The Role of Auctions and Negotiation in Housing Prices

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Using matched housing sales in Sydney and Melbourne, we show that how properties sell matters for housing price dynamics. Auction prices forecast better and display much less momentum than negotiated prices. They also forecast other leading indicators of local economic activity while negotiated prices do not. These findings are consistent with the two sales mechanisms transmitting buyer vs. seller shocks to prices differently and, in light of auction and bargaining theories, suggests the source of momentum in housing markets is sluggish sellers valuations. Other explanations, such as differences in precision, the types or locations of homes sold or sellers' decisions to hold auctions fail to explain our findings. Our estimates indicate that sellers and buyers have close to equal bargaining power in negotiations, auctions mostly reflect buyers' values and list prices sellers'.

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I. Introduction

The past financial crisis has brought the importance of housing price dynamics to the fore. Housing dominates household balance sheets and the feedback between its price and credit constraints can generate or amplify macroeconomic volatility.[1]

Housing prices are, however, an average of many individual transactions between buyers and sellers. How the two market sides interact is crucial in determining how they respond to shocks, whether sellers can sell their home should their financial circumstances change and whether sellers or buyers play a stabilising role in housing price dynamics.[2]

Conjecturing that more can be learned by accounting for price setting at the micro level, we study dynamics distinguishing between prices set at auctions and those set in negotiations. Working from basic auction and bargaining theories, we use the method of sale to identify differences in how sellers and buyers respond to new information or shocks. We find a sluggish seller explanation is consistent with aggregate price inertia, amplifying procyclical market liquidity. Buyers, however, update quickly.

Our focus is on housing price momentum, predictability and the speed with which prices respond to new information. Starting from a near census of transactions in Sydney and Melbourne, we use nearest neighbour (NN) and propensity score (PS) matching to form highly comparable quarterly samples of auction and negotiated sales using data from 1993 to 2016.[3] We estimate separate auction and negotiation hedonic price indices on these samples. These indices exhibit substantial differences in information content and momentum.

Auction price growth exhibits much less momentum (autocorrelation) than either negotiated price growth or overall price growth, both of which are highly autocorrelated. Indeed, the null of a random walk in auction prices cannot be rejected.

The auction price is a leading indicator, whereas negotiated prices lag the market. Testing for causality, in the Granger-causal sense, implies that auction prices are highly informative for forecasting future negotiated prices whereas the opposite is not true. Auction prices reduce the root mean squared prediction error (RMSE) of negotiated prices 1-quarter ahead by between 15 and 48%, while negotiated prices reduce the RMSE of auction prices by no more than 4%.

Auctions are also highly informative for predicting changes in local macroeconomic

[1] See, for example, Favilukis, Ludvigson and Van Nieuwerburgh (2017); Favara and Imbs (2015); Mian, Rao and Sufi (2013); Mian and Sufi (2011, 2009) and Iacoviello (2005) amongst others.

[2] Related papers include Arefeva (2017); Han and Strange (2015); Mian, Sufi and Trebbi (2015); Han and Strange (2014) and Genesove and Mayer (1997).

[3] Our unmatched data samples span 1993:I–2016:IV while the matched samples that require basic attributes data span 1998:I–2016:IV. Sydney and Melbourne make up 40% of Australian real estate transactions by volume, and 60% by value.

conditions such as nominal building activity, real state final demand and inflation. We find nothing similar for negotiations. These results are robust to not matching, using repeat-sales, controlling for the decision to use auctions, the conditioning set of home attributes, and analysis at more finely defined housing sub-markets.[4]

Why such large differences in momentum and predictive information? Our findings are consistent with auctions weighting buyer and seller values differently than negotiations, and asymmetry in the speed with which these values respond to shocks.

In negotiations bargaining takes place between a single buyer and seller.[5] In standard models both parties' values influence price.[6] Models with incomplete information, that can affect the probability and efficiency of trade, have the same implication.[7]

Auctions are different. In the open-outcry (English) auction used in Sydney and Melbourne, many buyers bid on a property to determine its price. Competition amongst buyers reduces the weight on the seller's value. Absent seller reserves, auction prices are solely determined by the distribution of buyers' values; even with seller reserves, theory predicts the weight on the seller's value to approach zero as the number of bidders increases, for private values.[8]

We exploit asymmetry in the weighting of buyer and seller values in price determination to identify the common temporal component in the values and how these evolve over time. Estimating a small state space model that posits auction, negotiated and list prices as weighted averages of two diffusion processes, thus permitting gradual and potentially asymmetric adjustment to common permanent shocks,[9] we find that: auction prices weight buyer values more highly than they do seller; negotiated prices are close to an equally weighed average of buyer and seller values; and list prices only reflect seller values.

We further find that buyer values update quickly in response to common shocks, with almost 60% of the information contained in a common shock incorporated by buyers within a quarter and 95% within three. Sellers are more sluggish: their values incorporate less than 15% of the common shock within a quarter and less than 40% within three.

Why do buyers respond to new information more quickly than sellers? A full explanation lies beyond this paper's scope, but we make some brief comments. First, differences

[4]The online Appendix report a battery of additional checks.

[5]'Negotiated' prices that follow (informal) bidding wars are best interpreted as auctions that have been misclassified as negotiations, implying that we underestimate the true differences between negotiations and auctions.

[6]The weight on the seller value in the price from a Nash bargain equals the buyers bargaining power.

[7]See, for example, Čopič and Ponsatí (2008); Ausubel, Cramton and Deneckere (2002); Chatterjee and Samuelson (1987) and Chatterjee and Samuelson (1983).

[8]For finite number of bidders, price responds more to buyer than seller values for a wide range of distribution pairs considered in the online Appendix, calibrated to match the auction sale rates we observe.

[9]Such shocks reflect innovations to the value of housing services, interest rates, expected capital appreciation and other aspects of future market conditions. We also allow for Gaussian measurement errors in prices.

in the matching institution, in which sellers list homes and prices while buyers do not list their preferences or even their identities, makes sellers' attributes more public than buyers'. Information on sellers diffuses quickly through their listing, de-listing and list price decisions, becoming common knowledge to sellers and buyers alike, while buyer shocks only become known when actualised in transacted prices and those prices publicised. Contemporaneous correlation in buyer values will then ensure that they be informationally advantaged vis a vis sellers.

Second, buyer and seller search processes differ. As buyers visit homes and sellers are visited, both update their knowledge of the market. Buyers' visits refine their knowledge on home attributes and sellers' 'ask' bids, conditional on those attributes, for homes most relevant to the individual buyer. A seller's observations of buyers' (rejected, unless overlapping) offers refine her assessment of the buyer value distribution for her specific home. This incremental information, which, gathered experientially, may be especially salient, is clearly different for buyers and sellers, and so there is no reason for them to respond to a market level shock to the same degree. Sellers also have the oppotunity to visit competing homes, but the marginal gain from doing so is small relative to that for buyers, for whom a visit is nearly always a pre-requisite to buying.[10]

Other potential explanations, such as differences in the types of home sold, the precision of information revealed in each mechanism, or the seller's choice of selling mechanisms, appear less relevant when explaining differences in price dynamics by sale method.

Our findings relate to a broad literature on slow adjustment in housing prices, selling mechanisms and housing market efficiency. Positive momentum in housing prices growth has been well documented. First observed by Case and Shiller (1989) for US single family homes and evident across many countries,[11] this phenomenon is at odds with a standard asset model for housing markets, which fail "utterly at explaining the strong, high frequency positive serial correlation of price changes"(Edward L. Glaeser, Joseph Gyourko, Eduardo Morales and Charles G. Nathanson, 2014). Search models also have difficulty in matching the momentum observed in prices growth.[12] Sellers who respond slowly to market conditions helps generate autocorrelation in both Caplin and Leahy's (2011) and Guren's (2015) models, but neither paper presents evidence in support of the

[10]Differential information flows or asymmetry between buyer and seller behaviour has been emphasised in previous research, e.g., Anenberg (2011) and Berkovec and Goodman (1996). Sellers may simultaneously be searching to buy, but given the substantial transaction costs of moving, are highly likely to be searching for a home very different (in location or attributes) to the one they are to selling - and many of those sell, then buy.

[11]See Titman, Wang and Yang (2014) for a more recent study showing this empirical regularity.

[12]Recent attempts to model housing price dynamics incorporate search frictions (Capozza, Hendershott and Mack (2004), Caplin and Leahy (2011), Díaz and Jerez (2013) and Head, Lloyd-Ellis and Sun (2014, 2016)), adaptive expectations (Sommervoll, Borgersen and Wennemo (2010)), momentum traders (Piazzesi and Schneider (2009)), and kinked demand curves (Guren (2015)). Yet these papers struggle to generate the high positive autocorrelation. Head, Lloyd-Ellis and Sun (2016), for example, explains less than half of the first autocorrelation coefficient in price growth and none of the second, while Díaz and Jerez's (2013) model generates no autocorrelation at all.

assumption as we do here.

Slow seller adjustment is consistent with additional housing market facts, such as: the greater cyclicality of sales than housing prices (Leamer, 2007); lower seller time on the market in 'hot' markets (Wheaton, 1990; Krainer, 2001); positive correlation between both the sale to list price ratio and short run demand growth (Genesove and Han, 2012), and between that ratio and expected price growth (Donald Haurin, Stanley McGreal, Alastair Adair, Louise Brown and James R. Webb, 2013). Other ongoing research by us provide evidence of a 'Phillips-curve' governing the relationship between price growth and the auction sales rate in Australia (see Appendix Figure A3 for preliminary findings). In short, seller sluggishness contributes to price growth momentum and illiquidity.

More generally, we study the role of sales mechanisms in affecting price dynamics. Theory compares outcomes such as efficiency, seller revenue and information aggregation across mechanisms, especially auctions (e.g. Bulow and Klemperer (2009); Kremer (2002); Bulow and Klemperer (1996)), but also between them and posted prices (Wang, 1998, 1995). An empirical literature compares price levels across different mechanisms (Lusht, 1996), especially on the Internet (e.g. Einav et al. (2015); Lucking-Reiley (1999)). Most theory and empirics has a single transaction focus. Uniquely, we provide empirical evidence on how different selling mechanisms map changes in the underlying distributions of buyer and seller valuations into aggregate price changes over time.[13]

II. Institutions and the data

Auctions and negotiations use the same listing process: sellers advertise their home's attributes, location and sometimes a non-binding list price. Buyers may visit the home. When an auction is used, its time and place, usually the home itself, are also listed.[14] Auctions open with the auctioneer suggesting a bid. From there, bids are incrementally raised, until no one is willing to bid higher.[15] The home sells to the highest bidder, who pays that bid, if it is acceptable to the seller.[16] Otherwise the home is not sold.[17] Negotiations have no formal structure and may be initiated at any time.

The data are a census of all home sales in Sydney and Melbourne between 1993 to 2016 from land title office records merged with listings in newspapers and the internet.[18] Sale prices are recorded for all but 0.2 per cent of the approximately 4 million transactions.

[13]Our work also connects to the literature on housing market efficiency such as Anundsen and Røed Larsen (2018) and Han and Strange (2015) and the references therein.

[14]Previously through newspapers and real estate agents, listings are now almost always via the internet.

[15]Both the auctioneer calling out prices that bidders accept and bidders nominating their own bids occur.

[16]Auctioneers may bid on the seller's behalf (once in Sydney, multiple times in Melbourne), but must disclose this at the time.

[17]It may subsequently sell by negotiation, whether on the same day or week, or months thereafter, but will not then be included in our analysis.

[18]The data are sourced from Australian Property Monitors (APM) – see online Appendix A.A1.

Basic attribute data – home type (cottage, detached house, semi-detached home, terrace, townhouse, villa, duplex, studio, unit), number of bedrooms and bathrooms, lot or building size, postal code, longitude and latitude – exist for 35 percent of transactions (the 'Basic Attributes' sample), with full data availability particulary sparse before 1998.

Table 1 reports sales frequencies in the Basic Attributes sample by sale mechanism and home type.[19] The distributions across the two mechanisms are similar, with detached houses making up the majority of sales, and apartments mostly the remainder.

Table 1—Sales Frequency by Property Type: UnMatched Sample

	Sydney		Melbourne	
	Auction	Negotiation	Auction	Negotiation
House types				
Detached house	66.41	58.24	71.72	71.32
Townhouse	4.87	8.24	5.34	5.22
Other houses	4.76	1.93	1.45	0.65
Apartment types				
Units	23.12	30.49	21.28	22.61
Other units	0.84	1.11	0.21	0.20
Total transactions	109,433	591,828	143,780	486,792

Note: Other houses: cottages, semi-detacheds, terraces, villas. Other units: duplexes, flats, studio apartments.

III. Matching and Price Measurement

To limit biases arising from differences in the composition of home attributes across the two mechanisms, we use matching and repeat–sales estimators. Our matching algorithms are applied to the Basic Attributes sample and begin by estimating a quarter-specific propensity score for auction use, conditioned on the basic attributes plus distance from the city core. For sales in each quarter, we exclude transactions with an estimated propensity score above 0.95 or below 0.05, or for which there is no transaction of the other mechanism type with an estimated propensity score within 0.1 of its own. For each auction sale, we then identify a single negotiated sale, in the same quarter and of the same home type, among those closest to it. We use both NN and PS methods for distance metrics.

We report attribute mean and standard deviations, for houses and apartments, by mechanism of sale, before and after NN matching in online Appendix B.2. Pre-matching, differences in the mean bedroom and bathroom numbers are small relative to standard deviations with the average house (apartment) having approximately 3 (2) bedrooms and 2 (1) bathrooms respectively across both cities. Lot size and geographic attributes differ,

[19]We exclude: related-party sales; negottations of homes originally listed for auction, before or within 90 days after an unsuccessful auction; and highly atypical homes. Online Appendix A.A1 describes our filtering.

with auctions held for houses with smaller lot sizes closer to each city's center (Figure 1). However, since there are more negotiations than auctions, there is still a large pool of negotiations in these areas from which to find high-quality matches.

Post-matching, mean differences are approximately zero for all attributes. For Sydney (Melbourne), the difference in the mean latitude-longitude of auction versus negotiated sales falls from 6.4 (2.1) miles to less than 0.04 (0.01) miles (i.e. about 70 (18) yards). As Appendix B.2 makes clear, these results hold across the distributions of all basic attributes and over time. Matching success extends beyond the matched-on attributes: the mean differences in both the number of times a property sells (turnover) and the Haurin (1988) idiosyncracy index also fall substantially with matching.[20]

After identifying matched samples for auctions and negotiations, we construct hedonic price indices.[21] The log sale price of home i sold at quarter t in postcode z is specified as

$$\ln P_{izt} = \alpha_z + \beta_t + \sum_j H_{ijt}\gamma_j + \sum_k X_{ikt}\delta_k + \sum_j \sum_k H_{ijt}X_{ikt}\lambda_{jk} + \varepsilon_{izt} \tag{1}$$

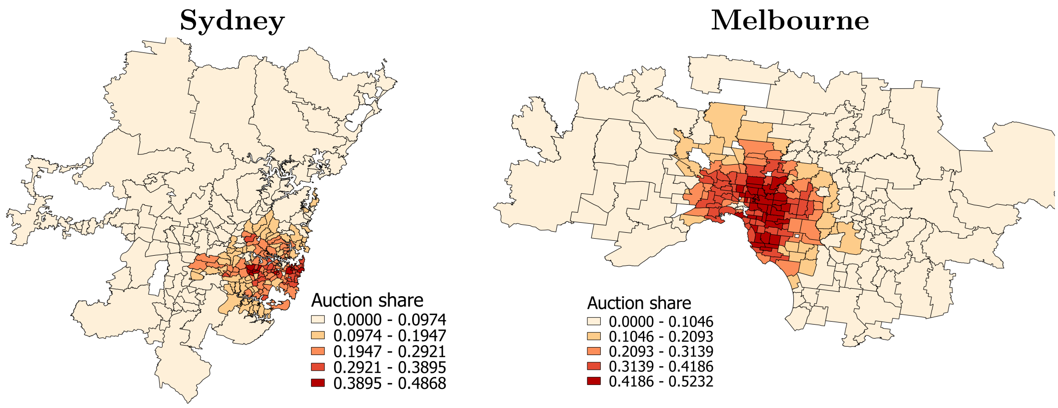


Figure 1. Auction Incidence by Postcode

which, in addition to the quarter and postcode fixed effects, includes home type dummies (H_{ijt}), along with the number of bedrooms, bathrooms and log lot/building size (X_{ikt}) and their interaction with home type ($H_{ijt}X_{ikt}$).[22] For each city, we estimate separate regressions on the auction and the negotiated sales samples.[23] The composition-adjusted price index for each sample is given by the estimated quarter effects ($\{\beta_t\}_{t=t_0}^T$). Figure 2 graphs the price indices, by mechanism, pre- and post-matching.

As an alternative to hedonic indices on matched samples, we also construct repeat-sales

[20]The annual turnover rate is approximately 6 per cent, broadly similar to the US rate over the same period.
[21]Hedonic price regressions accurately reflect composition-adjusted housing price changes (Hansen, 2009).
[22]Our robustness analysis also conditions on 34 additional attributes such as the number of parking spaces, dummies for ocean, mountain or bushland view, heating, air-conditioning, and swimming pool.
[23]Our results are robust to using a pooled sample.

indices using homes that sold more than once, regardless of attribute data availability. Common in the housing literature (Case and Shiller, 1989), these difference consecutive sale prices of the same home, so as to eliminate the value of time invariant attributes.[24]

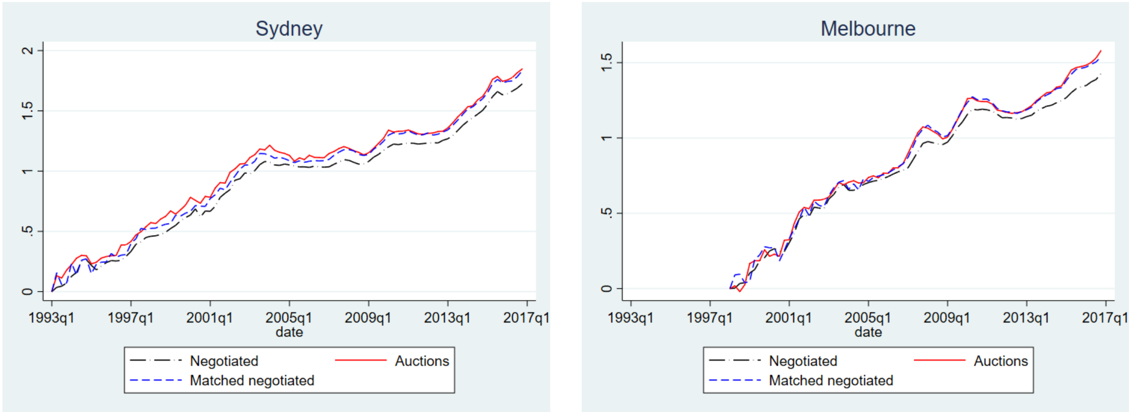


FIGURE 2. ESTIMATED HEDONIC LOG PRICE INDICES

IV. Empirical findings

A. *Momentum in prices growth*

Previous studies of city-level house prices, starting with Case and Shiller (1989), have taught us to expect substantial momentum (Head, Lloyd-Ellis and Sun, 2014; Glaeser et al., 2014; Titman, Wang and Yang, 2014; Cho, 1996). For example, Head, Lloyd-Ellis and Sun find, on average, first and second-order ACF coefficients of about 0.8 and 0.5 for US cities over a similar time frame (see also Capozza, Hendershott and Mack (2004); Schindler (2013)). We also find high momentum in the country-wide housing price indices collected in Mack, Adrienne, and Enrique Martínez-García (2011), whose mean first-order ACF coefficient is 0.7, with four fifths exceeding 0.5 (see the online Appendix). The coefficients are also highly persistent with mean fourth-order ACF of 0.45.

Similarly, we find negotiated price growth significantly autocorrelated (Table 2) with a clear rejection of a random walk (Table 3), for either city. By contrast, the random walk null cannot be rejected for auction price growth, and auction price momentum is always lower than that of negotiations, whatever our estimation method (Table 2).

The country-wide indices provide additional support for mininmal auction price momentum, for Norway, 90 per cent of whose housing sales are auctions (Olaussen, Oust and Ole, 2018; Anundsen and Røed Larsen, 2018), is an extreme outlier among the 23, mostly OECD, countries, with almost no persistence and a mere 0.09 first-order ACF.

[24]They have their faults. Sample selectivity due to differing turnover rates can affect a repeat-sales estimator more than an hedonic. Nor are they robust to changes in the return to attributes. Results with hybrid estimators that combine elements of both repeat-sales and hedonic methods are similar and available on request.

Also noteworthy is that Australia's ACF is among the least persistent.

TABLE 2—PRICE GROWTH AUTOCORRELATIONS

	$t-1$	$t-2$	$t-3$	$t-4$
Sydney – Hedonic				
All sales	0.46***	0.21**	0.13	0.08
Auctions	0.08	0.20*	0.06	0.10
Negotiations	0.40**	0.15**	0.02	0.08
NN Matched negotiations	0.33***	0.21*	0.08	0.18
Sydney – Repeat-sales				
All sales	0.67***	0.44***	0.27*	0.26
Auctions	0.11	0.21*	-0.13	0.17
Negotiations	0.71***	0.49***	0.33**	0.28
Melbourne – Hedonic				
All sales	0.45***	0.15	-0.03	-0.21
Auctions	0.21*	0.11	-0.02	-0.08
Negotiations	0.36***	0.15	-0.04	-0.23
NN Matched negotiations	0.24**	0.12	-0.10	-0.04
Melbourne – Repeat-sales				
All sales	0.60***	0.38***	0.17*	0.10
Auctions	0.16	0.11	0.01	-0.06
Negotiated	0.65***	0.44***	0.28**	0.16

Note: (a) The price measures are estimated using the hedonic index with all attributes. NN Matched negotiations are based on the negotiated sales sample after NN matching. (b) ***, ** and * denote significance at the 1, 5 and 10 per cent levels respectively using Bartlett's formula for an MA(q) process.

TABLE 3—TESTS FOR PRICE GROWTH MOMENTUM WITH HEDONIC INDICES

	Sydney			Melbourne		
H_0 :	UM	NN	PS	UM	NN	PS
$\mathrm{E}\left[\Delta a_{t+1} \mid \Delta a_{t-j}\right]$	1.17	1.53	1.48	1.23	1.72	1.72
$= \mathrm{E}\left[\Delta a_{t+1}\right]$	(0.33)	(0.21)	(0.22)	(0.31)	(0.16)	(0.16)
$\mathrm{E}\left[\Delta p_{t+1} \mid \Delta p_{t-j}\right]$	2.41*	3.64***	2.14*	3.63***	4.95***	4.46***
$= \mathrm{E}\left[\Delta p_{t+1}\right]$	(0.06)	(0.01)	(0.09)	(0.01)	(0.00)	(0.00)

Note: for $j \geq 0$. The information set includes controls for seasonality and the GST. UM, NN and PS denote the unmatched, nearest neighbour matched and propensity score matched samples respectively. In this and all subsequent tables, p-values are denoted in parentheses.

B. *Predictability*

We now turn to the relative information content in auction and negotiated prices when predicting each other. Granger-causality tests proposed by Toda and Yamamoto (1995), show auction prices predicting subsequent changes in negotiated prices, but not vice versa, whether the indices are constructed on the full sample without matching, or with either

NN or PS matching (Table 4, upper panel). Similar results hold for the repeat-sale indices (Table 5), hybrid measures or even simple price medians.[25]

Table 4—Causality and Information Content with Hedonic Price Indices

	Sydney			Melbourne		
H_0 :	UM	NN	PS	UM	NN	PS
$\mathrm{E}\left[p_{t+1} \mid a_{t-j}, p_{t-j}\right]$	44.12***	28.57***	22.12***	26.41***	38.42***	95.85***
$= \mathrm{E}\left[p_{t+1} \mid p_{t-j}\right]$	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\mathrm{E}\left[a_{t+1} \mid a_{t-j}, p_{t-j}\right]$	1.23	8.56	8.05	10.37*	8.28	3.06
$= \mathrm{E}\left[a_{t+1} \mid a_{t-j}\right]$	(0.94)	(0.13)	(0.15)	(0.07)	(0.14)	(0.69)
Directed information						
$DI(a_t \to p_t)$	0.21	0.17	0.13	0.15	0.23	0.48
$DI(p_t \to a_t)$	-0.03	0.03	0.03	0.04	0.03	-0.02

Note: (a) for $j \geq 0$. UM, NN and PS denote the unmatched, nearest neighbour matched and propensity score matched samples respectively. (b) $DI(p_t \to a_t) \equiv ln\left(\Sigma_1^{a_t}/\Sigma_2^{a_t}\right)$ $(DI(a_t \to p_t) \equiv ln\left(\Sigma_1^{p_t}/\Sigma_2^{p_t}\right))$ denotes Geweke's measure of past linear dependence (directed information). $\Sigma_1^{a_t}$ $(\Sigma_1^{p_t})$ and $\Sigma_2^{a_t}$ $(\Sigma_2^{p_t})$ denote the asymptotic variances of the restricted and unrestriced models for auction (negotiated) prices.

Table 5—Causality and Information Content with Repeat-sales

	Sydney			Melbourne		
H_0 :	UM	NN	PS	UM	NN	PS
$\mathrm{E}\left[\widetilde{p}_{t+1} \mid \widetilde{a}_{t-j}, \widetilde{p}_{t-j}\right]$	9.25*	23.55***	36.15***	21.68***	62.30***	40.72***
$= \mathrm{E}\left[\widetilde{p}_{t+1} \mid \widetilde{p}_{t-j}\right]$	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\mathrm{E}\left[\widetilde{a}_{t+1} \mid \widetilde{a}_{t-j}, \widetilde{p}_{t-j}\right]$	6.94	9.04	2.10	0.94	6.46	7.40
$= \mathrm{E}\left[\widetilde{a}_{t+1} \mid \widetilde{a}_{t-j}\right]$	(0.23)	(0.11)	(0.83)	(0.97)	(0.26)	(0.19)
Directed information						
$DI(\widetilde{a}_t \to \widetilde{p}_t)$	0.03	0.11	0.17	0.10	0.28	0.19
$DI(\widetilde{p}_t \to \widetilde{a}_t)$	0.01	0.03	-0.02	-0.03	0.01	0.02

Note: See notes under Table 4, but now $\widetilde{a}_t$ denotes repeat-auction, and $\widetilde{p}_t$ repeat-negotiated prices. UM denotes the unmatched weighted-repeat sales index (Case and Shiller, 1989) and NN (PS) repeat-sales indices constructed on samples where each pair of auction sales (for the same home) is matched with a pair of negotiations, by quarters of the initial and second sale, home type (exactly), longitude, latitude and log size using a nearest neighbour (propensity score) metric.

How much more informative are auctions than negotiated prices when predicting future prices? Tables 4 and 5 (lower panels) report past linear dependence (Geweke, 1982). A measure of directed information (Amblard and Michel, 2013), this captures the relative information content in each series, and is approximately equal to the percentage decline in the one quarter ahead root mean squared forecasting error (RMSE) of one price index from including the other price index's lags.

With and without matching, they show a one-seventh to one-half reduction in the negotiated price RMSE by including lagged auction prices. The information contribution

[25]The results using hybrid and median rices are available from the authors on request.

of lagged negotiated prices to predicting auction prices is essentially zero.

Table 6 highlights that the information contribution of auction prices is not confined to the housing market but extends to a range of local macroeconomic variables, including the value of local building activity, real interest rates, real output and inflation. Negotiated prices are not similarly Granger-causal predictive. These VAR specifications are similar to those used to summarize dynamics for Head, Lloyd-Ellis and Sun (2014) 's search model of the US housing market and by Iacoviello (2005) to identify housing price's effects on the US macro economy.[26]

Table 6—Causality tests with controls for macroeconomic conditions

	Sydney VARs			Melbourne VARs		
H_0 :	a_t, p_t v_t, r_t	a_t, p_t y_t, r_t	a_t, p_t y_t, r_t, π_t	a_t, p_t v_t, r_t	a_t, p_t y_t, r_t	a_t, p_t y_t, r_t, π_t
$p_t \overset{gc}{\nrightarrow} a_t$	1.23	3.32	3.88	1.75	3.79	6.69
$p_t \overset{gc}{\nrightarrow} v_t$	6.05			4.51		
$p_t \overset{gc}{\nrightarrow} r_t$	2.62	5.08	3.14	3.20	4.96	5.93
$p_t \overset{gc}{\nrightarrow} y_t$		2.56	2.09		4.94	4.96
$p_t \overset{gc}{\nrightarrow} \pi_t$			3.00			4.72
$a_t \overset{gc}{\nrightarrow} p_t$	55.37***	79.06***	59.56***	31.03***	64.14***	52.14***
$a_t \overset{gc}{\nrightarrow} v_t$	10.90**			8.63*		
$a_t \overset{gc}{\nrightarrow} r_t$	9.12**	12.61***	7.52*	1.26	3.47	1.93
$a_t \overset{gc}{\nrightarrow} y_t$		7.62*	6.20		9.65**	16.21***
$a_t \overset{gc}{\nrightarrow} \pi_t$			6.38*			2.91

Note: $x_t \overset{gc}{\nrightarrow} z_t$ denotes a test of the null hypothesis that x_t does not Granger cause z_t. a_t denotes auction prices, p_t negotiated prices, v_t the nominal value of building approvals, r_t the city-specific ex post real interest rate, y_t real state final demand and π_t state inflation. The macroeconomic data are outlined in Appendix A.A2.

V. Robustness

We present several robustness checks. These mostly require subsets of the data sufficiently small that matching is no longer feasible. The first explores whether the auction itself or the characteristics of sellers who choose auctions explains our earlier causality findings. Pre-auction sales, homes selected for auction but sold before the auction takes place, provide a useful set of transactions with which to compare.[27] If the information content in auctions is conveyed by sellers' decisions to use an auction, rather than the auction mechanism itself, one would expect successful negotiations prior to auction to also lead negotiated prices, although perhaps less strongly. In fact, we find no evidence that

[26] Replacing nominal with real auction and negotiated prices leaves the results qualitatively unchanged.

[27] We can not claim that homes sold prior to a scheduled auction are a random subset of homes scheduled for auction, even conditional on home attributes. Yet there is inherently random element at play: randomly occuring pre-auction sales occur under optimal sale mechanisms for sequential entry of bidders (McAfee and McMillan, 1988 and Cremer, Spiegel and Zheng, 2009. The arrival of a sufficiently high valuing buyer makes it worthwhile to accept his offer, rather than wait for competition at the auction.

pre-auction prices predict negotiated prices (Table 7). This is not due to the small number of transactions which underlie the pre-auction price index, as its Granger-causality by negotiated prices (the second row of the table) shows.

Table 7—Causality and Directed Information with Pre-auction Prices

	Sydney		Melbourne	
H_0 :	Basic attributes	Limited attributes	Basic attributes	Limited attributes
$\mathrm{E}\left[p_{t+1} \mid p_{t-j}, s_{t-j}\right]$	3.34	2.59	3.47	4.49
$= \mathrm{E}\left[p_{t+1} \mid p_{t-j}\right]$	(0.65)	(0.76)	(0.48)	(0.34)
$\mathrm{E}\left[s_{t+1} \mid p_{t-j}, s_{t-j}\right]$	41.49***	34.09***	35.65***	34.34***
$= \mathrm{E}\left[s_{t+1} \mid s_{t-j}\right]$	(0.00)	(0.00)	(0.00)	(0.00)
Directed Information				
$DI(s_t \to p_t)$	0.00	-0.01	0.00	0.00
$DI(p_t \to s_t)$	0.16	0.16	0.24	0.17

Note: for $j \geq 0$. 'Limited attributes' control for lot size, postcode, and property type only.

Table 8—Causality with Prices Adjusted for Selection

	Sydney			Melbourne		
H_0	No adjust.	In price	In price & VAR	No adjust.	In price	In price & VAR
$\mathrm{E}\left[\widehat{p}_{t+1} \mid \widehat{p}_{t-j}, \widehat{a}_{t-j}\right]$	40.91***	46.61***	35.12***	13.81***	17.55***	19.00***
$= \mathrm{E}\left[\widehat{p}_{t+1} \mid \widehat{p}_{t-j}\right]$	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\mathrm{E}\left[\widehat{a}_{t+1} \mid \widehat{p}_{t-j}, \widehat{a}_{t-j}\right]$	3.52	3.84	3.67	4.24	3.60	2.32
$= \mathrm{E}\left[\widehat{a}_{t+1} \mid \widehat{a}_{t-j}\right]$	(0.17)	(0.15)	(0.16)	(0.24)	(0.31)	(0.51)

Note: The tilde denotes estimation on the repeat-sales sample. 'No adjust.' uses a VAR with the standard hedonic index (i.e. no adjustment for seller selection). 'In price' uses a VAR with selection-adjusted price indices as estimated in (C1) to (C3) in the online Appendix (i.e. adjusting for selection when measuring prices but not within the information set used to test for causality). In VAR uses a VAR with selection-adjusted price indices and the time dummy coefficients in (C1) (i.e. adjusted for selection when measuring prices and includes it in the information set when testing for causality).

Adjusting the price indices for sellers' decisions to go to auction does not alter our main predictability findings either. We re-estimate the two main price indices using a control function approach that conditions the probabilitiy of using the current sale mechanism on the previous one, but excludes the latter from the pricing equation (i.e. a Heckman endogenous switching regression).[28]

Table 8 presents causality findings with no selection adjustment (as before), with adjustment in the indices' construction, and with both adjustment in index construction and inclusion of the estimated quarter-specific shocks from the auction incidence (i.e., selection) equation in the information set in the Granger causality test VARs. None of

[28]See Appendix C for further detail

these adjustments alter our earlier results.[29] In fact, controlling for selection *increases* the information content in auction prices when predicting negotiated prices.

Our findings are a general phenomenon, and are not driven by certain areas or types of homes. Table 9 shows the causality tests *within* local districts.[30] The null of no causality from lagged auction prices to negotiated prices is rejected in all 23 districts of the two cities. No district shows negotiated prices as informative as auctions.

Table 10 shows our Granger causality results hold when stratifying by alternative types of homes: restricting the samples to detached homes only, including a much broader set of attributes when estimating the hedonic price regressions,[31] using a much larger sample but fewer attributes,[32] and stratifying homes below or above mean idiosyncracy (Haurin, 1988).[33] All these robustness checks support our earlier findings.

Table 9—Directed information within Districts

	$DI(p_t \to a_t)$	$DI(a_t \to p_t)$	Auction share
		Sydney	
Baulkham Hills	0.03	0.11	0.06
Blacktown	0.00	0.11	0.06
City and Inner South	0.03	0.12	0.24
Eastern Suburbs	0.04	0.22	0.35
Inner South West	0.04	0.06	0.20
Inner West	0.03	0.06	0.30
North Sydney	0.06	0.07	0.17
Northern Beaches	0.11	0.22	0.11
Outer South West	0.01	0.10	0.03
Outer West	0.02	0.21	0.02
Parramatta	0.03	0.11	0.13
Ryde	0.02	0.07	0.22
South West	0.08	0.10	0.13
Sutherland	0.11	0.13	0.14
		Melbourne	
Inner	0.04	0.08	0.18
Inner East	0.08	0.10	0.26
Inner South	-0.03	0.09	0.23
North East	0.03	0.14	0.15
North West	0.03	0.05	0.12
Outer East	0.05	0.08	0.06
South East	0.14	0.21	0.06
West	0.04	0.14	0.09

Note: Prices are estimated using a hedonic index with basic attributes on the unmatched samples.

[29] One could alternatively include the auction share directly in the VAR. The inference is similar.

[30] We use the Australian Bureau of Statistics' Statistical Area 4 designation, along with the 2011 ABS postcode-district concordance. These sub-city groupings are designed to reflect local labor markets defined by joint local residential and work location choices.

[31] The full set of controls is discussed further in the online Appendix.

[32] This helps control for potential non-randomness in the recording of basic or detailed attributes data.

[33] This measures a home's atypicality by the weighted mean of the ratios of attributes' absolute deviation from its mean, with weights based on the estimated hedonic price coefficients.

Table 10—Additional Causality Tests

	Sydney		Melbourne	
	$H_0 : a_t \overset{gc}{\nrightarrow} p_t$	$H_0 : p_t \overset{gc}{\nrightarrow} a_t$	$H_0 : a_t \overset{gc}{\nrightarrow} p_t$	$H_0 : p_t \overset{gc}{\nrightarrow} a_t$
Detached homes only	19.19***	0.53	9.17***	1.09
Limited attributes[(a)]	18.32***	8.93	40.34***	4.20
Detailed attributes[(b)]	20.86***	0.04	3.96***	1.72
Above avg. idiosyncracy[(c)]	7.09***	2.00*	8.05***	1.03
Below avg. idiosyncracy	30.01***	0.36	9.52***	0.57

Note: [(a)] See note to Table 7. [(b)] Detailed attributes controls for basic and 34 additional attributes (see Appendix **??**). [(c)] Samples of sales with Haurin index weakly above and strictly below its estimated mean (Haurin, 1988).

Table 11—Momentum and Causality with List Prices

Momentum[(a)]	$t-1$	$t-2$	$t-3$	$t-4$
		Sydney		
List prices	0.54	0.42	0.33	0.25
Negotiated prices	0.40	0.27	0.13	0.08
		Melbourne		
List prices	0.47	0.17	0.14	0.11
Negotiated prices	0.43	0.00	-0.03	0.02
Causality[(b)]	**Sydney**		**Melbourne**	
List and negotiated prices	UM	NN	UM	NN
$H_0 : \mathrm{E}[l_{t+1} \mid l_{t-j}, p_{t-j}] = \mathrm{E}[l_{t+1} \mid l_{t-j}]$	26.97***	36.74***	15.39***	21.15***
$H_0 : \mathrm{E}[p_{t+1} \mid l_{t-j}, p_{t-j}] = \mathrm{E}[p_{t+1} \mid p_{t-j}]$	5.26	8.612*	3.27	23.29***
List and auction prices				
$H_0 : \mathrm{E}[l_{t+1} \mid l_{t-j}, a_{t-j}] = \mathrm{E}[l_{t+1} \mid l_{t-j}]$	20.30***	52.65***	24.11***	37.60***
$H_0 : \mathrm{E}[a_{t+1} \mid l_{t-j}, a_{t-j}] = E[a_{t+1} \mid a_{t-j}]$	6.71	2.90	1.26	7.14

Note: [(a)] Autocorrelation coefficients are computed using the "None" indices. [(b)] for $j \geq 0$. Auction, negotiated and list prices are denoted by a_t, p_t and l_t. None denotes the full (unmatched) sample with only limited attributes (property type, log lot/building size and postcode). NN denotes NN-matched samples with basic attributes.

Table 11 closes this section with estimates of the informativeness of list prices. This series is noisier than the others, as the data do not always report list prices. List prices exhibit even greater momentum than negotiated prices (upper panel). For Sydney, both auction and negotiated prices are informative of future list prices, but not vice versa; in Melbourne, this holds for auctions, but negotiated and list prices are equally informative in predicting each other with the NN-matched indices (lower panel). Broadly speaking one can order the series by momentum and information content as list prices, negotiated prices, auction prices, where list prices have the highest momentum and least information content, and auctions the opposite.

VI. Interpreting our results through price formation theory

Modelling the co-dynamics of auction, negotiated and list prices allows us to separately identify the evolution of buyer and seller values. How we interpret them is informed by theories of price formation. It is well known that auction prices reflect the distribution of buyers' values, and in particular the right tail of that distribution.[34] In the absence of a seller reserve price, only the distribution of buyers values matters. With a seller reserve, the sellers' valuations matters as well, but only has a direct effect on price when the sellers valuation lies between the highest and second-highest bidders valuations.[35] The online Appendix shows that, for a range of assumptions about seller behaviour and Melbourne and Sydney auction sale rates, auctions place a greater weight on the distributions of buyer values than they do the sellers.

Negotiated prices should be more equally reflective of the buyer's and seller's value. With Nash bargaining, price equals a weighted average of the buyer's and seller's value, with the weight on the former equal to the seller's bargaining power. Provided this is not exceptionally high (we estimate close to equal bargaining power in the data), price will be more reflective of the seller value than at auction. These insights also apply to a much richer set of information and bargaining enviroments as discussed in Myerson (1984) and Ausubel, Cramton and Deneckere (2002) and for posted price mechanisms as well (see Caplin and Leahy (2011) and Díaz and Jerez (2013)).

List prices may signal a sellers' or dwellings' type (Albrecht, Gautier and Vroman, 2016; Wang, 2011), encourage buyer visits (Han and Strange, 2016), and act as a reference point for subsequent negotiations (Yavaş and Yang, 1995). They are set by sellers before the negotiating buyer's first offer, and although they may be determined by the *seller's*

[34]In English auctions, with conditionally independent private values the price equals the second highest bidders' valuation. With affiliated values, the whole distribution of buyers' values matters, although the weight assigned to the second-highest bidders' value is still most important.

[35]There is an always indirect effect through selection, i.e. whether auction is successful or not.

assessment of buyers' information or preferences, they are ultimately determined by the seller's information.

A. *A state space model of auction, negotiated and list prices*

The above comments motivate a simple state space model in auction, negotiated and list prices which accommodates dynamics in buyer and seller values. We model each of these three price indices as a separate convex combination of two underlying diffusion processes of a common permanent shock, plus Gaussian white noise.[36] Later, we will conceive of each diffusion process as capturing (the value of) a different side of the market. There can be no more than two diffusion shocks and one common permanent trend, as the three series are cointegrated with two cointegrating vectors. Table 12 shows this in its upper panel and, in its lower, that the sum of the estimated and normalized cointegrating coefficients is insignificanly different from zero, reflecting the NN-matching's success in controlling for composition changes.

Table 12—Cointegration Analysis

	Sydney		Melbourne	
Maximum rank[(a)]	Trace statistic	5% Critical value	Trace statistic	5% Critical value
0	66.72**	42.44	51.09**	42.44
1	32.54**	25.32	25.50**	25.32
2	5.56	12.25	5.77	12.25
Cointegration vectors[(b)]	β_1	β_2	β_1	β_2
a_t	1.00	0.00	1.00	0.00
l_t	0.00	1.00	0.00	1.00
p_t	-1.05	-1.00	-1.00	-1.02
	(0.06)	(0.04)	(0.08)	(0.07)
c	0.04	-0.09	-0.05	-0.05
t	0.003	0.001	-0.0002	0.003
	(0.0008)	(0.0007)	(0.0002)	(0.001)

Note: [(a)] ** denotes rejection of the null of the maximal rank by sequential application of Johansen trace test with type-I error fixed at 5 percent. All tests allow for constant and linear trend in the cointegrating relationship. [(b)] Coefficients on auction and list prices in the cointegrating vectors normalised to the identity matrix. Standard errors reported where identified.

[36]We include the latter to account for estimation errors in construction of the price indices.

The estimated model is:

$$z_t = \mu_z + z_{t-1} + \eta_t \tag{2}$$

$$v_{1,t} = \alpha_1 v_{1,t-1} + (1-\alpha_1) z_t \tag{3}$$

$$v_{2,t} = \alpha_2 v_{2,t-1} + (1-\alpha_2) z_t \tag{4}$$

where z_t is the permanent common shock and the unobserved states $(v_{1,t}, v_{2,t})$ are its two potentially lagged diffusions, with speeds of adjustment α_1 and α_2.

Auction (a_t), negotiated (p_t) and list (l_t) prices are weighted averages of the two diffusion processes plus the Guassian white noise:[37]

$$a_t = \mu_a t + \gamma_a v_{1,t} + (1-\gamma_a) v_{2,t} + \varepsilon_t^a \tag{5}$$

$$p_t = \gamma_p v_{1,t} + (1-\gamma_p) v_{2,t} + \varepsilon_t^p \tag{6}$$

$$l_t = \mu_l t + \gamma_l v_{1,t} + (1-\gamma_l) v_{2,t} + \varepsilon_t^l \tag{7}$$

and $(\gamma_a, \gamma_p, \gamma_l) \in [0,1]^3$. The restriction that the weights sum to one is required for consistency with the [1,-1] cointegrating coefficient vector substantiated by Table 12.

We estimate the model using Bayesian methods, assuming flat (uniform) priors for all parameters (see the online Appendix for further detail). Table 13 reports the results. The estimates suggest one highly autocorrelated diffusion process $(v_{1,t})$ and a substantially less autocorrelated one $(v_{2,t})$ with α_1 and α_2 estimated at 0.84 (0.89) and 0.39 (0.56) in Sydney (Melbourne) respectively. Auctions place a low weight on the more autocorrelated process, with estimates for γ_a of 0.18 (0.26) in Sydney (Melbourne). Negotiated prices are very close to a simple average of the two processes with estimates of γ_p of 0.47 and 0.53. List prices place the most weight on the more highly autocorrelated process with γ_l estimated at 0.96 and 0.83.

With price determination theories positing that auctions mainly reflect buyers' values, list prices mainly sellers' values, and negotiated prices a convex combination of the two, these estimates lead us to label $v_{2,t}$ as average buyer value and $v_{1,t}$ as average seller value. We then conclude that buyers update more quickly in response to permanent common shocks than do sellers. One can visualise this statement easily through the impulse response functions to the common shocks (Figure 3).

[37] We also allow for deterministic trends in prices, and thus the implied cointegrating relationships. In the data, the estimated trends are small (Table 12).

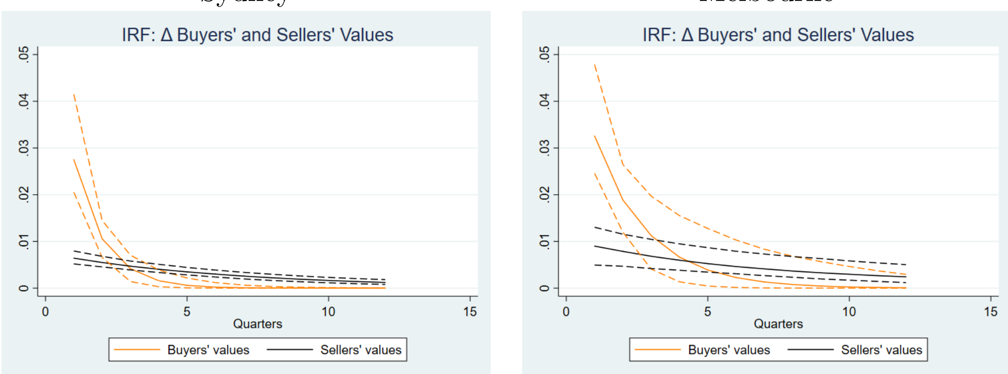
TABLE 13—STATE SPACE MODEL ESTIMATES: 2001:I TO 2016:IV

	Sydney			Melbourne		
	Point estimate	90% HPD interval		Point estimate	90% HPD interval	
γ_a	0.18	0.11	0.25	0.26	0.00	0.53
γ_p	0.47	0.45	0.49	0.53	0.32	0.77
γ_l	0.96	0.92	1.00	0.83	0.57	1.00
α_1	0.84	0.82	0.86	0.89	0.82	0.96
α_2	0.39	0.35	0.42	0.56	0.28	0.88

Note: Bayesian estimates using Metropolis-Hastings. HPD interval denotes highest posterior density interval.

FIGURE 3. ESTIMATED MOMENTUM IN BUYERS' AND SELLERS' VALUES

Sydney Melbourne



Note: Estimated autocorrelation of change in buyer and seller values with 90% highest posterior density intervals.

VII. Competing Explanations

Here we consider competing explanations.

Buyer values are likely to incorporate *'common values'*, as they arise endogenously in search environments with uncertainty over market conditions (Merzyn, Virag and Lauermann, 2010). 'Common value' logic then suggests that, by incorporating information from more than one buyer, a single auction price will tend to more closely estimate the 'true' value of continued buyer search, and so future prices, than a negotiated price.[38] Most of the error for either index is likely be aggregated away in index construction, but what remains, being a temporary error in the price level, will lead to negative first order autocorrelation in price growth. That implies more negative autocorrelation in negotiated price growth than auction, opposite to our findings.

Shocks *diffusing across the buyer population* over time will cause auction and negotiated prices to temporarily diverge. Auction prices will respond strongly to even a partially diffused, private value, positive shock, as its recipients will outbid other buyers, but weakly to a negative shock, whose recipients will be outbid. As negotiated prices will equally reflect positive and negative shocks, auction prices will lead negotiated prices for positive shocks, but lag for negative. (The online Appendix offers a simple example, as well as addressing affiliated values.) Cross buyer population value diffusion would thus be a candidate explanation for our findings, were the differential effect of positive shocks greater than that of negative shocks, in absolute value. However, when we permit auction prices to respond asymmetrically to positive and negative permanent shocks, either we find no asymmetry (Sydney) or a greater sensitivity to negative shocks (Melbourne), so that the evidence is, here too, at odds with the competing explanation (online Appendix Table D2).[39]

Finally, auction results, which are published quickly in newspaper and company Internet sites, may have *greater saliency.* Disproportionate use of past auction sales to form valuations might then explain the Granger causality results. However, if values are being based on past auction prices, then negotiated prices should inherent their dynamic behavior. The substantially greater autocorrelation in negotiated price growth belies that, however.

[38] See Kremer (2002), for example, which establishes this result using limiting arguments.

[39] The new parameter forces us to restrict auction prices to respond to only one of the diffusions. As before, it responds to the less autocorrelated one.

VIII. Conclusion

We started by noting the importance of housing price dynamics to the macroeconomy. Here, we have married microeconomic concerns about market microstructure to macroeconomic concerns about price risk and illiquity. Our results suggest differential speeds of information acquisition are consistent with several other established housing market facts and help to explain both price momentum and the procyclality of transaction volumes. We think these findings are of interest to macroeconomists concerned with price dynamics and their implications for household credit constraints and wealth effects on consumption, but also for microeconomists interested in how price formation can matter for price dynamics.

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Additional Material for the Online Appendix

A. Data, International Comparison and Further Findings

A1. Data

The data were purchased from Australian Property Monitors (APM), a specialist real estate data firm in Australia. APM relies on a number of external sources, including the NSW Department of Finance and Services for property sales data in Sydney and the State of Victoria for property sales data in Melbourne. For more information about these data, see the Copyright and Disclaimer Notices at the end of this Appendix.

The unit record data include all residential property listings and transactions for home sales between 1993:I and 2016:IV. We restrict the sample to final sales transactions, which include information on a homes' price, location (longitude/latitude), street address (in Sydney the full address is available, in Melbourne all information except the house or unit number is available), the type of home, postcode, the number of bedrooms, the number of bathrooms and the lot size of a house (or building area in the case of units).[40] To adjust for the fact listing prices are only observed for more recent subset of sales, and that complete attributes data are only available for Melbourne from 1998 onwards, Table A1 reports the sub-samples we use when working with alternative price measures and models.[41]

Table A1—Estimation samples

	Sydney	Melbourne
Hedonic unmatched samples	1993:I–2016:IV	1997:II–2016:IV
Hedonic unmatched samples with list prices	1998:I–2016:IV	2001:1–2016:IV
Hedonic matched samples	1998:I–2016:IV	1998:I–2016:IV
Hedonic matched samples with list prices	2001:I–2016:IV	2001:1–2016:IV
Repeat-sales unmatched samples	1993:I–2016:IV	1993:I–2016:IV
Repeat-sales matched samples	1993:I–2016:IV	1993:III–2016:IV

Note: Hedonic and repeat-sales matched samples apply to both NN (nearest neighbour) and PS (propensity score) matching estimators on the all-sales and repeat-sales sample respectively. The hedonic indices estimated are described in the main text while the repeat-sales index is that used by Case and Shiller (1989).

We additionally have data on 34 other binary variables listed in Table A2 together with their hedonic coefficients estimated on the unmatched sample of negotiated sales from 1993:I to 2016:IV. We make use of these detailed attributes data in Table 10.

[40]We have the census of transactions, and date them according to the date of transaction and not publication. A related issue is the distinction between the contract date and the settlement date. However, the difference between the two is very similar on average for both sale mechanisms and in both cities.

[41]The samples used maximise the sample period conditional on the index being estimated and whether matching, attributes data, and list prices are required. Repeat-sales data are, for example, available over the full sample period since these do not require attributes data or listing price information.

Table A2—Coefficients on detailed attributes in hedonic log price regressions

Attribute	Sydney		Melbourne	
Study	0.04***	(0.001)	0.07***	(0.001)
Separate dining	0.00**	(0.001)	0.00*	(0.001)
Family room	0.01***	(0.002)	0.00**	(0.002)
Sun room	-0.02***	(0.002)	0.00	(0.003)
Billiard room	0.20***	(0.009)	0.07***	(0.023)
Rumpus room	-0.01***	(0.001)	0.03***	(0.001)
Fireplace	0.06***	(0.001)	0.09***	(0.002)
Walk–in–wardrobe	0.02***	(0.001)	0.01***	(0.001)
Courtyard	0.01***	(0.001)	0.02***	(0.001)
Internal laundry	-0.01***	(0.001)	0.00**	(0.002)
Heating	0.02***	(0.001)	0.00***	(0.001)
Sauna	0.03**	(0.015)	0.23***	(0.045)
Air–conditioning	0.02***	(0.001)	-0.02***	(0.001)
Balcony	0.02***	(0.001)	0.01***	(0.001)
Barbeque	0.00	(0.001)	0.00***	(0.002)
Polished timber floor	-0.02***	(0.001)	0.00***	(0.001)
Ensuite	-0.02***	(0.001)	-0.04***	(0.001)
Spa	0.01***	(0.001)	0.01***	(0.001)
Garage	0.04***	(0.001)	0.02***	(0.001)
Lock–up–garage	0.00***	(0.001)	0.02***	(0.001)
Pool	0.03***	(0.001)	0.07***	(0.002)
Tennis court	0.07***	(0.004)	0.08***	(0.007)
Been renovated	-0.04***	(0.003)	-0.01	(0.006)
Alarm	0.05***	(0.001)	0.06***	(0.001)
Water view	0.23***	(0.004)	0.24***	(0.024)
Harbour view	0.30***	(0.005)	0.29***	(0.109)
Ocean view	0.19***	(0.006)	0.42***	(0.052)
City view	0.08***	(0.012)	0.12***	(0.034)
Bush view	-0.08***	(0.008)	-0.05	(0.042)
District view	-0.04***	(0.008)	0.09***	(0.022)
Bay view	0.14***	(0.015)	0.32***	(0.021)
Park view	-0.02	(0.015)	0.00	(0.030)
River view	0.17***	(0.024)	0.18***	(0.052)
Mountain view	0.10***	(0.037)	0.01	(0.047)

Note: ***, ** and * denote significance at the 1, 5 and 10 per cent levels. Standard errors are in parentheses.

We apply a number of filters to the raw data, excluding:

1) Related party transactions (less than 2% of all sales);

2) Transactions deemed outside the statistical norms for a given home in a given area at a given point in time (as identified by APM, less than 0.02 % of sales);

3) Pre-auction sales where a home is listed for auction but sold prior to auction via negotiation (0.6% of sales, though we use these sales in our robustness checks);

4) Post-auction sales where a home is unsuccessfully auctioned (the seller reserve is not met) but then subsequently sold via negotiation (0.45% of sales);

5) Sales in the top and bottom 1 percentiles of the unconditional covariates distribution as measured separately using bedrooms, bathrooms, and size and stratifying by whether the home is a house or unit (2% of sales); and

6) Sales with an undisclosed or invalid transaction price (0.2% of sales).

The effects of these filters and requiring complete attributes data for bedrooms, bathrooms and land size on sample size are reported in Table A3. Our results are qualitatively similar if these filters are not applied.

Table A3—Sales Frequency by Selling Mechanism

	Sydney		Melbourne	
	Houses	Units	Houses	Units
	Partial attributes observed – prior to filtering			
Auctions	141,445	53,232	217,484	59,062
	(11.37%)	(7.42%)	(16.59%)	(10.90%)
Negotiations	1,110,317	664,931	1,093,425	483,187
	(88.63%)	(92.59%)	(83.41%)	(89.11%)
All sales	1,252,776	718,163	1,310,909	542,249
	All attributes observed – after filtering			
Auctions	83,211	26,222	112,883	30,897
	(17.05%)	(12.30%)	(23.10%)	(21.77%)
Negotiations	404,832	186,996	375,758	111,034
	(82.95%)	(87.70%)	(76.90%)	(78.23%)
All sales	488,043	213,218	488,641	141,931

Note: Excludes related-party sales. Percentages, which relate to the column sum, are reported in parentheses.

A2. Local Macroeconomic Indicators

In the main text we report the predictive content of auctions and negotiations when forecasting local macroeconomic indicators. The *nominal value of building approvals* is the state-wide value of private residential building approvals for Victoria and New South Wales, sourced from the Australian Bureau of Statistics (ABS). The *real interest interest rate* is the nominal central bank interest rate (the official overnight cash rate from the Reserve Bank of Australia) less one-quarter ahead city-specific realised CPI inflation (ABS). *Real output* is real state final demand, the sum of value added consumption, investment and government expenditure. *State-level inflation* is the state-wide implicit price deflator (IPD).

A3. International comparison

Mack, Martínez-García et al. (2011) compile nominal housing prices for 23 countries. Prices are measured on a conceptually similar basis.[42] Table A4 reports the mean, standard deviation and autocorrelations in quarterly prices growth between 1993:I and 2015:I.

TABLE A4—INTERNATIONAL HOUSING PRICE COMPARISON: 1993:I TO 2015:I

Country	Mean	SD	Min	Max	$\rho_{t,t-1}$	$\rho_{t,t-2}$	$\rho_{t,t-3}$	$\rho_{t,t-4}$
Australia	1.61	1.87	-2.19	6.26	0.71	0.42	0.14	0.04
Belgium	1.26	0.92	-0.58	3.98	0.83	0.71	0.57	0.47
Canada	1.19	1.58	-3.21	5.71	0.50	0.10	0.12	0.26
Croatia	2.77	12.28	-19.09	90.09	0.41	0.25	0.10	-0.05
Denmark	1.30	2.30	-7.42	6.28	0.69	0.39	0.28	0.32
Germany	0.30	0.57	-0.95	1.56	0.89	0.82	0.73	0.62
Finland	1.16	1.54	-3.85	4.41	0.69	0.39	0.32	0.29
France	1.01	1.69	-3.62	4.03	0.74	0.63	0.57	0.56
Ireland	1.62	3.28	-6.46	9.55	0.88	0.77	0.75	0.72
Israel	1.59	2.61	-4.34	9.84	0.50	0.35	0.38	0.33
Italy	0.48	1.43	-2.43	3.00	0.91	0.81	0.76	0.70
Japan	-0.77	0.44	-1.69	-0.10	0.94	0.86	0.78	0.68
Luxembourg	1.32	1.43	-2.97	5.18	0.46	0.43	0.41	0.14
Netherlands	1.18	1.87	-3.92	5.30	0.70	0.68	0.63	0.68
New Zealand	1.58	1.94	-4.24	7.68	0.74	0.50	0.37	0.26
Norway	1.66	1.85	-4.39	7.01	0.09	-0.01	0.05	0.13
S. Africa	2.59	2.15	-2.61	8.56	0.79	0.54	0.41	0.30
S. Korea	0.60	1.63	-7.30	5.85	0.66	0.41	0.21	0.09
Spain	0.95	2.15	-2.86	5.73	0.88	0.79	0.76	0.78
Sweden	1.39	1.42	-4.43	3.79	0.65	0.40	0.20	0.10
Switzerland	0.32	0.78	-1.64	1.44	0.89	0.78	0.69	0.66
UK	1.58	2.34	-5.30	8.20	0.42	0.13	0.14	0.28
US	0.80	1.32	-3.12	3.80	0.74	0.53	0.65	0.68

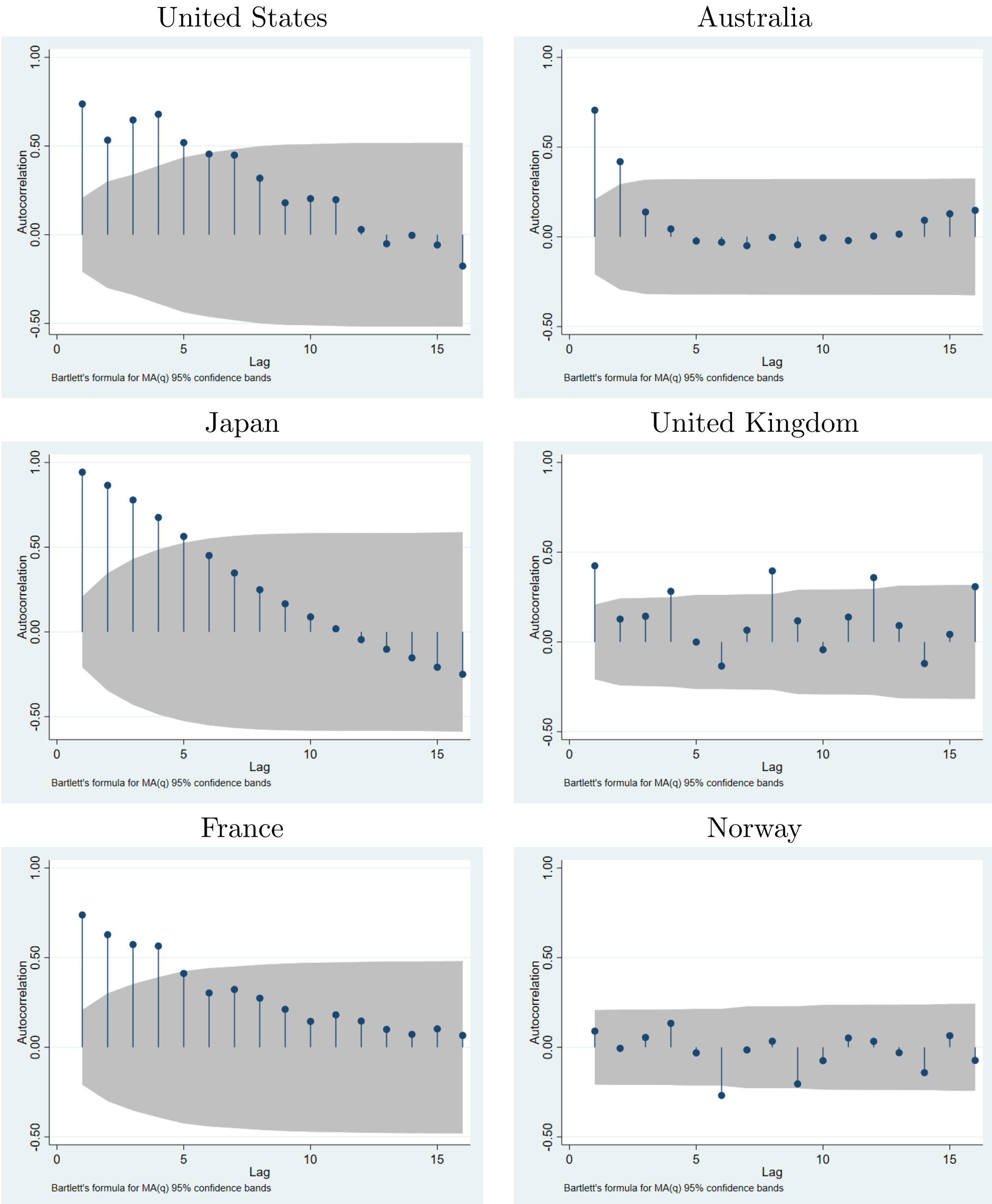
Note: Data are sourced from Mack, Martínez-García et al. (2011). $\rho_{t,t-j}$ denotes the autocorrelation in quarterly nominal price growth between period t and period $t-j$.

Figure A1 displays autocorrelation functions for three countries known for a high share

[42] Although there are differences in the approaches used to measure prices across countries, these price indices are conceptually similar using a range of techniques to control for changes in the composition of homes sold over time including mix-adjustment (Australia, United Kingdom), hedonic estimation and mix-adjustment (France, Japan, Norway) and repeat-sales (United States). Using repeat-sales or hedonic methods for Australia, for example, results in similar autocorrelation estimates.

of negotiations – the United States, Japan and France – and for three with a non-trivial share of structured auctions – Australia, the United Kingdom and Norway. Where negotiations overwhelmingly dominate, first and second-order ACF coefficient estimates lie between 0.6 and 0.8, with significant autocorrelation lasting well beyond two quarters. Where auctions are more common, the ACFs are noticeably smaller and less persistent.

Figure A1. International Autocorrelation Functions: Housing Prices Growth



Note: Based on authors' calculations. Data are from Mack, Martínez-García et al. (2011).

A4. Cross-correlograms with All-Sales Prices Growth and the Auction Sales Share

Figure A2 reports cross correlations with lags and leads of all-sales prices growth for auction and negotiations in each city, before and after matching where the red vertical line identifies the maximal correlation. Whereas growth in all sales prices has a highest correlation with a lead of 1 quarter for negotiated prices – and so are potentially useful for predicting subsequent changes in them – the highest correlation with auction prices is a lag of 1 quarter. That is, auction prices may have scope to predict future growth in all-sales prices, but it seems less likely that negotiated prices do so.

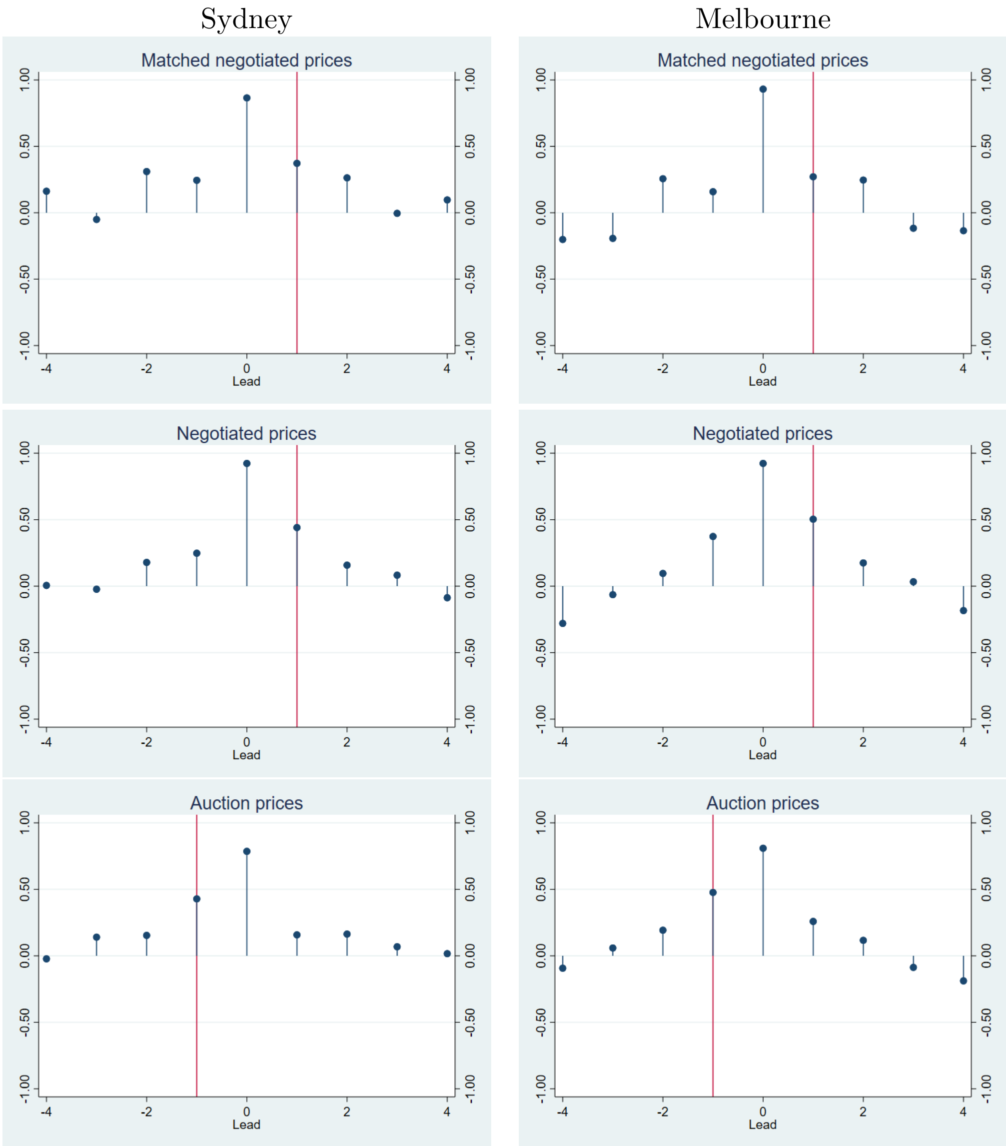


Figure A2. Cross Correlations with Lags and Leads of All-Sales Prices Growth

Note: The figure reports the cross-correlations between auction or negotiated price growth and all-sales price growth. The vertical red line denotes the highest non-contemporaneous correlation.

Figure A3 shows scatter plots of the auction sales rate against auction prices and negotiated prices in each city. There is strong evidence of a Phillips-curve with higher price growth in either auction or negotiated prices being positively associated with the auction sales rate. We define the sales rate as the number of successful auction sales divided by the total number of auctions held (excluding withdrawn and postponed auctions). Including the latter yields very similar results.

Sydney Melbourne

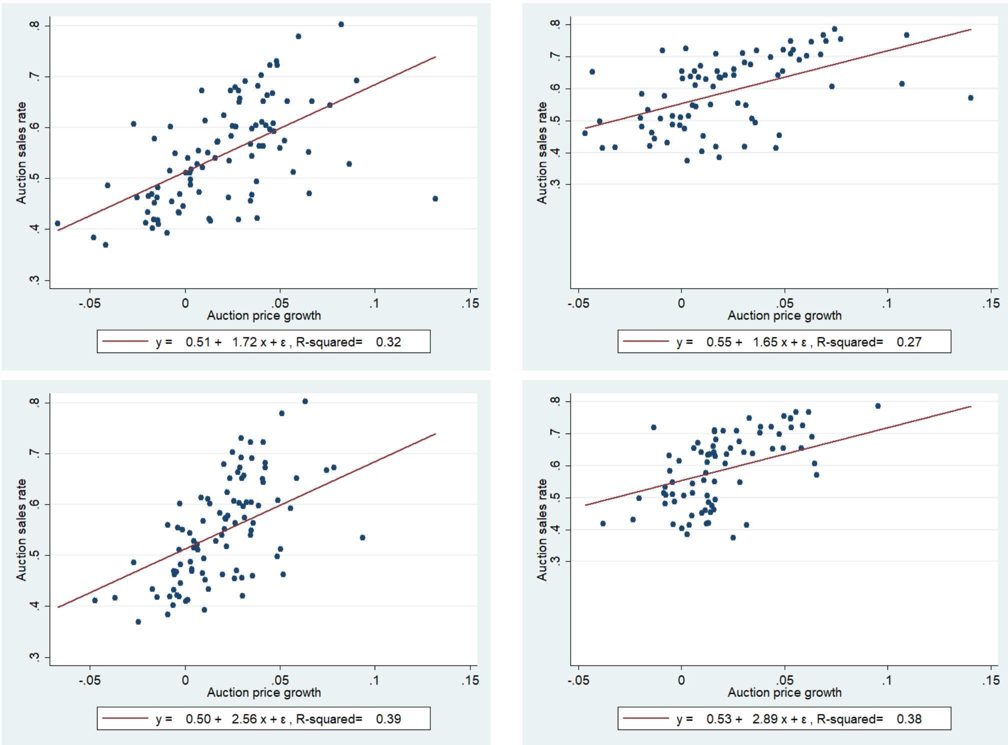


Figure A3. Auction Sales Rates vs. Price Growth

Changes in the auction sales share (successful auction sales divided by total auction and negotiated sales) is relevant for the unmatched sample findings. Figure A4 reports simple cross-correlograms between all sales prices growth and the auction sales share. Changes in the auction sales share do not lead growth in overall prices, while past overall price conditions predict future movements in the auctions sales share.

Sydney Melbourne

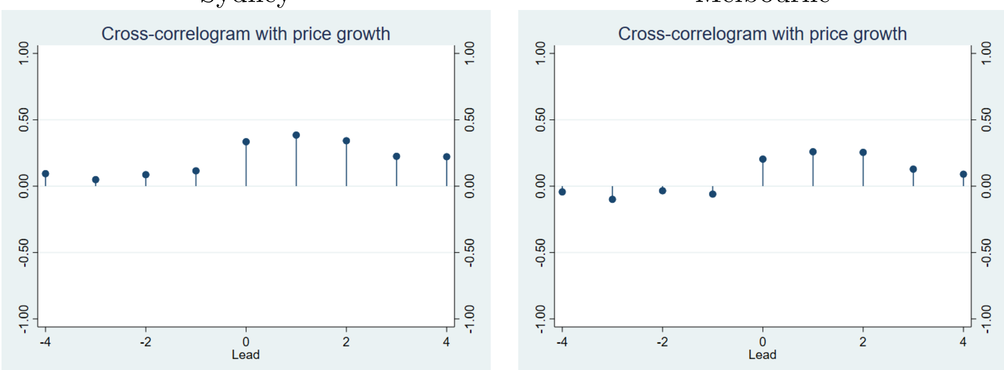


Figure A4. Correlogram: Auction sales share

B. Matching

B1. The Matching Algorithms

Results based on nearest neighbor and propensity score matching are reported in the main text. Here we outline the two algorithms used.

When using nearest neighbour (NN) matching, for each quarter q in 1993:Q1 (1998:Q1) to 2016:Q4 in Sydney (Melbourne): [43]

1) Estimate a logit-based propensity score of the transaction being an auction. 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 (CBD) General Post Office. [44]

2) Remove observations with an estimated propensity score, $\widehat{e}_{iq}$, outside of the interval $[0.05, 0.95]$ (i.e. remove sales conditionally very likely or unlikely to have been auctioned).

3) Remove any auction (negotiation) for which there does not exist a corresponding negotiation (auction) with estimated propensity score within 0.1 caliper.

4) Denote the remaining set of auctions (negotiations) in quarter q as $\mathcal{A}_q$ ($\mathcal{P}_q$). [45] 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.[46] 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 a matrix weighting the distance measure between covariates. [47] Matching is undertaken with replacement and ties are broken randomly.

[43] Very few records with complete attributes data are recorded for Melbourne prior to 1998 thus restricting the sample period for that city.

[44] 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.

[45] Results are robust to different intervals or optimally selected trims in each quarter (Imbens and Rubin, 2015).

[46] We also tried a Euclidean-based approximation of the distances between neighboring homes where we replace longitude and latitude as measured in degrees using the WGS 1984 datum with the Euclidean distance metric $d\left(x,y,z\right) = \|\left(x_i - x_j, y_i - y_j, z_i - z_j\right)\|$ where $x_k = R\cos\left(\theta_k\right)\cos\left(\phi_k\right)$, $y_k = R\cos\left(\theta_k\right)\sin\left(\phi_k\right)$ and $z_k = R\sin\left(\theta_k\right)$ where $\theta_k = \lambda_{1k}\frac{\pi}{180}$, $\phi_k = \lambda_{2k}\frac{\pi}{180}$, $R = 3958.76$ miles is the value used for the average Earth radius and λ_{1k} and λ_{2z} denote latitude and longitude measured in degrees for home k. Applying this approximation when evaluating the distance of each home from the CBD resulted in an absolute average error of 5 (14) yards for Sydney (Melbourne) and a maximal error of 231.9 (98.5) yards and had little effect on the resulting matched price indices.

[47] For Sydney, with exact matching on home type, bedrooms and bathrooms, we use the inverse of the sample variance-covariance matrix (Mahalanobis). For Melbourne, where we require exact matching on home type only, we use only the diagonal component of the same matrix as this results in less volatile matched sample negotiated price estimates. The results are similar if we reverse these choices.

5) Construct a matched negotiated sales sample for quarter q collating the set of pair-wise matches (one for each auction in quarter q) identified in Step (5). Denote this sample $\mathcal{P}_q^M$.

6) Append the quarterly samples of matched negotiated sales to form a single matched negotiated sales sample (i.e. $\mathcal{P}^M = \bigcup_{q\in 1993:1-2016:4} \mathcal{P}_q^M$). Do the same for the quarterly samples of auction sales used in matching: $\mathcal{A}^M = \bigcup_{q\in 1993:1-2016:4} \mathcal{A}_q$.

After constructing the matched samples, one can then estimate log hedonic price regressions on each matched sample ($\mathcal{P}^M$ and $\mathcal{A}^M$) in the usual way. Figure B1 reports the results from doing so. It also includes a hedonic index of list prices, which uses the listing price used by the seller for the matched negotiations.

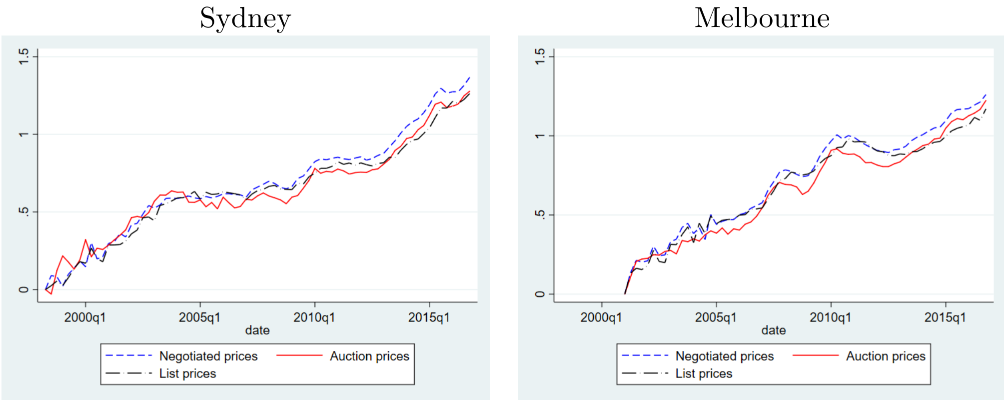


Figure B1. List, negotiated and auction prices on the matched sample

When using propensity score (PSM) matching, the algorithm differs only in Step (5) where closeness is now measured by the estimated propensity score: $j(i)$, the closest negotiation is such that:

$$j(i) \in \arg\min_{k\in\mathcal{P}_q} \|\widehat{e}_k - \widehat{e}_i\|$$

where $\|.\|$ is the standard Euclidean norm and $\widehat{e}_k$ denotes the estimated propensity score for obsrvation k. The propensity scores are estimated using a logit model with the basic attributes, plus the distance to the city center.

B2. Match Quality

We provide multiple indicators of match quality. Tables B1 and B2 report means and standard deviations of attributes for house and apartment sales by selling mechanism before and after matching. Figures B2 and B3 show the full unmatched and matched distributions. Figures B4 and B5 graph how differences between the unmatched and matched attributes over time. Figure B6 shows the estimated propensity score distributions before and after matching. In the full sample cross-section and over time the differences in means and standard deviations of attributes after matching are small.

Since we are interested in price dynamics, within-quarter covariate balance also matters. Figure B4 (B5) shows quarter-level, cross-mechanism differences in house (apartment) mean characteristics for auctions and negotiations, in Sydney and Melbourne, with and without NN matching. With the exception of the very earliest quarters, where complete attribute data are missing for most transactions, matching substantially reduces the differences, in many quarters nearly to zero. [48]

[48]The introduction of the goods and services tax (GST) in the September quarter of 2000, applied to new home purchases in Australia, does affect the quality of apartment matches temporarily in that quarter. The effects are much less pronounced when matching house sales.

Table B1—Mean attributes of auctions and negotiations – House Sales

	Auctions		Negotiations		Overlap measures			
X	$E[X_a]$	σ_a	$E[X_p]$	σ_p	Raw Δ	Nor. Δ	$\log\left(\frac{\sigma_a}{\sigma_p}\right)$	π_X
Sydney Houses – Before matching								
Beds	3.37	(0.90)	3.45	(0.84)	-0.07	-0.09	0.14	0.05
Baths	1.77	(0.77)	1.77	(0.75)	-0.01	-0.01	0.07	0.02
Latitude	-33.86	(0.11)	-33.80	(0.19)	-0.07	-0.47	-1.06	0.01
Longitude	151.12	(0.13)	151.06	(0.23)	0.07	0.35	-1.19	0.01
Log size	6.29	(0.65)	6.53	(0.66)	-0.24	-0.37	-0.04	0.09
Distance	14.96	(11.68)	28.87	(19.01)	-13.91	-0.88	-0.97	0.09
H index	0.56	(0.46)	0.48	(0.35)	0.08	0.21	0.55	0.09
Turnover	1.13	(0.38)	1.34	(0.57)	-0.20	-0.42	-0.81	N/A
# of Obs.	83,211		404,832					
Sydney Houses – After matching								
Beds	3.38	(0.90)	3.38	(0.90)	0.00	0.00	0.00	0.00
Baths	1.77	(0.77)	1.77	(0.77)	0.00	0.00	0.00	0.00
Latitude	-33.87	(0.08)	-33.87	(0.08)	0.00	0.00	0.00	0.05
Longitude	151.12	(0.10)	151.12	(0.10)	0.00	0.00	0.01	0.05
Log size	6.27	(0.65)	6.27	(0.63)	0.01	0.01	0.06	0.06
Distance	13.38	(8.19)	13.35	(8.25)	-0.03	0.00	0.01	0.06
H index	0.22	(0.16)	0.23	(0.18)	0.01	0.06	0.19	0.08
Turnover	1.14	(0.38)	1.09	(0.31)	0.05	0.14	0.44	N/A
# of Obs.	79,623		79,623					
Melbourne Houses – Before matching								
Beds	3.09	(0.75)	3.31	(0.72)	-0.21	-0.29	0.10	0.09
Baths	1.58	(0.62)	1.70	(0.59)	-0.12	-0.20	0.12	0.13
Latitude	-37.82	(0.09)	-37.85	(0.15)	0.03	0.21	-0.95	0.00
Longitude	145.04	(0.11)	145.06	(0.22)	-0.02	-0.12	-1.44	0.00
Log size	6.19	(0.58)	6.36	(0.62)	-0.18	-0.30	-0.13	0.05
Distance	13.43	(7.44)	24.19	(12.32)	-10.75	-1.06	-1.00	0.09
H index	0.24	(0.14)	0.20	(0.11)	0.03	0.26	0.46	0.13
Turnover	1.13	(0.36)	1.31	(0.55)	-0.18	-0.39	-0.84	N/A
# of Obs.	112,883		375,758					
Melbourne Houses – After matching								
Beds	3.09	(0.75)	3.09	(0.75)	0.00	0.00	0.01	0.00
Baths	1.58	(0.63)	1.58	(0.63)	0.00	0.00	0.00	0.00
Latitude	-37.82	(0.09)	-37.82	(0.09)	0.00	0.00	0.00	0.05
Longitude	145.04	(0.10)	145.04	(0.10)	0.00	0.00	-0.01	0.05
Log size	6.18	(0.58)	6.18	(0.57)	0.00	0.01	0.04	0.06
Distance	13.07	(6.74)	13.01	(6.74)	-0.05	-0.01	0.00	0.05
H index	0.23	(0.13)	0.23	(0.14)	0.00	0.01	0.13	0.09
Turnover	1.13	(0.37)	1.09	(0.30)	0.04	0.13	0.37	N/A
# of Obs.	110,763		110,763					

Note: (a) Latitude and Longitude are measured using the WGS 1984 datum. Log size is the natural logarithm of total lot size in square metres. H index is Haurin's (1988) measure of idiosyncracy, Distance is to the city centre (the CBD General Post Office), and Turnover is the number of each property's sales within the relevant sub-sample. (b) Raw Δ is the raw mean difference: $E[X_a] - E[X_p]$. Nor. Δ is normalised mean difference: $E[X_a] - E[X_p] / \sqrt{(\sigma_a^2 + \sigma_p^2)/2}$. (c) $\pi_X = 1 - F_{X,a}\left(F_{X,p}^{-1}\left(1 - \frac{\alpha}{2}\right)\right) + F_{X,a}\left(F_{X,p}^{-1}\left(\frac{\alpha}{2}\right)\right)$, with $F_{X,a}$ ($F_{X,p}$) the empirical CDF for covariate X on the auction (negotiation) sample, with $\alpha = 0.05$ for continous X (latitude, longitude and size) and $\alpha = 0$ for discrete.

Table B2—Mean attributes of auctions and negotiations – Apartment Sales

	Auctions		Negotiations		Overlap measures			
X	$E[X_a]$	σ_a	$E[X_p]$	σ_p	Raw Δ	Nor. Δ	$\log\left(\frac{\sigma_a}{\sigma_p}\right)$	π_X
Sydney Apartments – Before matching								
Beds	2.10	(0.66)	2.01	(0.65)	0.09	0.13	0.04	-0.03
Baths	1.39	(0.53)	1.39	(0.52)	0.00	0.00	0.03	0.00
Latitude	-33.88	(0.07)	-33.85	(0.11)	-0.03	-0.28	-0.91	0.02
Longitude	151.19	(0.08)	151.14	(0.12)	0.05	0.45	-0.76	0.01
Log size	7.08	(0.89)	7.32	(0.99)	-0.23	-0.25	-0.20	0.09
Distance	8.37	(7.18)	13.66	(11.16)	-5.29	-0.56	-0.88	0.03
H index	0.26	(0.16)	0.23	(0.15)	0.03	0.19	0.05	0.04
Turnover	1.12	(0.35)	1.39	(0.60)	-0.27	-0.54	-1.07	N/A
# of Obs.	26,222		186,996					
Sydney Apartments – After matching								
Beds	2.09	(0.66)	2.09	(0.66)	0.00	0.00	0.00	0.00
Baths	1.38	(0.53)	1.38	(0.53)	0.00	0.00	0.00	0.00
Latitude	-33.87	(0.08)	-33.87	(0.08)	0.00	0.00	0.00	0.05
Longitude	151.20	(0.07)	151.19	(0.07)	0.00	0.01	0.02	0.05
Log size	7.06	(0.89)	7.06	(0.87)	0.00	0.00	0.03	0.05
Distance	7.50	(5.19)	7.38	(5.16)	0.12	0.02	0.01	0.05
H index	0.26	(0.16)	0.24	(0.26)	0.01	0.07	-1.01	0.04
Turnover	1.12	(0.36)	1.08	(0.28)	0.05	0.15	0.51	N/A
# of Obs.	24,983		24,983					
Melbourne Apartments – Before matching								
Beds	2.13	(0.69)	2.13	(0.73)	0.00	0.00	-0.11	-0.03
Baths	1.27	(0.47)	1.31	(0.50)	-0.04	-0.07	-0.10	0.03
Latitude	-37.84	(0.07)	-33.85	(0.10)	0.00	0.08	-0.81	0.01
Longitude	145.02	(0.07)	145.03	(0.13)	-0.01	-0.10	-1.26	0.00
Log size	6.49	(1.08)	6.54	(1.23)	-0.05	-0.04	-0.26	0.07
Distance	9.40	(6.02)	13.46	(11.19)	-4.06	-0.45	-1.24	0.01
H index	0.20	(0.14)	0.25	(0.15)	-0.05	-0.33	-0.10	0.40
Turnover	1.12	(0.35)	1.27	(0.52)	-0.15	-0.35	-0.79	N/A
# of Obs.	30,897		111,034					
Melbourne Apartments – After matching								
Beds	2.13	(0.69)	2.13	(0.68)	0.00	0.00	0.02	0.00
Baths	1.27	(0.47)	1.27	(0.47)	0.00	0.00	0.00	0.00
Latitude	-33.84	(0.06)	-33.84	(0.06)	0.00	0.00	0.02	0.05
Longitude	145.02	(0.07)	145.02	(0.07)	0.00	0.00	-0.02	0.05
Log size	6.49	(1.08)	6.49	(1.07)	0.00	0.00	0.01	0.05
Distance	9.13	(5.56)	9.03	(5.68)	0.10	0.02	-0.04	0.03
H index	0.30	(0.13)	0.20	(0.19)	0.10	0.62	-0.66	0.07
Turnover	1.12	(0.35)	1.07	(0.27)	0.05	0.16	0.48	N/A
# of Obs.	30,441		30,441					

Note: See note under Table B1.

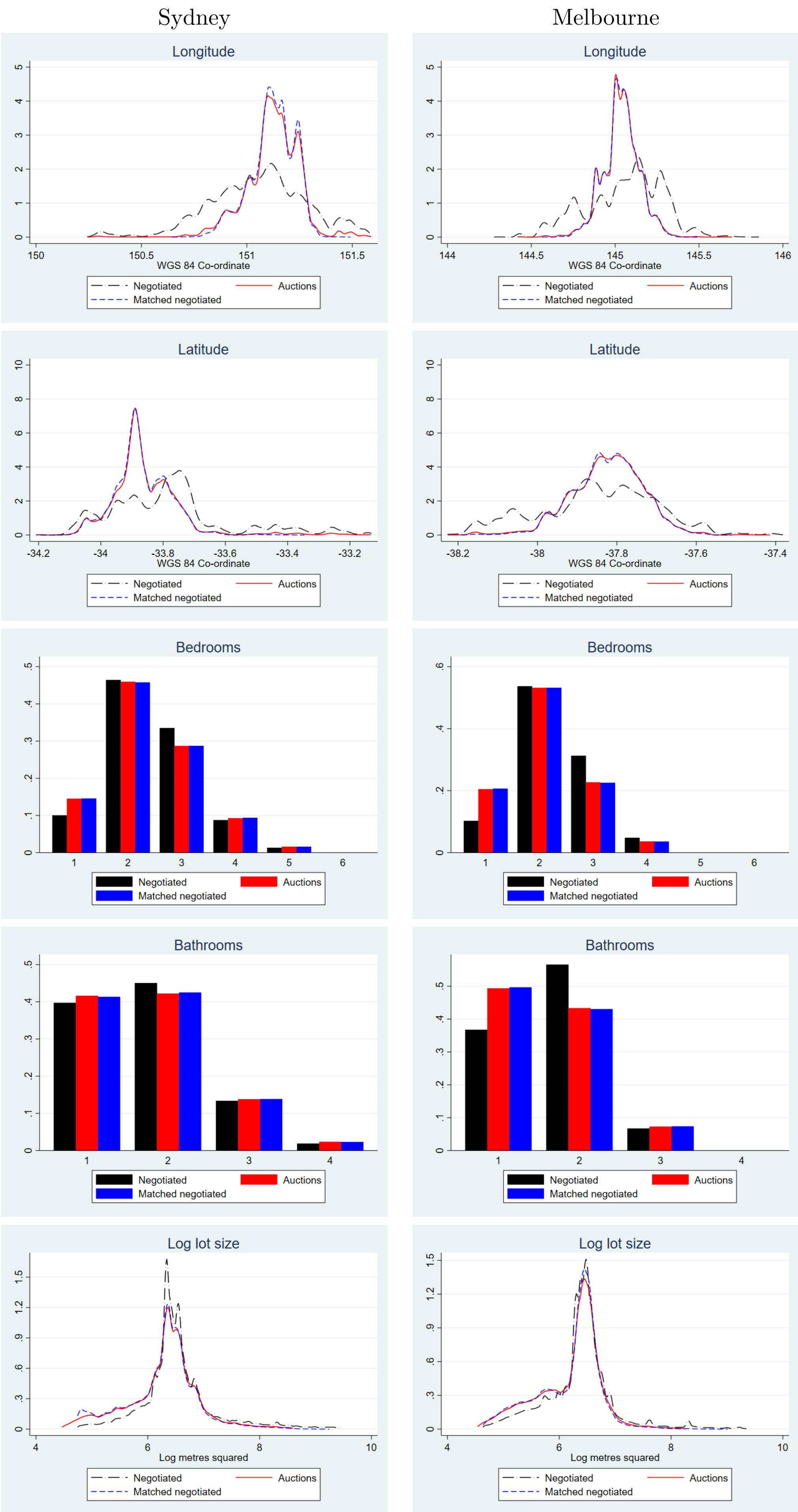


Figure B2. Covariate Balance – Houses

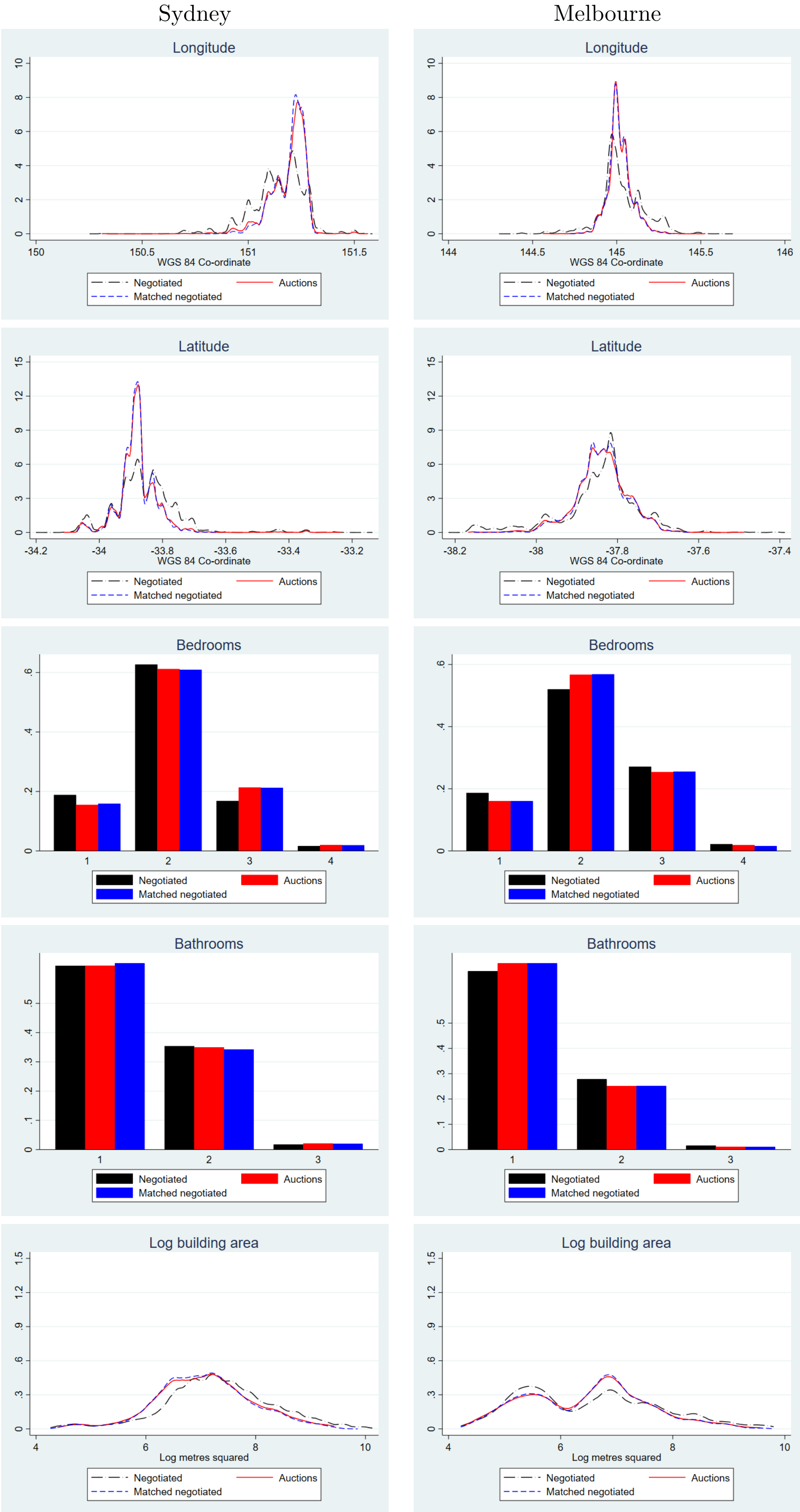


Figure B3. Covariate Balance – Apartments

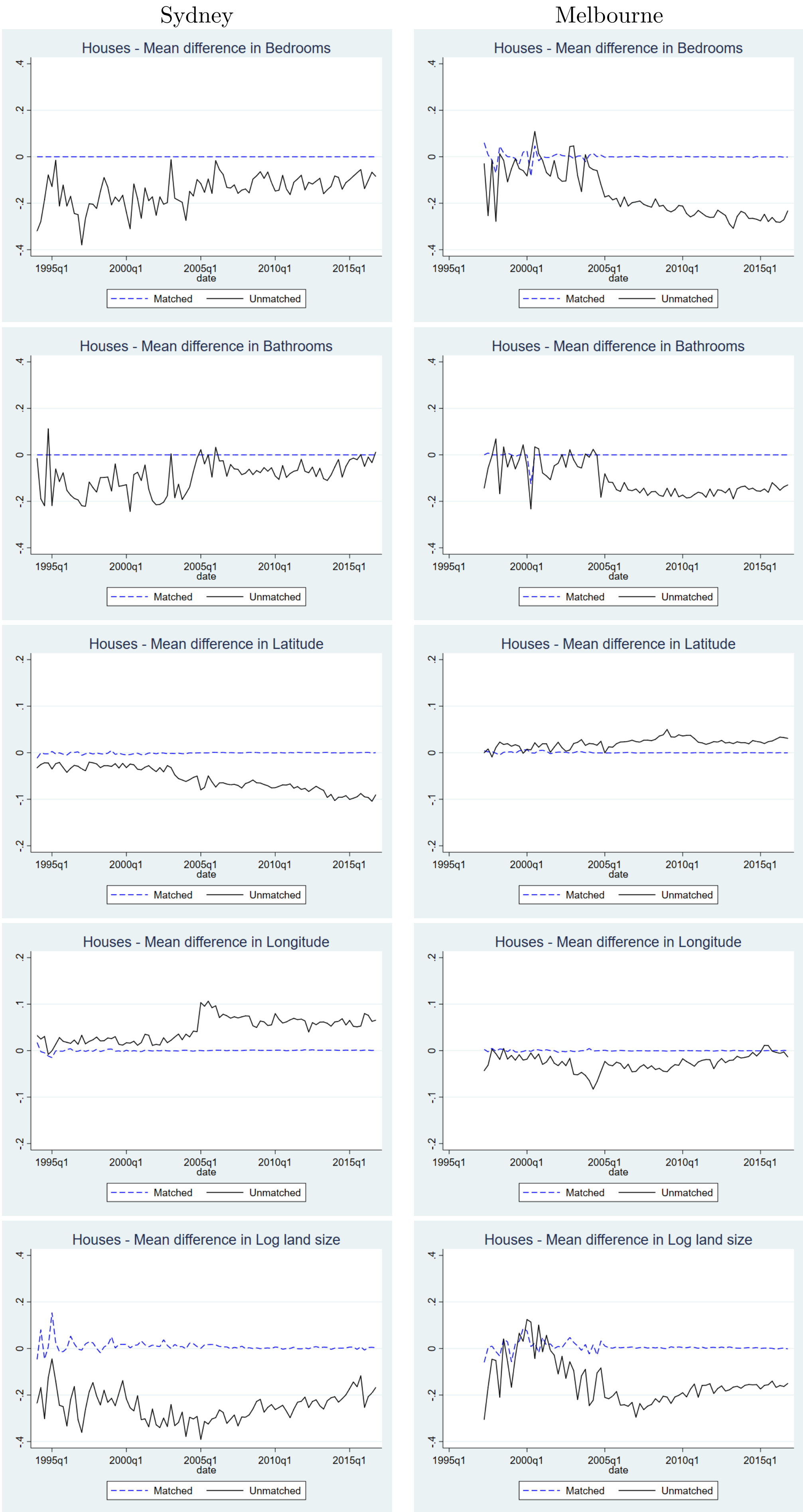


FIGURE B4. DIFFERENCES IN MEAN HOUSE CHARACTERISTICS OVER TIME

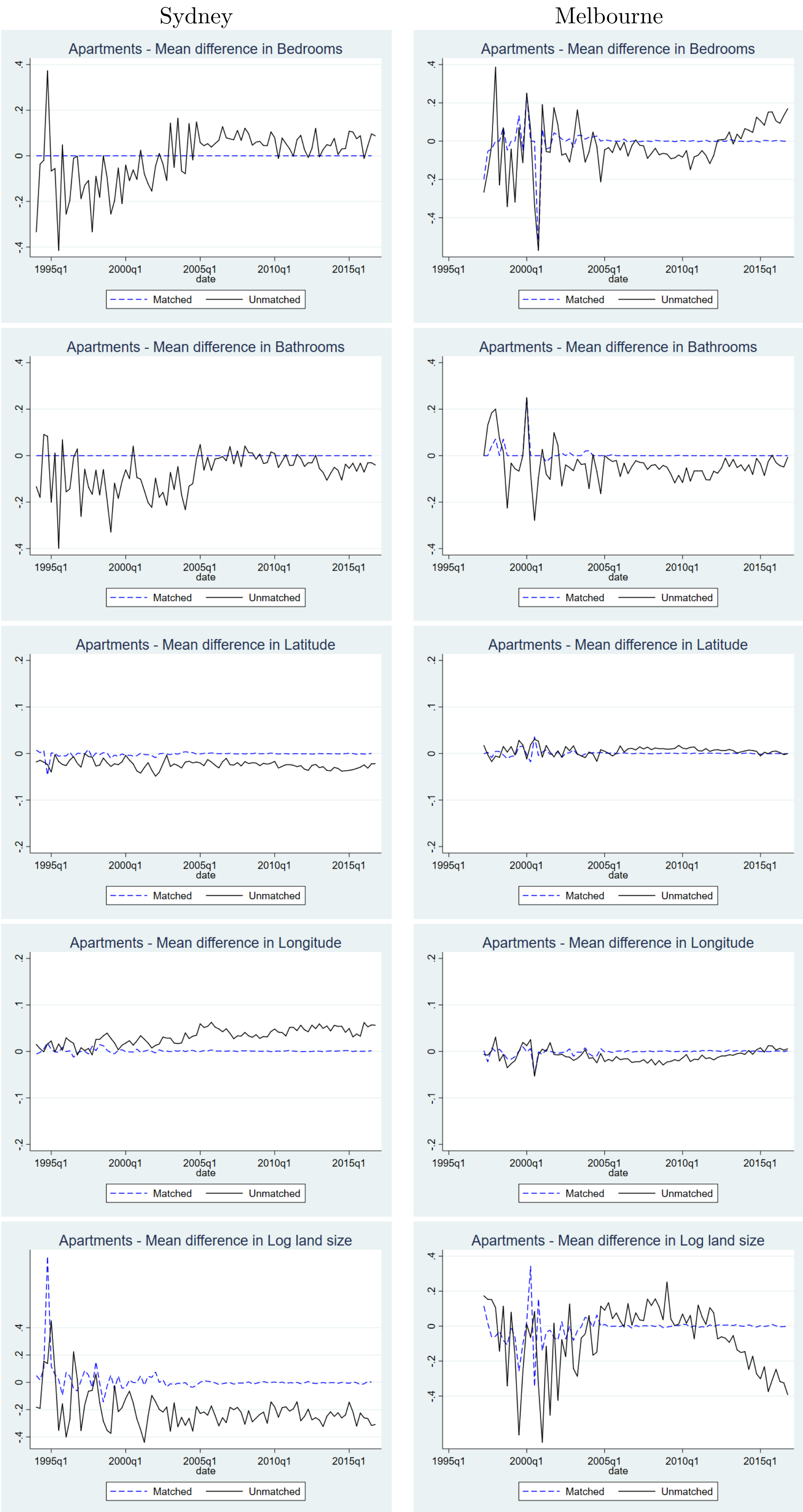


Figure B5. Differences in mean apartment characteristics over time

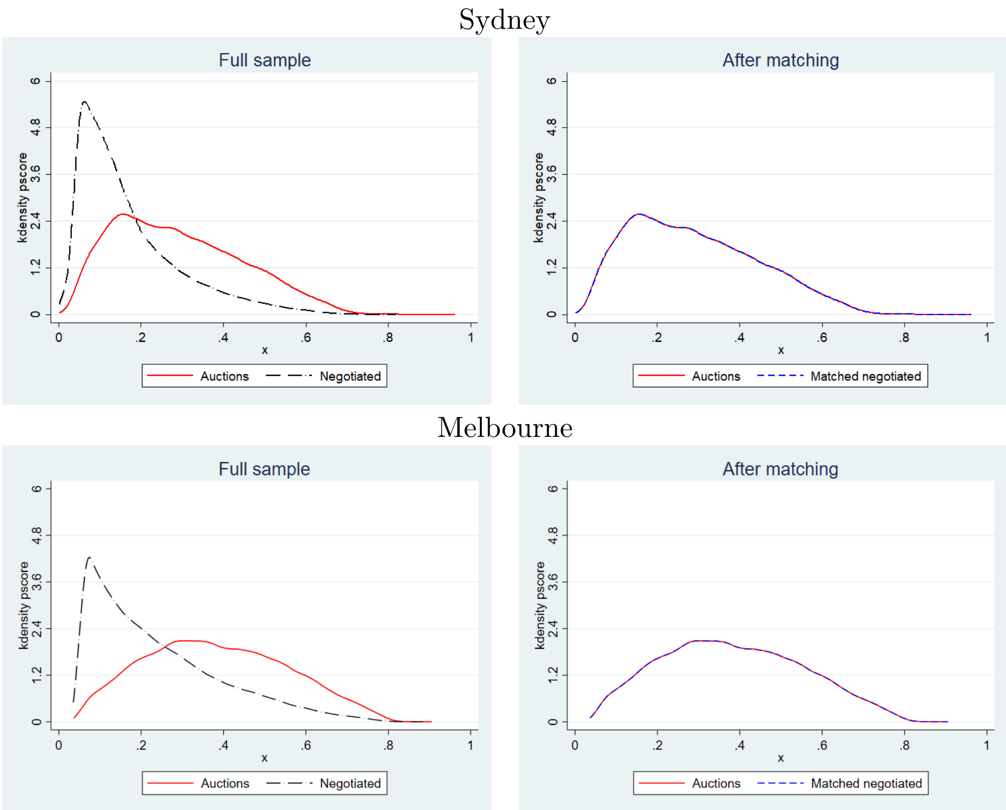


Figure B6. Estimated propensity score distributions

Note: Kernal density graphs for the estimated propensity score for auction using a logistic model that includes all home attributes and geodetic distance to the city centre.

C. Controlling for Sellers' Decisions to use an Auction

Here we consider whether our results are robust to accounting for the decision to use an auction. We assume these choices and price dynamics are jointly determined by the endogenous selection model:

$$\text{(C1)} \qquad \mathbb{1}^a_{ijt} = \begin{cases} 1 \text{ if } w'_{ijt}\kappa + \sum_{t=1}^{T} D_{it}\psi_t + \phi \mathbb{1}^{a,+}_{ijt} + \sum_k H_k \times \mathbb{1}^{a,+}_{ijt}\phi_k \geq u_{ijt} \\ 0 \text{ if } w'_{ijt}\kappa + \sum_{t=1}^{T} D_{it}\psi_t + \phi \mathbb{1}^{a,+}_{ijt} + \sum_k H_k \times \mathbb{1}^{a,+}_{ijt}\phi_k < u_{ijt} \end{cases}$$

$$\text{(C2)} \qquad \ln p_{ijt} = \begin{cases} w'_{ijt}\theta^a + \sum_{t=t_1}^{T} D_{it}\beta^a_t + \varepsilon^a_{ijt} \text{ if } \mathbb{1}^a_{ijt} = 1 \\ w'_{ijt}\theta^p + \sum_{t=1}^{T} D_{it}\beta^a_t + \varepsilon^p_{ijt} \text{ if } \mathbb{1}^a_{ijt} = 0 \end{cases}$$

$$\text{(C3)} \qquad \begin{bmatrix} u_{ijt} \\ \varepsilon^a_{ijt} \\ \varepsilon^p_{ijt} \end{bmatrix} \sim N\left(\mathbf{0}_{3\times1}, \begin{bmatrix} \sigma^2_u & \sigma_{ua} & \sigma_{up} \\ \sigma_{ua} & \sigma^2_a & \sigma_{ap} \\ \sigma_{up} & \sigma_{ap} & \sigma^2_p \end{bmatrix}\right)$$

where β^a_t and β^p_t are the estimated selection-adjusted price indices for auctions and private treaties at time t, $\mathbb{1}^a_{ijt}$ is an indicator function equal to one if home i sold in postcode j at time t is an auction and zero otherwise, $\mathbb{1}^{a,+}_{ijt} = 1$ is an indicator function if the home was ever previously sold via an auction (i.e. $\mathbb{1}^{a,+}_{ijt} = 1$ if $\mathbb{1}^a_{ij\tau} = 1$ for any $\tau < t$ and is zero otherwise), and the vector w'_{ijt} includes all covariates in the hedonic price equation (i.e. $w'_{ijt} := [\alpha'_i \quad H'_{jt} \quad X'_{ik} \quad vec(H_{ij}X'_{ik})']$). The underlying assumption here is that homes previously auctioned are more likely to be auctioned again, but that the previous mechanism of sale should have no bearing on the current price outcome, conditional on the mechanism choice.[49]

Evaluating marginal effects (the increase in the probability of auction) at the conditional means, across all homes and by type of home sold, we see that homes that are previously auctioned are much more likely to be auctioned again. The increase in the probability of auction, for the mean home increases by 0.44 (0.24) in Sydney (Melbourne) once the home has been sold previously through an auction. Conditioning on the type of home sold, we see that there is some evidence in Sydney that the strength of this association varies by the type of home sold (being stronger for home types with a low propensity for auction if they haven't been auctioned before), whereas for Melbourne it is similar across all home types. In short, previous auction incidence is highly correlated with a seller's decision to use an auction again.

To quantify the role of selection on the information content in prices, we test for Granger causality in three VARs. The first uses our standard hedonic index discussed in the main

[49]We allow for the correlation between a home auctioned previously and in the current period to vary according to the house type.

Table C1—First-stage selection estimates

	Sydney		Melbourne	
	$\Delta\,\Pr(\mathbb{1}^{a}_{ijt}=1\vert.)$	(S.E.)	$\Delta\,\Pr(\mathbb{1}^{a,+}_{ijt}=1\vert.)$	(S.E.)
$\mathbb{1}^{a,+}_{ijt}=1$	0.44***	(0.004)	0.24***	(0.002)
Cottage ($\mathbb{1}^{a,+}_{ijt}=1$)	0.06	(0.065)	.	(.)
Duplex ($\mathbb{1}^{a,+}_{ijt}=1$)	0.22	(0.178)	0.23***	(0.063)
House ($\mathbb{1}^{a,+}_{ijt}=1$)	0.31***	(0.014)	0.23***	(0.004)
Semi ($\mathbb{1}^{a,+}_{ijt}=1$)	0.52***	(0.193)	.	(.)
Studio ($\mathbb{1}^{a,+}_{ijt}=1$)	0.72***	(0.229)	.	(.)
Terrace ($\mathbb{1}^{a,+}_{ijt}=1$)	0.53***	(0.126)	0.22***	(0.027)
Townhouse ($\mathbb{1}^{a,+}_{ijt}=1$)	0.61***	(0.021)	0.28***	(0.019)
Unit ($\mathbb{1}^{a,+}_{ijt}=1$)	0.58***	(0.016)	0.26***	(0.011)
Villa ($\mathbb{1}^{a,+}_{ijt}=1$)	0.18	(0.229)	0.21	(0.162)

Note: Marginal probability changes based on the first-stage probit regression for (C1) and evaluated at the mean (or conditional mean where appropriate). Note estimates for cottage, semi-detached, and studio homes are omitted (dropped) for Melbourne due to their very small samples after restricting the sample to repeat-sales. Standard errors are in parentheses.

text (1), but restricting the sample to be the same repeat-sales as used for our endogenous selection model. [50] The second uses the selection-adjusted price indices as per (C2) and so parametrically controls for time-varying seller selection when measuring prices. The third uses the selection price indices and additionally includes the time coefficients in the selection equation. The results are reported in Table 8 in the main text.

[50] Repeat-sales are required since the first-stage auction probability model conditions on the previous transaction mechanism.

D. Non-linearity in Auction Prices?

Table D1 shows correlations between auction price and negotiated price growth, that condition on the direction of auction price changes (in levels or relative to the sample average), as well at the unconditional sample correlation. The results do not support asymmetry in the auction price response. For Sydney, the correlation between negotiated and auction prices is in fact higher when auction price growth is negative or slower than average, which is at odds with the auction mechanism ampligying positive price shocks. The Melbourne results are similar. Conditioning on whether auction prices are rising or falling in level terms makes little difference to the conditional sample correlations.

Table D1—Conditional Correlations: Auction and negotiated Prices

	$\rho(\Delta p_t, \Delta a_t)$	$\rho(\Delta p_t, \Delta a_t) \mid \Delta a_t > 0$	$\rho(\Delta p_t, \Delta a_t) \mid \Delta a_t > \overline{\Delta a_t}$	$\rho(\Delta p_t, \Delta a_t) \mid \Delta a_t < 0$	$\rho(\Delta p_t, \Delta a_t) \mid \Delta a_t < \overline{\Delta a_t}$
Sydney	0.48	0.36	0.33	0.49	0.41
	(95)	(67)	(48)	(28)	(47)
Melbourne	0.51	0.26	0.33	0.24	0.47
	(73)	(54)	(31)	(19)	(42)

Note: [(a)] Number of observations used in calculating correlation reported in parentheses. $\overline{\Delta a_t}$ and $\overline{\Delta p_t}$ denote the mean rates of growth in auction and negotiated prices.

We also estimate structural models with a piecewise-linear response in auction price growth, conditioning on the whether the (log) change in buyers' values is positive or negative. Retaining the assumptions that negotiated and list prices are governed by (6) to (2), and imposing the restrictions that negotiated sales are equally reflective of the two diffusion processes for permanent shocks while negotiated sales only weight one of them, we estimate the following two models that allow for a non-linear response in auction prices to permanent shocks in the less autocorrelated diffusion process:

$$(A1') \qquad \Delta a_t = \mu_a + \gamma_2^{a,+} \mathbb{1}_{\Delta v_{2,t} \geq x} \Delta v_{2,t} + \gamma_2^{a,-} \mathbb{1}_{\Delta v_{2,t} < x} \Delta v_{2,t} + \varepsilon_t^a - \varepsilon_{t-1}^a$$

where $\mathbb{1}_{(.)}$ is a binary indicator function equaling one when the condition in its subscript (argument) is satisfied and zero otherwise. We consider two reference points: $x = 0$, permitting auction prices to response differently to positive and negative shocks, and $x = \overline{v}_2$, so that the asymmetry is around the mean rate of change in $\Delta v_{2,t}$, implying differential responses to shocks above and below the mean.

Neither does Table D2 support non-linearity. In Sydney, coefficient equality cannot be rejected. In Melbourne, equality is rejected but in the wrong direction, with the response to positive (above mean) shocks *less than* than for negative (below mean) shocks.

Table D2—Nonlinearity in Auction prices

	Sydney		Melbourne	
	$x=0$	$x=\overline{v}_2$	$x=0$	$x=\overline{v}_2$
$\gamma_2^{a,+}$	1.03	1.03	0.89	0.89
	(0.038)	(0.036)	(0.031)	(0.032)
$\gamma_2^{a,-}$	0.97	0.97	1.11	1.11
	(0.038)	(0.036)	(0.031)	(0.032)
μ_a	-0.003	-0.003	0.004	0.003
	(0.001)	(0.001)	(0.002)	(0.002)
$H_0:\gamma_2^{a,+}=\gamma_2^{a,-}$	*0.47*	*0.46*	*0.00*	*0.00*

Note: Point estimates are computed using two-step maximum likelihood and incorporate second-step estimation uncertainy only. Standard errors are in parentheses and p-values are in italics.

E. Theory

A simple example makes clear that accounting for failed transactions does not fundamentally change the conclusion that auctions are much more sensitive to shifts in the buyer value distribution than the seller. We assume the buyer and seller distributions uniform on $\left[\kappa^b, 1+\kappa^b\right]$ and $[\kappa^s, 1+\kappa^s]$ respectively, and a reserve price set non-strategically equal to the seller value and announced at the auction's start. Then the average auction price is the expectation of the maximum of the second highest bidder valuation (denoted ν_2^b) and the seller reserve (ν^s), conditional on ν^s being less than the highest bidder valuation (v_1^b) (otherwise, there is no sale), or

$$E\left(v_2^b|v_2^b \geq v^s\right)\frac{\Pr\left(v_2^b \geq v^s\right)}{\Pr\left(v_1^b \geq v^s\right)} + E\left(v^s|v_1^b \geq v^s > v_2^b\right)\frac{\Pr\left(v_1^b \geq v^s > v_2^b\right)}{\Pr\left(v_1^b \geq v^s\right)}$$

which can also be viewed as a weighted average of the second highest buyer and seller valuations, with varying weights. With sufficiently many bidders, typically six is enough, and with sufficient overlap in the buyer and seller distributions to match observed sales rates, the probability of the seller value determining the auction price is small and insensitive to changes in either support (κ^b or k^s).

Figure E1 makes this point by graphing the auction price and sales rate, for six bidders, as functions of κ^b (κ^s) in the left (right) panel, with κ^s set equal to 0.3 ($\kappa^b=0$).[51] The baseline $\kappa^s-\kappa^b=0.3$ matches the observed mean auction sales rate (the middle dashed line) in the two cities. The figure shows that, within the range of observed sales rates (the top and bottom dash lines indicate the maximum and minimum across the two cities), the auction price moves nearly one for one with perturbations to the buyer value

[51]At higher bidder numbers, results are even starker. For two bidders, shocks to k^s have substantial effects, but they are still half as large as for κ^b. We have no data on the number of bidders at individual auctions, but newspaper reports range between one and 45. Six seems typical.

distribution ($\Delta\kappa^b$), but changes little with those to the seller ($\Delta\kappa^s$). In contrast, the expected negotiated price under equal bargaining power equals $\left(1 + k^b + k^s\right)/2$, so that price is equally affected by buyer and seller shocks, when the two distributions do not overlap.[52] Section VI finds that bargaining power is (nearly) equal in Sydney (Melbourne).

To generalize from the uniform distributions case, we maintain bounded supports but now allow for Generalized Pareto distributions $F_B = 1 - (1 - (x - \kappa^b))^c_B$ for buyers and $F_S = 1 - (1 - (x - \kappa^s))^c_S$ for sellers. We check that the numerical derivative of the simulated expected negotiated price with respect to κ^s exceeds that of the simulated expected auction price, for $(c_B, c_S) \in 1/5, 1/4, 1/3, 1/2, 3/4, 1, 4/3, 2, 3, 4, 5^2$ and such that the sales rate falls within the range given above. As above, we focus on N=6. We consider not only the above case in which the auction price equals the second highest buyer value with a transaction taking place if that value exceeds the seller's value (Scenario I), but also that in which the transaction takes place if the highest buyer value exceeds the seller value and price equal to the maximum of the second highest value and the seller value (Scenario II) and that of an optimally chosen reserve price, with a transaction if the highest buyer value exceeds it and then the auction price equal to the maximum of the reserve price and the second highest buyer value (Scenario III). We find that the seller weight is indeed higher in equal bargaining power negotiated prices so long as both buyer and seller distributions are not to skewed to the left (low values of cB and cS).

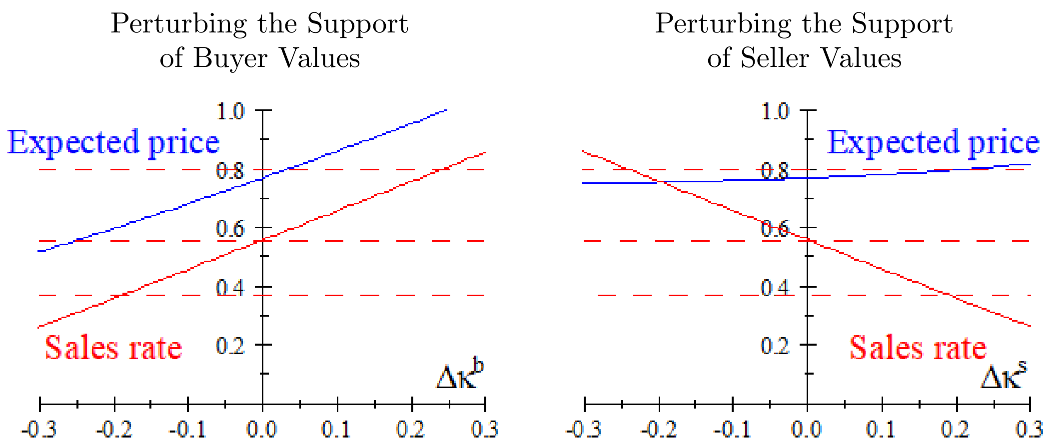


Figure E1. Auction Price Response to Common Shocks to Buyer and Seller Values

A simple example has a fraction a of buyers receiving a positive, one dollar shock in the

[52]More generally, the expected negotiated price is

$$(1-\psi)\, E\left(v^b | v^b \geq v^s\right) + \psi E\left(v^s | v^b \geq v^s\right) = \begin{cases} \frac{1}{3}\kappa^s + \frac{2}{3}k^b - \frac{1}{3}\psi + \frac{1}{3}\kappa^s\psi - \frac{1}{3}k^b\psi + \frac{2}{3} & \text{if } \kappa^s \geq k^b \\ -\frac{3a - 6\kappa^b + \psi - 3\kappa^s\psi + 3\kappa^b\psi + 3(\kappa^s)^2 - 3\left(\kappa^b\right)^2 - 2}{6\kappa^b - 6\kappa^s + 3} & \text{if } \kappa^s < k^b \end{cases}$$

where ψ is the weight on the seller valuation – the buyer bargaining power.

first period, and $1-a$ in the second. Buyer values are identical prior to the shock. Then price at any given auction increases by 1 if at least two bidders there have received it; the expected price at auction increases by $q(a) \equiv 1-(1-a)^{N}-N(1-a)^{N-1}a$, and by the remaining $1-q(a)$ in the next period. In negotiations, price increases in the first period so long as the buyer has received the shock, and zero otherwise. Percentage-wise, then, auction prices increase more than negotiated prices so long as $q(a)>a$, which holds for $a \in (a^{*}(N), 1)$, where a^{*} is a declining function of N. For example, $a^{*}(4)=0.24$ and $a^{*}(8)=0.04$. In contrast, for a negative shock, the auction price falls only if all or all but one, bidders have received it, so that the expected decrease is $1-q(1-a)$. Auction prices fall less than private-treaty prices so long as $1-q(1-a)<a$, which holds for $a \in (1-a^{*}(N), 1)$.

Can affiliated values rescue this argument? Such models are difficult and, to our knowledge, no one has analysed one with a signal distribution that shifts over time. Thus our impressionistic comments. If bidders do not observe others' exits, price will depend only on the second order statistic of bidder signals, so that the same lead-lag relationship will hold as for private values. If exits are observed, then all signals matter. Yet none of the theoretically worked out cases generate a relationship like what we see. For linear affiliated values, the second order statistic matters more than the other signals, which are weighted equally, which returns us to the private values case. For the uniform distribution, the auction price equals the average signal plus the gap between the first and second order bid statistics, divided by the number of bidders. Thus, for large numbers of bidders, the percentage change in price per additional unit of valuation will be similar to that for negotiated prices.

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