 | 0.003 | 0.004 | 0.003 |
| | (6.24e-04) | (0.0009) | (0.0018) | (0.0014) | (0.003) |
| $\sigma_{\alpha^b}$ | 2.42e-05 | 1.88e-06 | 0.0005 | 0.0004 | 0.0006 |
| | (6.13e-06) | (8.58e-06) | (4.97e-05) | (4.52e-5) | (4.15e-05) |
| $\sigma_\beta$ | 8.39e-06 | 0.0009 | 0.0041 | 0.0044 | 0.0056 |
| | (4.13e-06) | (0.0004) | (0.0011) | (0.0010) | (0.0008) |
| $\sigma_N$ | 0.007 | 0.018 | 0.006 | 0.006 | 0.004 |
| | (3.56e-04) | (0.0009) | (0.0008) | (0.0008) | (0.0012) |
| $\sigma_A$ | 0.021 | 0.023 | 0.023 | 0.023 | 0.026 |
| | (5.14e-04) | (0.0009) | (0.0005) | (0.0005) | (0.0005) |
| $\epsilon^s(\sigma^s_{\text{logit}})$ | | | 0.0764 | 0.0003 | 0.003 |
| | | | (0.0083) | (0.0008) | (0.0001) |
| $\epsilon^b(\sigma^b_{\text{logit}})$ | | | 0.0764 | 0.0463 | 0.0002 |
| | | | (0.0083) | (0.0030) | (0.0008) |

logit model of preference shocks, flow utility shocks are now estimated to be more persistent, though less precisely. All other parameter estimates remain similar.

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