The Role of Auctions and Negotiation in Housing Prices

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Using Sydney and Melbourne transactions, we show that how properties sell matters for housing price dynamics. Auction prices forecast better and display much less momentum than negotiated prices. This is consistent with the two mechanisms transmitting buyer vs. seller shocks to prices differently and, in light of auction and bargaining theories, suggests the source of momentum is sluggishness in sellers' valuations. Other explanations, such as differences in precision, slow diffusion of shocks among buyers, or endogenous selection of the sales mechanism, fail to explain our findings. Our estimates also indicate that sellers have at most equal bargaining power in negotiations.

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The last financial crisis made apparent the importance of housing market dynamics. However, these dynamics are not easily reconciled to the usual models. Perhaps most resistant to explanation is the highly positive autocorrelation in price growth (momentum). First observed by Case and Shiller (1989) for US single family homes and a repeated finding across countries and time,[1] this phenomenon is at odds with a standard asset model for housing markets. As noted by Glaeser, Gyourko, Morales and Nathanson (2014), "The model fails utterly at explaining the strong, high frequency positive serial correlation of price changes."

Recent attempts to model housing price dynamics incorporate search frictions

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

(Capozza, Hendershott and Mack (2004), Caplin and Leahy (2011), Díaz and Jerez (2013) and Head, Lloyd-Ellis and Sun (2014)), adaptive expectations (Sommervoll, Borgersen and Wennemo (2010)), momentum traders (Piazzesi and Schneider (2009)), and kinked demand curves (Guren (2015)). Yet these papers have limited success in generating the high degree of 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.

This paper first shows that price momentum is much smaller or even absent for auction than negotiated sales. Using 1992 to 2012 Sydney and Melbourne sales (around 40 per cent of all Australian sales), we find very different autocorrelation properties for prices determined through bilateral negotiation (hereafter private-treaty) than auction. Although, as previously found, private-treaty price growth is highly autocorrelated, auction price growth is much less so. Indeed, we cannot reject the null that auction prices are informationally efficient and follow a random walk with drift. We then exploit the differential structure of auctions and negotiations to argue that the momentum we observe in private-treaty prices, and by extension that observed by others, reflects sluggish seller response. Sellers who respond slowly to market conditions help generate autocorrelation in both Caplin and Leahy's (2011) and Guren's (2015) models, but neither paper presents evidence in support of the assumption.

In addition to being informationally efficient, we find auction prices useful for predicting future housing prices. This is true for both private-treaty and overall average prices. It is consistent with auction prices quickly updating in response to changes in a common stochastic trend in housing prices. In contrast, we find that private-treaty prices are useful for predicting neither auction nor overall average prices. Notably, private-treaty prices only fully reflect changes in the common stochastic trend with a lag of almost a year. These findings are striking - as auctions make up less than 17 per cent of transactions, a priori, one would expect private-treaty prices to be the more informative measure.

Why such large differences in efficiency and information content? We argue that these findings are consistent with auctions weighting buyer and seller valuations differently from negotiations, and sellers adjusting slowly to market conditions.

Negotitations typically take place between one buyer and one seller.[2] In standard complete or incomplete information bargaining models, both seller and buyer values influence price.[3] Indeed, with equal bargaining weights, which our results support, and buyers and sellers drawing independently from equally dispersed uniform distributions, shifts in the support of either distribution effect price equally.

Auctions are different. In the open-outcry (English) auction used in Sydney and Melbourne, many buyers bid on a property. Absent seller reserves, auctions are solely determined by the distribution of buyer valuations. Even with seller reserves, price responds more to buyer than seller valuations in the uniform distributions case of Section III.A and for a wide range of distribution pairs considered in the online Appendix, calibrated to match the sale rates (hereafter clearance rates) we observe.

The scope for slower seller adjustment to changing market conditions is supported by a number of housing market phenomena. These include: greater cyclicality of sales than housing prices (Leamer (2007)); lower seller time on the market in 'hot' markets (a stylized fact for Wheaton (1990) and Krainer (2001), and documented in Genesove and Han (2012))[4]; positive correlation between the transaction to list price ratio and short run demand growth (Genesove and Han (2012)), and positive correlation between that ratio and unexpected or expected price growth (Haurin et al. (2013)). Our data provide additional supporting evidence: list prices, which should approximate seller reservation values, lag both auction and private-treaty prices, and a 'Phillips-curve' governs the relationship between price growth and the clearance rate. List prices also allow us to estimate seller bargaining power: a relatively precise 0.5 for Sydney, while one insignificantly different from both equal and no bargaining power for Melbourne.

Why seller values lag buyers' is beyond the scope of our investigation, but we make some brief comments. First, the asymmetric matching institution, in which sellers list homes and prices, while buyers do not list their preferences or even their identities, makes seller search more public than buyer search. Consequently,

[2] With bidding wars, other buyers' values also affect private-treaty prices. This can be interpreted as misclassification of some private-treaty sales better thought of as auctions, implying that we underestimate the difference in the behaviour of (true) private-treaty and auction prices.

[3] For complete information, see surveys by Fudenberg and Tirole (1991) and Napel (2002) . For incomplete information, see Ausubel, Cramton and Deneckere (2002) and references cited therein, as well as Copic and Ponsatí (2008).

[4] Head et al. (2014), however, provide a model in which seller time on the market anti-cyclicality arises instead out of the short run fixity of housing and demand shock persistence.

information on seller shocks diffuse quickly through their listing, de-listing and list price decisions, becoming common knowledge to sellers and buyers alike, while buyer shocks only become publicly known when actualised in transacted prices and those prices publicised. On the other hand, buyers may more easily absorb new information during search. Whereas sellers may choose to be passive once having listed their property, allowing an agent to represent them, buyers are generally active in visiting properties themselves.[5]

Second, the high dimensionality of the buyer problem, which includes not only price but also home attributes - fixed for the seller -, forces the buyer to constantly reassess willingness to pay cross-sectionally. With psychological, information or decision costs already incurred, buyers may be more prepared to reassess their valuations over time as the market changes. Third, buyers moving into an area may be more attuned to changes in future housing services values than sellers, who, on net, are moving out (Leamer (2007)). Guren (2015) notes that if buyer arrivals are concave in the seller list price, strategic complementarity assures that these various phenomena need not necessarily affect a large share of sellers to have large effects.[6]

We also consider other explanations for the joint behaviour of prices. One is that by incorporating information from more than one buyer, auction prices more precisely estimate an underlying common-value component in buyer valuations.[7] Common values arise endogenously in search environments with uncertainty over market conditions, as Merzyn, Virag and Lauermann (2010) stress. Being forward looking, the value of continued buyer search should be a good predictor of future prices. In addition, auction theory suggests that the winning bid at an auction will reflect the common-value component given a sufficient number of bidders – converging to it if that is the only component of buyer valuations and to a function of it if there is a private-value component as well.

Price indices, however, are averages of many transactions. Although a single auction may more accurately reflect market conditions, that need not be so for the

[5] Differential information flows or asymmetry between buyer and seller behaviour has been emphasised in previous research, see for example Anenberg (2011) and Berkovec and Goodman (1996).

[6] Equity lock-in and loss aversion, which explain seller price rigidity in downturns, appear less relevant here because prices in our data are generally increasing (Stein (1995), Genesove and Mayer (1997, 2001), Engelhardt (2003), and Anenberg (2011)).

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

average auction price. There are seven (Melbourne) to ten (Sydney) times as many private-treaty transactions as auctions. Thus, a lesser precision in a private-treaty price from incorporating fewer signals of the common value could be offset by the larger set of signals incorporated into the average price through more transactions. We find the number of transactions so large relative to price dispersion at the individual transaction level that aggregation effectively offsets any precision gains that might originate at the transaction level.

Auctions also differ from negotiations in drawing the price from the right tail of the buyer distribution. Diffusion over time of common buyer shocks through the buyer distribution will lead to a lead-lag relationship between auction and private-treaty prices. However the predicted relationship differs from what we observe.

Another possible explanation is that auction transactions garner greater publicity than negotiated transactions, being more dramatic, attended by more people, and having their results published in newspapers and auction company websites. If market participants form expectations conditioning on observed past transactions, the publicity given to those previous transactions will matter.[8] We find support for this explanation only if we assume that sellers alone use lagged auctions information – otherwise it implies that auction and private-treaty prices have more similar autocorrelation properties than they do.

Finally, we consider whether our results are sensitive to the measurement of prices, endogenous selection of the sale mechanism, and the characteristics and location of homes sold. Using alternative measures of price, including fewer attribute controls to maximise sample size, or using repeat-sales indices to better control for unobserved attributes, has little effect on our findings.[9] Nor does the use of price indices that adjust for endogenous selection. Focusing on within-group variation, first within sub-city districts and then by the type of homes sold, has little effect either. Even at the district level or by home type, auction prices remain locally informative and Granger cause private-treaty prices, but the reverse is not true.

With its non-trivial share of non-foreclosure auctions, Australia is particularly

[8] We have the full set 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.

[9] Using fewer attributes increases the autocorrelation of price growth, consistent with serially correlated changes in the composition of homes sold (Hansen (2009)). However, it has little effect on the relative information content of auction vs. private-treaty prices and auction price growth remains much less autocorrelated than private-treaty price growth.

useful for investigating price formation. Our findings should also be of interest for other countries because of the increasing frequency of bidding wars in housing markets elsewhere (Han and Strange (2014)).

Interest in housing price formation and forecastability stems from both macro and micro policy concerns. Mortgage performance, solvency and stability of the banking system, household collateral, investment and saving, all depend on housing price changes (Iacoviello (2005), Iacoviello and Neri (2010)). The dramatic run-up in prices and subsequent falls in many countries was key to the global financial crisis, and has generated wider interest in housing prices dynamics.

More generally, this paper concerns the role of sales mechanisms in price formation. Much literature compares outcomes such as efficiency, seller revenue and information aggregation across mechanisms, especially auctions (see for example, Bulow and Klemperer (1996, 2009), Kremer (2002)), but also between them and posted prices (Wang (1993, 1998)). An empirical literature compares price levels across different mechanisms, especially on the Internet (e.g., Lucking-Reiley (1999), Einav et al. (2015)). Most theory and empirics has a single transaction focus. This paper provides empirical evidence on how different selling mechanisms map changes in the underlying distribution of buyer and seller valuations into average price changes over time.

The next section discusses the data and construction of the price indices. Section II discusses the differences in autocorrelation between the two price measures, their relative information content when forecasting future price growth, and their sensitivity to permanent and temporary shocks. Section III interprets our findings in the light of alternative theories of price formation and the final section concludes.

I. Data and Measurement

Our primary data source is a census of housing sales in Sydney and Melbourne between 1992:I and 2012:IV provided by Australian Property Monitors (APM). It updates data used by Prasad and Richards (2008) and Hansen (2009).[10]

Private-treaty is the most common mechanism used for selling housing in these two cities. Successful sales where an auction mechanism was used (or planned to

[10] In providing these data, APM relies on a number of external sources. These include 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 in the online Appendix.

be used) make up around 12 per cent of the Sydney sample and 17 per cent for Melbourne (Table 1, columns one and two).

Table 1—Overview of Sales Mechanisms Used

	Percentage of total observations[(a)]		Percentage filtered for analysis[(b)]	
Transaction type	Sydney	Melbourne	Sydney	Melbourne
Pre- or post-auction	2.73	3.72	na	na
Sold at auction	8.83	13.01	9.30	13.90
Private treaty	88.46	83.26	90.70	86.10
Auction frequency	11.56	16.73	9.30	13.90
Total observations	1 763 032	1 677 925	1 652 585	1 498 549

Note: [(a)]Percentage of total observations where an auction was used (or planned to be used) as part of a successful sale; [(b)]percentage of observations after removing identified pre- and post-auction sales, private-treaty sales where an auction was used in the 90 days prior to the exchange of contracts.

In the following, we restrict attention to properties sold at auction when measuring auction prices and properties sold via bilateral negotiation (with no auction offering in the previous 90 days), when measuring private-treaty sales (Table 1, columns three and four). [11] Using hedonic price regressions similar to those discussed below, the average conditional price difference between a property sold through an auction and through a private-treaty is 4.2 (5.1) per cent for Sydney (Melbourne).[12]

To compute the indices we use hedonic log price regressions, which, at the city level, Hansen (2009) has shown to accurately estimate the composition-adjusted price change in housing. The specification includes quarter dummies, postcode dummies and home attributes. For each city, we run separate regressions for auctions and private-treaty sales.

The attributes are the number of bedrooms, number of bathrooms, log-property size [13], property-type (house, semi-detached, terrace, townhouse, cottage, villa, unit, apartment, duplex, studio) and the interaction of property-type with each of the first three variables. When estimating recursively to generate out-of-sample forecasts, we use the maximal sample size and include property-type controls only. When generating in-sample estimates, we include all controls and their interaction effects for Sydney, but only include property-type controls for Melbourne unless

[11] See Table 1, Note (b).
[12] This is measured using an additional auction sale dummy variable.
[13] For houses, size is the total land area in square metres. For units or apartments, it is typically a measure of the building area, but can also be the internal area depending on the data source.

stated otherwise. Our estimates span 1992:I (1993:I) to 2012:IV for Sydney (Melbourne).

Figure 1 reports, for each city, two-quarter-ended annualised growth of separate hedonic price indices for auction, private-treaty and all-sales prices. Although highly correlated, the three indices are not fully synchronised, with auction prices leading all-sales and private-treaty prices, most notably around turning points.

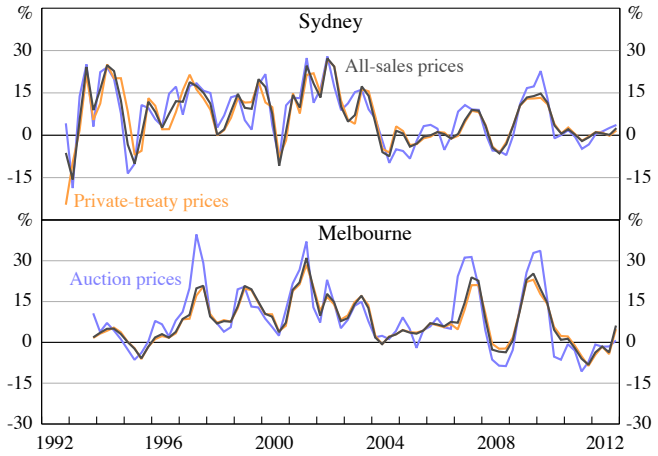

Figure 1. Auction, Private-treaty and All-sales Prices: Two-quarter-ended annualised growth

II. Prediction

This section examines three questions: do auction and private-treaty prices

1) have different autocorrelation properties?

2) perform differently when predicting out-of-sample?

3) perform differently when predicting one another in-sample?

The first question speaks to the well-established literature showing housing price growth to be highly positively autocorrelated (e.g., Case and Shiller (1989), Cutler, Poterba and Summers (1991), Cho (1996) and Capozza, Hendershott and Mack (2004)). Differences in momentum allow us to discriminate between alternative models of housing market dynamics. The second addresses whether gains in predictive content are available in real time.

We also consider in-sample analysis for three reasons: using the full sample avoids revisions to the estimated price indices that may affect out-of-sample forecasting;

it allows us to relax the finite lag VECM representation assumption otherwise maintained;[14] and out-of-sample analysis can entail a loss of information and power (Inoue and Kilian (2005)).

A. *Momentum*

Figure 2 show that all-sales price growth is positively autocorrelated for up to one year, with the strongest correlations for the first two quarterly lags. All of the positive autocorrelation in aggregate price growth for Sydney arises from private-treaty prices; there is no evidence for positively autocorrelated auction price growth. Indeed, auction prices follow a random walk with drift. This striking result suggests auction prices fully incorporate all relevant information on prices within a quarter.

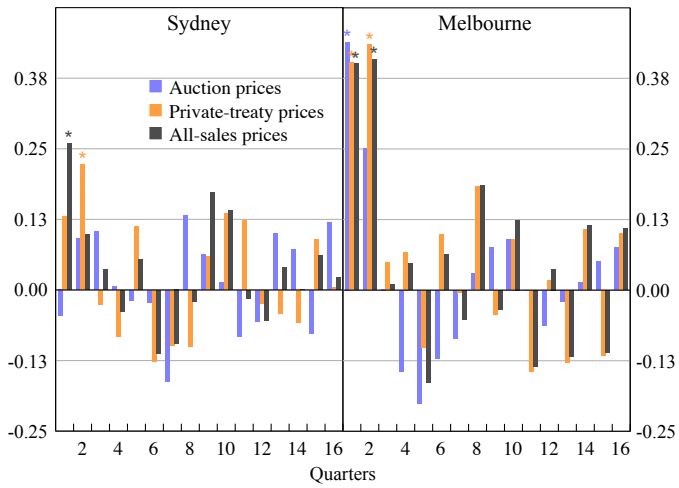

Figure 2. Autocorrelation Functions for Prices Growth

Note: Asterisks denote significance at 5 per cent level when using Bartlett's MA(q) formula.

For Melbourne, most of the autocorrelation in all-sales price growth is also driven by private-treaty price growth, although there is some weak evidence of first-order autocorrelation in auction price growth.[15]

B. *Out-of-sample*

We now consider whether price indices conditioned on the sale mechanism are useful for predicting all-sales price growth in real time. Specifically, we consider

[14] Although a VECM with finite lags is a natural framework for modelling prices given that they are likely to share the same common trend, it is not an immediate implication of theory. In Section III we build up a case to support this representation, rather than assume it is valid.

[15] The autocorrelation function for Melbourne auction price growth is even smaller if one includes detailed attributes data when estimating the hedonic price indices and using the sample from 1997:IV onwards.

whether including lagged auction prices or lagged private-treaty prices improves upon the one-quarter-ahead forecasts of all-sales price growth in a single equation autoregressive model. We compare the following three forecasting models[16]

$$(1) \qquad \Delta s_t = \mu_s + \sum_{j=1}^{J} \phi_j \Delta s_{t-j} + \varepsilon_t^s$$

$$(2) \qquad \Delta s_t = \mu_s + \Gamma_s s_{t-1} + \Gamma_a a_{t-1} + \sum_{j=1}^{J} \phi_j \Delta s_{t-j} + \sum_{j=1}^{J} \gamma_j^a \Delta a_{t-j} + \varepsilon_t^{s,a}$$

$$(3) \qquad \Delta s_t = \mu_s + \Gamma_s s_{t-1} + \Gamma_p p_{t-1} + \sum_{j=1}^{J} \phi_j \Delta s_{t-j} + \sum_{j=1}^{J} \gamma_j^p \Delta p_{t-j} + \varepsilon_t^{s,p}$$

where s_t is the all-sales housing price index, a_t the auction price index and p_t the private-treaty price index. Equation (1) is the benchmark model, a univariate autoregression in s_t. (2) adds auction price lags, and allows s_t and a_t to be cointegrated. (3) incorporates private-treaty price lags instead. The online Appendix (Section VI, Table 23) provides evidence for cointegration, though similar results are obtained below without this assumption.

To measure out-of-sample prediction accuracy, we define

$$\sigma_i^2 \equiv E\left(\hat{s}_{t+1|t}^i - s_{t|t} - \left(s_{t+1|t+1} - s_{t|t+1}\right)\right)^2$$

for $i = 1, 2, 3$ as the mean-squared prediction errors (MSPEs) for one-quarter-ahead all-sales price growth associated with Equations (1), (2) and (3) respectively. $\hat{s}_{t+1|t}^i \equiv E\left(s_{t+1}^i \mid I_t\right)$ is the one-quarter-ahead forecast of s based on Equation i, using the information available at time t. $s_{t|\tau}$ is the measured value of s at t given all available information up to time $\tau \geq t$. We consider whether the MSPEs are statistically different among (1), (2) and (3) using pairwise comparisons and McCracken (2007)'s MSE-t test statistic.[17]

Table 2 shows that Equation (2) outperforms the benchmark model: there is information content in lagged auction prices. In both cities, the MSPEs for (2) are

[16] Herein, for out-of-sample forecasting tests, we use four (three) lags for Sydney (Melbourne). This is based on likelihood-ratio and residual serial correlation tests, as well as information criteria. For Melbourne, quarterly seasonal dummies are included as additional control variables, consistent with evidence of seasonality.

[17] This is equivalent to Diebold and Mariano (1995)'s S_1 test statistic. We use the critical values tabulated in McCracken (2007), which notes that for nested predictions equations, the normal may ill approximate S_1's distribution. Clark and West's (2007) MSPE-adj t statistic yields similar results.

significantly lower relative to the benchmark model by about 10 and 18 per cent for Sydney and Melbourne (rows one and three). In contrast, private-treaty prices do not significantly improve upon the benchmark model (rows two and four).

Table 2—Pairwise Nested Model MSPE Comparison

	$\frac{\sigma^2_{y\in\{a,p\}}}{\sigma^2_s}$	MSE-t statistic
Sydney		
$H_0 : \sigma^2_s - \sigma^2_a = 0$	0.90**	0.85
$H_0 : \sigma^2_s - \sigma^2_p = 0$	0.93	0.26
Melbourne		
$H_0 : \sigma^2_s - \sigma^2_a = 0$	0.82**	1.46
$H_0 : \sigma^2_s - \sigma^2_p = 0$	0.97	0.17

Note: The alternative hypothesis is that the MSPE of the restricted model, σ^2_s, is greater than the unrestricted alternative (either σ^2_a or σ^2_p); recursive estimation starts with sample period 1992:I-2007:I (Sydney) and 1993:I-2008:III (Melbourne); ***, ** and * denote significance at 1, 5 and 10 per cent levels.

We next consider whether the price indices are useful in predicting one another out-of-sample. Allowing for auction and private-treaty price to share a common stochastic trend, the unrestricted model used for our tests is given by

$$\Delta a_t = \mu_a + \alpha_a (a_{t-1} - \beta p_{t-1}) + \sum_{j=1}^{J} \Gamma_j^{aa} \Delta a_{t-j} + \sum_{j=1}^{J} \Gamma_j^{ap} \Delta p_{t-j} + \varepsilon_t^a \tag{4}$$

$$\Delta p_t = \mu_p + \alpha_p (a_{t-1} - \beta p_{t-1}) + \sum_{j=1}^{J} \Gamma_j^{pa} \Delta a_{t-j} + \sum_{j=1}^{J} \Gamma_j^{pp} \Delta p_{t-j} + \varepsilon_t^p \tag{5}$$

The null hypotheses are (1) auction prices do not Granger cause private-treaty prices, $H_0 : \alpha_p = \Gamma_j^{pa} = 0$ for all j, and (2) private-treaty prices do not Granger cause auction prices, $H_0 : \alpha_a = \Gamma_j^{ap} = 0$ for all j. The McCracken (2007) and Clark and West (2007) tests in Table 3 reject the first null in both cities, but fail to reject the second in Sydney (and only find weak evidence to reject it in Melbourne). These results confirm that auction prices are more useful, when forecasting out-of-sample.

C. In-sample

Table 4 revisits the causality tests using Toda and Yamamoto (1995)'s in-sample approach, and including all attribute data.[18] The first four rows support the previous findings. For both cities, they reject the null that auction prices do not Granger

[18] Conditioning on the assumption of cointegration provides similar results.

Table 3—Out-of-sample Granger Causality Tests

	Sydney	Melbourne
H_0 : Auction prices do not Granger cause private-treaty prices		
MSE-t	1.55***	1.38**
MSPE-adj t	2.82***	2.34***
H_0 : Private-treaty prices do not Granger cause auction prices		
MSE-t	–1.06	0.63*
MSPE-adj t	0.50	1.46*

Note: ***, ** and * denote significance at 1, 5 and 10 per cent levels of significance respectively; MSE-t is the Diebold and Mariano test statistic for a nested model forecast comparison as discussed in McCracken (2007); MSPE-adj t is Clark and West (2007)'s alternative statistic; estimates and out-of-sample forecasts are generated recursively with initial in-sample estimation period 1992:I-2002:III for Sydney and 1993:I-2002:III for Melbourne.

cause private-treaty prices, but are unable to reject the opposite.

Table 4—In-sample Granger Causality Tests

	All controls	
Null hypothesis	Sydney	Melbourne
$a_t \overset{GC}{\nrightarrow} p_t$	69.96***	12.57***
	(0.00)	(0.01)
$p_t \overset{GC}{\nrightarrow} a_t$	5.59	3.70
	(0.35)	(0.45)
$E\left(a_t \vert \mathcal{I}_{t-1}^{a,p}\right) = a_{t-1}$	7.60	11.84
	(0.58)	(0.11)
$E\left(p_t \vert \mathcal{I}_{t-1}^{a,p}\right) = p_{t-1}$	79.47***	29.25***
	(0.00)	(0.00)

Note: ***, ** and * denote significance at 1, 5 and 10 per cent levels. $\overset{GC}{\nrightarrow}$ is a test for non-Granger causality; a_t is the auction price, p_t the private-treaty price and $\mathcal{I}_{t-1}^{a,p}$ the information set at time $t-1$ (conditioning on lagged auction and private-treaty prices). All controls includes property type and interactions with the number of bedrooms, the number of bathrooms, and the logarithm of the size of the property. The Melbourne sample is restricted to 1997:IV onwards and includes seasonality controls; p-values are in parentheses.

We conduct two further in-sample specification checks. The first shows that auction prices follow a random walk with drift and cannot be explained using lagged price information (Table 4, rows (5)–(6)).[19] That is, auction prices are informationally efficient. This is striking given previous evidence of substantial price momentum across countries and time. For private-treaties, there is clear evidence of informational inefficiency – lagged auction and private-treaty prices are useful in predicting them (Table 4, rows (7)–(8)).

The second, shown in Table 5, checks whether the error-correction specification

[19] This result is also confirmed using a univariate test that regresses auction price growth on lags of auction price growth (i.e. imposing the restrictions that private-treaty prices do not Granger cause auction prices and that auction prices are I(1) in levels). The p-value for Sydney (Melbourne) is 0.35 (0.13).

of the auction–private-treaty price relationship makes economic sense. Consistent with our previous findings, while private-treaty prices respond positively to the lagged deviation between auction and private-treaty prices, auction prices do not respond to it. Normalising on auction prices, the cointegration parameters, β, also look reasonable and not too far from 1, as expected.

Table 5—Cointegration and Adjustment Parameter Estimates

	Auction prices		Private-treaty prices	
Sydney				
Cointegration parameter		1	$-\beta$	-1.05***
		(.)		(0.01)
Adjustment parameter	α_a	–0.10	α_p	0.42***
		(0.23)		(0.15)
Melbourne				
Cointegration parameter		1	$-\beta$	-1.08***
		(.)		(0.01)
Adjustment parameter	α_a	–0.02	α_p	0.18**
		(0.14)		(0.07)

Note: Cointegration and adjustment parameter estimates are obtained using Johansen MLE and normalising the coefficient on auction prices to 1; ***, ** and * denote significance at 1, 5 and 10 per cent levels respectively and are with respect to 0 for the adjustment parameters and 1 for the cointegration parameters corresponding to Equations (4) and (5); standard errors are reported in parentheses.

The online Appendix (Section V.C) explores four aspects of robustness. The first is measurement of the underlying price indices. Using alternative hedonic or repeat-sales prices indices has little effect on our results (Table 13). Second, we account for endogenous selection of the sales mechanism by sellers. Adding controls for auction incidence and the clearance rate to account for selection does not change the previous causality findings and selection appears to lag price dynamics rather than lead them (Table 15). Neither does adjusting the underlying price indices for endogenous selection using a Heckman style structural model (Gatzlaff and Haurin (1997)) in which the past sale mechanism is allowed to determine the current propensity to use an auction but not the current price directly, (Table 17). We also show robustness to inflation adjustment (Table 19), unsurprising given the low and stable inflation Australia had over most of our period.[20]

Finally, we consider within-group price variation. Within city districts, auctions continue to be more informative about local price trends than private-treaties (Ta-

[20] The momentum literature considers both nominal (Titman, Wang, and Yang (2014)) and real prices (e.g. Case and Shiller (1989)).

ble 20). The same is true within property-type (Table 22). Together, these checks suggest our findings reflect differences in price formation by mechanism of sale, rather than more general housing market conditions that may be correlated with it.

III. Interpreting the Results through Theory

We now examine a number of theoretical models aimed at interpreting the previous findings. All models are grounded in the micro structure of price formation. All conceive of prices as jointly determined by a pair of seller and buyer valuation distributions that evolve over time. The models differ in their predictions for how these distributions change in the short run, and in how auctions and negotiations map shifts in the distributions into price changes. Since the two price indices are cointegrated, the locations of these two distributions must follow the same stochastic trend in the long run. We assess these models according to both auxiliary data and variates of a small estimated state space model.

A. The Preferred Explanation: Asymmetric Weighting of Buyer and Seller Valuations

Our preferred explanation is that, relative to private-treaty prices, auction prices are more responsive to buyer than to seller shocks, and seller valuations lag buyers'. The first element is immediately evident when comparing the continuously ascending bid auction and the Nash bargaining solution. In the former, with which we model the English auction used in Australian housing markets, price equals the second highest bidder valuation. In the latter, price is a weighted average of the buyer and seller valuations.[21] Thus at auctions, a common shock to all bidder valuations increases the winning bid one for one. In negotiations, price increases only by the weight on the buyer valuation (i.e., seller bargaining power).

The above assumes no seller reserve at auction and no overlap of the buyer and seller distributions. How their presence alters our claim depends on how the reserve price is formed and the particulars of the distributions. These issues are explored in the online Appendix (Section V.A). However a simple example makes clear that accounting for failed transactions does not fundamentally change the result.

[21] What matters is not the Nash bargain per se, but that negotiated prices reflect both the seller and buyer valuation. This is generally true in bargaining models with either complete or two-sided incomplete information (e.g., Myerson (1984) and Ausubel, Cramton and Deneckere (2002)). It is also consistent with seller price posting models (Caplin and Leahy (2011) and Díaz and Jerez (2013)).

We assume 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 valuation 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, except that the weights are endogenous. The key point is that with sufficiently many bidders, typically six or more is enough, and with sufficient overlap in the distributions of buyer and seller valuations to match observed clearance rates, the probability of the seller valuation determining the auction price is small and insensitive to changes in either support (κ^b or k^s).

Figure 3 makes this point by graphing the auction price and clearance rate as functions of κ^b (κ^s) in the left (right) panel, with κ^s set equal to 0.25 ($\kappa^b = 0$), and for six bidders.[22] The baseline choice of $\kappa^s - \kappa^b = 0.25$ is chosen to match the observed auction clearance rate (the horizontal black line) in the two cities. The figure shows that, within the range of clearance rates consistent with the data (the minimum and maximum across the two cities are indicated by red dashed lines), the auction price moves nearly one for one with perturbations to the distribution of buyer valuations ($\Delta\kappa^b$), but is little changed with respect to perturbations in the seller valuation distribution ($\Delta\kappa^s$). In contrast, the expected private-treaty price under equal bargaining power equals $\left(1 + k^b + k^s\right)/2$, so that the price is still equally affected by buyer and seller shocks when buyer and seller distributions overlap.[23] Section III.D finds that bargaining power is equal in Sydney and insignificantly different from equality in Melbourne.

[22] 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, if somewhat on the low side.

[23] More generally, the expected private-treaty 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.

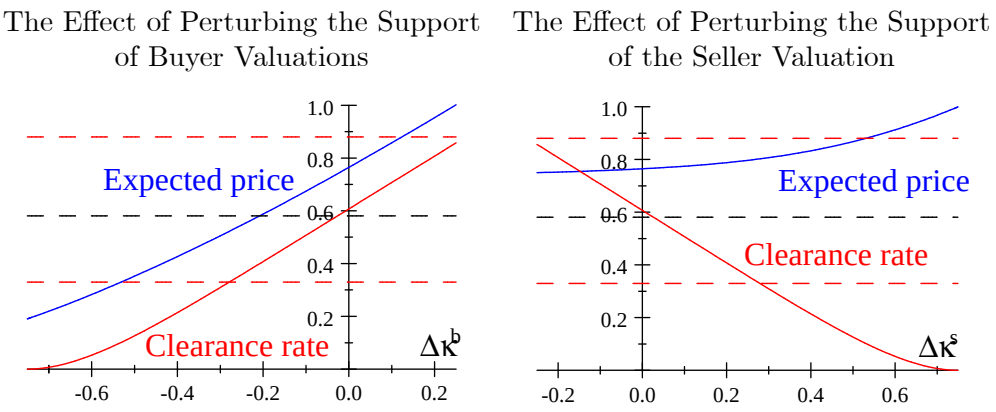

FIGURE 3. ASYMMETRY IN THE RESPONSE OF PRICE

The second element in our preferred explanation is that seller valuations lag. As noted earlier, several previously documented phenomena of seller time on the market and the sale to list price ratio are consistent with that assumption. We provide additional evidence for seller sluggishness below.

In such an environment, with a unit root valuation process, prices behave qualitatively according to our findings: auction prices Granger cause private-treaty prices, but not vice versa, the two prices are cointegrated, auction prices follow a random walk and there is positive momentum in private-treaty, but not auction, prices.

Formally, let the common component of buyer and seller valuations be the unit root process $z_t = \mu + z_{t-1} + \eta_t$, with η_t white noise. Buyer and seller valuations differ in that buyers capture all information in the common trend (z_t) contemporaneously, while sellers only do so with a lag $((1-\alpha)\, z_t + \alpha z_{t-1})$. Then, auction and private-treaty prices are given by

$$a_t = z_t \tag{6}$$

$$p_t = (1 - \alpha\psi)\, z_t + \alpha\psi z_{t-1} \tag{7}$$

ψ is the weight put on the seller valuation; it equals the buyer surplus share.

This system generates all the documented time series properties: $a_t - p_t = \alpha\psi\eta_t$, so private-treaty and auction prices are cointegrated with VECM representation $\Delta a_t = \eta_t, \Delta p_t = (a_{t-1} - p_{t-1}) + (1 - \alpha\psi)\, \eta_t$; the two series admit a VAR (in levels) with $E\left[a_t \mid a_{t-1}, p_{t-1}\right] = E\left[p_t \mid a_{t-1}, p_{t-1}\right] = a_{t-1}$, so that auction prices Granger cause private-treaty prices but not vice-versa; and private-treaty prices display

momentum, $Cov\left(\Delta p_t, \Delta p_{t-1}\right) = \psi\alpha\left(1-\alpha\psi\right)Var\left(\eta_t\right)$, while auction prices do not, $Cov\left(\Delta a_t, \Delta a_{t-1}\right) = 0$.

So far, the model lacks temporary shocks. Although unimportant for auctions prices,[24] they are a non-negligible part of private-treaty price shocks. It is straightforward to incorporate them by adding a stationary autoregressive moving average (ARMA) process to (7). The resulting VECM representation continues to hold approximately, but, first, lagged growth terms in auction and private-treaty prices are added, and second, the coefficients on the cointegration term reflect the ARMA process as well as the basic parameters given above. Incorporating temporary shocks thus frees up the specification from the strict cross equations restrictions in (6) and (7), as observed empirically.

B. The Precision Explanation

One reason why temporary shocks may play a role in private-treaty but not auction price changes is that temporary shocks may represent the time and mechanism specific aggregation of noisy signals around the 'true' value of search. The value of search is an important component of buyer willingness to pay, and depends on expectations of future market conditions. If buyers have noisy signals of the true expectation, there will be a common value component to their valuations. In that case, theory predicts conditioning on an individual auction price will provide a more precise prediction for future market conditions, and thus future prices, than conditioning on an individual private-treaty price.

The English auction is particularly good at aggregating information. When there is a common component in bidders' valuations, and bidding strategies can condition on other bidders' exits from the bidding process, the auction price incorporates information from every buyer who bids.[25] In contrast, prices determined through negotiation between a single buyer and seller incorporate information from those two parties only. Thus, an auction price may be a much less noisy predictor of future prices than a private-treaty price.

This argument requires that auction prices be less dispersed than private-treaty prices. Yet the root mean squared error (RMSE) of the hedonic regressions under-

[24] We cannot reject the null that all shocks to auction prices are permanent, for both cities, in-sample.

[25] E.g., Appendix D in Klemperer (1999). This holds more generally in affiliated values models (Milgrom and Weber (1982)).

lying the price indices are similar for the two mechanisms (Table 6). For Sydney, the RMSE is actually higher for auction prices. Furthermore, there are many more private-treaty than auction transactions – ten times more in Sydney and six times in Melbourne (Table 1); consequently, the price indices' standard errors are about 3 times larger for auctions than for private-treaties in Sydney, and twice as large for Melbourne. Indeed, even for auctions the number of transactions per quarter is so large that the contribution of transaction level variance to the variance of quarterly growth must be minimal, as comparing the standard deviation of quarterly price growth to the ratio of the RMSE to the square root of the average number of underlying observations shows (Table 6, columns three and four). Similar results obtain for repeat-sales regressions considered in the online Appendix (Section V.C, Table 13).

Table 6—RMSE of Hedonic Price Regressions

	RMSE	N	$\frac{RMSE}{\sqrt{N}}$	St. Dev.
		Sydney		
Auction	0.27	911	0.009	0.034
Private	0.24	5 034	0.003	0.031
		Melbourne		
Auction	0.34	2 604	0.007	0.030
Private	0.36	16 128	0.003	0.022

Note: RMSE is the root mean squared error of the corresponding regression; N is the average number of observations per quarter; and St. Dev. is the standard deviation of quarterly prices growth.

Near equal RMSEs for the two mechanisms does not imply a rejection of common value auction theory or the absence of a common value component. Other factors, such as the variance of unobserved quality, also contribute to the RMSE. However, along with the comments on the number of observations, it does indicate that any explanation of our findings based on temporary shocks cannot be sourced at the individual transaction level.

Unequal temporary shock variances might still explain why the price indices differ in predictive ability, if those shocks are common to many underlying transactions and not eliminated by aggregation. One possible source is changing bargaining weights. Although some bargaining may take place after a winning bid is rejected at auction, bargaining is not integral to the auction process; shocks to bargaining weights could thus explain why temporary shocks are so much more important for private-treaty prices than auction prices. Volatility in bargaining weights does not

arise naturally in the Nash bargaining solution, but arise in other solutions and in environments with changing private information (Kennan (2010)).

C. Kalman Filter Estimates

We amend (6)–(7) to allow auction and private-treaty averages to be noisy indicators of permanent common shocks:

$$a_t = \beta z_t + \varepsilon_t^a \tag{8}$$

$$p_t = (1 - \alpha\psi)\, z_t + \alpha\psi z_{t-1} + \varepsilon_t^p \tag{9}$$

where ε_t^a and ε_t^P are each white noise. β is added to account for the non-unitary coefficient in the error correction term documented earlier. The price indices remain cointegrated in this extended model; the remaining qualitative properties of (6)–(7) continue to hold if $Var\,(\varepsilon_t^a)$ is small. Obviously α and ψ are not separately identified. A necessary condition for the precision explanation to be valid is $Var\,(\varepsilon_t^a) \leq Var\,(\varepsilon_t^p)$. The preferred model corresponds to $0 < \alpha\psi < 1$.

Tables 7 (8) present Kalman Filter estimates of model (8)–(9) for Sydney (Melbourne), respectively, under various restrictions and generalizations.[26] The basic model's estimates (Column (1)) are much more in line with the preferred than with the precision explanation. On the one hand, with $\widehat{\alpha\psi}$ equal to 0.52 in Sydney and 0.70 in Melbourne, the private-treaty price puts about half (seventy percent) of its weight on the lagged state variable in Sydney (Melbourne). On the other hand, the precision model does very poorly. In Sydney, the variances of the temporary shocks are very similar, and one cannot reject their equality. The failure of the precision model for Melbourne is starker, with the temporary shock variance about twenty times larger than for auctions than for private-treaty. The remaining columns show that Column (1)'s restrictions on the lags – none for the auction price and one (two) lags for the Sydney (Melbourne) private-treaty price – are not rejected by the data.

D. Evidence from List Prices

List prices are set solely by sellers and so should reflect seller information only.[27] Incorporating list prices into the preferred model we then have that auction prices reflect buyer information only, private-treaty prices reflect both buyer and seller

[26] In this and the following tables, we set shock correlations to zero when identification requires it.

[27] This could include seller beliefs about buyer valuations, but not uncorrelated contemporaneous shifts in the actual buyer distribution.

Table 7—Structural Unobserved Componsents Models – Sydney

Coefficient	(1)	(2)	(3)
A: z_t	1	1	0.79***
	(.)	(.)	(0.14)
A: z_{t-1}			0.21
			(0.14)
P: z_t	0.44***	0.45***	0.21
	(0.10)	(0.10)	(0.14)
P: z_{t-1}	0.52***	0.48***	0.75***
	(0.10)	(0.15)	(0.14)
P: z_{t-2}		0.03	
		(0.09)	
σ_η^2	1.17***	1.21***	1.16***
	(0.27)	(0.31)	(0.27)
σ_a^2	0.18*	0.16	0.44***
	(0.11)	(0.14)	(0.13)
σ_p^2	0.22***	0.22***	0.13
	(0.06)	(0.06)	(0.11)
$corr(\varepsilon_t^a, \varepsilon_t^p)$	-0.54	-0.64	
	(0.39)	(0.58)	
	Associated p-values		
$H_0 : \sigma_a^2 = \sigma_p^2$	0.81	0.70	0.16
$H_0 : \sigma_a^2 = \sigma_{ap} = 0$	0.00***	0.00***	
Log Likelihood	363.19	363.44	362.51

Note: ***, ** and * denote significance at 1, 5 and 10 per cent levels. Standard errors in parentheses. Variance estimates and their standard errors are multiplied by 1000. σ_η^2 is the variance of the permanent shock, η_t. σ_a^2 and σ_p^2 are the variances of the temporary shocks to auction and private-treaty prices respectively, $corr\left(\varepsilon_t^a, \varepsilon_t^p\right)$ their correlation and σ_{ap} their covariance.

information, while list prices reflect seller information only; also, private-treaty prices lag auction prices, and list prices lag private-treaty prices.

We form a list price index in the manner used for the other indices, assigning a property to its first quarter of listing. As list prices are seldom used for auctions, we only use those for private treaty sales.[28] Lacking list prices for sales prior to 1998:II, our sample size drops to only 58.[29]

We first run Granger causality tests for list prices and the two other series (Table 9). Our Sydney results are perfectly in line with the preferred model: both auction and private-treaty prices Granger cause list prices, but list prices Granger causes neither. The first statement holds for Melbourne as well. However, there, list prices do Granger cause private-treaty prices.

[28] Including list prices for auctions has little overall effect on the results. We lack information on properties offered for sale by private-treaty that were withdrawn from the market.

[29] Nevertheless, the shorter sample allows us to use hedonic indices with all attributes data.

Table 8—Structural Unobserved Componsents Models – Melbourne

Coefficient	(1)	(2)	(3)
A: z_t	1	1	0.81***
	(.)	(.)	(0.21)
A: z_{t-1}			0.28
			(0.21)
P: z_t	0.22	0.50***	0.41***
	(0.15)	(0.08)	(0.12)
P: z_{t-1}	0.70***	0.12*	0.19***
	(0.15)	(0.07)	(0.07)
P: z_{t-2}		0.30***	0.40***
		(0.05)	(0.10)
σ_η^2	0.68***	1.04***	0.95***
	(0.14)	(0.21)	(0.20)
σ_a^2	1.04***	0.89***	0.87***
	(0.37)	(0.16)	(0.15)
σ_p^2	0.05	0.03	0.04***
	(0.06)	(0.02)	(0.02)
$corr(\varepsilon_t^a, \varepsilon_t^p)$	0.29		
	(0.78)		
	Associated p-values		
$H_0 : \sigma_a^2 = \sigma_p^2$	0.01***	0.00***	0.00***
$H_0 : \sigma_a^2 = \sigma_{ap} = 0$	0.00***		
Log Likelihood	348.16	360.25	360.94

Note: See notes to Table 8. Additionaly, Melbourne data are seasonally adjusted prior to estimation.

Expanding the state space model to include list price index l_t separately identifies α and ψ under the model

$$a_t = \beta z_t + \varepsilon_t^a \tag{10}$$

$$p_t = (1 - \alpha\psi)\, z_t + \alpha\psi z_{t-1} + \varepsilon_t^p \tag{11}$$

$$l_t = (1 - \alpha)\, z_t + \alpha z_{t-1} + \varepsilon_t^l \tag{12}$$

Table 10, Columns (1) and (2), presents Kalman Filter estimates of this model. Although the samples are shorter, the result that private-treaty prices lag the cycle continues to hold in both cities. Where precisely estimated, in Sydney, the bargaining weight on the seller valuation, ψ, is estimated at 0.5 (equal bargaining power) and the backward looking component in sellers valuations, α, at 0.83. As $\psi = 0$ ($\psi = 1$) would imply the same autocorrelation properties for private treaties as for auction prices (list prices), the data rejects the boundary cases: private-treaties prices are consistent with a convex combination of both buyer and seller values.

Table 9—Granger Causality Results Including List Prices

Null Hypothesis	Sydney	Melbourne
H_0 : List prices do not	3.36	4.36
Granger Cause auction prices	(0.50)	(0.22)
H_0 : List prices do not	1.47	21.72***
Granger Cause private-treaty prices	(0.83)	(0.00)
H_0 : Auction prices do not	21.20***	9.42**
Granger Cause list prices	(0.00)	(0.02)
H_0 : Private-treaty prices do not	10.32**	10.35**
Granger Cause list prices	(0.04)	(0.02)

Note: ***, ** and * denote significance at 1, 5 and 10 per cent levels of significance; test statistics constructed using the approach outlined in Toda and Yamamoto (1995); p-values in parentheses.

For Melbourne, $\widehat{\psi} = 0.82$ – insignificantly different from both equal and zero seller bargaining power[30] – and $\widehat{\alpha} = 0.31$. Overall, list prices behave according to our preferred model and allow us to identify the bargaining weight.

E. Evidence from Auction Clearance Rates

Figure 4 is a quarterly scatter plot of price growth and clearance rates, superimposed by the line of best fit. The contemporaneous correlations are 0.37 in Sydney and 0.40 in Melbourne. To see how sluggish seller valuations generates such a relationship, let a buyer's valuation at time t be $z_t + b$, where z_t is again the common component of buyer and seller valuations, while b is specific to the buyer-property match and drawn from some distribution. Let the seller valuation be $(1-\alpha)\, z_t + \alpha z_{t-1} + s$, with s specific to the seller and drawn from some other distribution. Then the probability of sale is

$$\Pr\left(b^{(1)} - s \geq -\alpha\eta_t\right) \equiv h\left(\alpha\eta_t\right)$$

with $b^{(j)}$ the jth order statistic of b. The expected auction price is

$$\begin{aligned} a_t &= z_t + E_{b,s:N}\left[\max\left(b^{(2)}, s\right) \,\middle|\, b^{(1)} \geq s - \alpha\eta_t\right] \\ &\approx z_t - q^a \alpha\eta_t \end{aligned}$$

[30] Price posting (Díaz and Jerez (2013) and Caplin and Leahy (2011)) is an alternative interpretation of $\psi = 1$.

Table 10—Unobserved Components Models with Listing Prices

Parameter	Sydney (1)	Melbourne (2)	Sydney (3)	Melbourne (4)
β	1.02***	1.06***	0.98***	1.06***
	(0.03)	(0.01)	(0.06)	(0.01)
α or $\delta^{\dagger}$	0.83***	0.31**	0.75***	0.13
	(0.23)	(0.14)	(0.14)	(0.12)
α_2 or $\delta_2^{\dagger}$		0.17**		0.08**
		(0.10)		(0.05)
ψ	0.50***	0.82***	0.54***	0.87**
	(0.13)	(0.23)	(0.09)	(0.53)
σ_η^2	0.54***	0.98***	0.87***	0.79***
	(0.13)	(0.22)	(0.21)	(0.18)
σ_a^2	0.66***	0.43***		0.64***
	(0.20)	(0.13)		(0.17)
σ_p^2	0.25***	0.18***	0.28***	0.13***
	(0.08)	(0.06)	(0.05)	(0.06)
σ_l^2	0.08**	0.86***	0.85***	0.90***
	(0.09)	(0.18)	(0.16)	(0.19)
$corr\left(\varepsilon_t^a, \varepsilon_t^p\right)$	0.71***			
	(0.12)			
$corr\left(\varepsilon_t^a, \varepsilon_t^l\right)$	-0.55***			
	(0.17)			
$corr\left(\varepsilon_t^p, \varepsilon_t^l\right)$	-0.87**		0.58***	
	(0.47)		(0.09)	
μ	1.35***	1.93***	1.35	1.92***
	(0.31)	(0.41)	(2.72)	(0.37)
H_0 : No	p-values		p-values	
lagged diffusion††	0.00	0.00	0.00	0.03
Log Likelihood	425.33	364.16	401.07	358.08

Note: ***, ** and * denote significance at 1, 5 and 10 per cent levels of significance. Variances estimates and their standard errors are multiplied by 1000; Melbourne data are seasonally adjusted prior to estimation and include an additional lag for the diffusion of common shocks. $^{\dagger}\alpha$ refers to columns one and two, δ refers to columns three and four. ††No lagged diffusion denotes $H_0 : \alpha = 0$ ($\delta = 0$) for Sydney and $H_0 : \alpha = \alpha_2 = 0$ ($\delta = \delta_2 = 0$) for Melbourne.

with the probability and expectation taken with respect to the joint distribution of s and N draws of b, and

$$q^a \equiv \frac{\partial E_{b,s:N}\left[\max\left(b^{(2)}, s\right) \,\middle|\, b^{(1)} - s \geq x\right]}{\partial x} \text{ evaluated at } x = 0.$$

The correlation between auction prices and the probability of sale is given by

$$\begin{aligned} Cov\left(\Delta a_t, h\left(\alpha\eta_t\right)\right) &\approx \left(1 - \alpha q^a\right)\alpha h'\left(0\right)\sigma_\eta^2 \\ &> 0 \text{ if } \alpha q^a < 1 \end{aligned}$$

Thus, provided the product of lagged information diffusion and the clearance effect on auction prices, αq^a, is not too large, auction prices and the clearance rate will be positively correlated. The calculations in the online Appendix (Section V.A) show that $q^a < 1$ for all pairs of the Generalised Pareto distributions that we consider, with $2 \leq N \leq 30$, differences in support that match observed clearance rates, and for alternative assumptions about the reserve price.

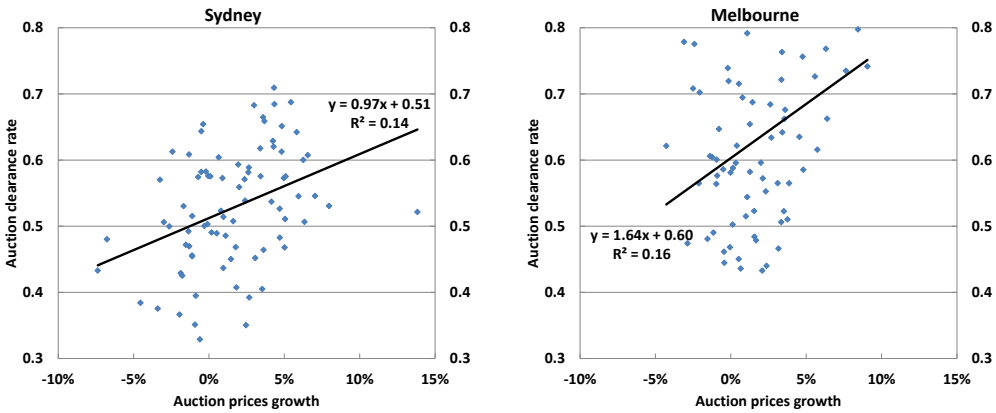

Figure 4. Scatter Plot of Auction Price Growth against the Clearance Rate

F. *Differential Weighting of the Buyer Valuation Distribution*

Auctions and negotiations weight different parts of the buyer distribution differently. If shocks diffuse through the buyer population over time, this can affect the lead-lag relationship between auction and private-treaty prices. The resulting pattern, however, differs from our empirical findings.

Under private values, positive shocks to valuations of a fraction of the buyer population are felt more in auction prices, while negative shocks are felt more in negotiations, given a sufficient number of auction bidders. For a positive shock, those receiving it tend to outbid other buyers, and so price reflects the shock; when negative, the recepients are outbid and price does not reflect it. In negotiations, in contrast, price reflects the shock regardless of sign, whenever a "shocked" buyer is present. This reasoning suggests that auction prices lead private-treaty prices when shocks are positive, but lag when negative. As usual, unconsummated sales blur the distinction, but the general claim that the right tail of the buyer distribution is relatively more important in auctions presumably continues to hold.

A simple example has a random fraction a of buyers receive a positive shock in

the first period, and $1-a$ in the second. Buyers' valuations are identical prior to the shock. Then price at any given auction increases by the amount of the shock if at least two bidders there have received it; the expected price at auction increases, per unit of the shock, 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 private treaties, 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 private-treaty 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 $1-q(1-a)$. Percentage-wise, auction prices fall less than private-treaty prices so long as $1-q(1-a) < a$, which holds for $a \in (1-a^*(N), 1)$.

In principle, this mechanism could explain our results if the auction-leading-private treaty effect is larger than the converse. In the online Appendix (Section V.B), the lagged cross correlation of auction and private-treaty price growth provides a gross check on the explanation. If the explanation is correct, auction price growth should be positively correlated with one-period-ahead growth in private-treaty prices when auction prices are increasing, and private-treaty price growth positively correlated with one period ahead growth in auction prices when private-treaty prices are falling. We find the explanation inconsistent with the data, as private-treaty price growth does not lead auction price growth when private-treaty prices are falling, or rising less than usual. As an alternative structural check, we estimate non-linear models that allow for contemporaneous and lagged asymmetry in the response of auction prices that depends on the direction of change in the permanent component of prices. The results find no evidence of asymmetry consistent with lagged diffusion of shocks to buyers (online Appendix, Section V.B, Table 12).

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 other bidders dropping out, price will be a function only of 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 bidder signals matter. Yet none of the cases that

have been worked out generate a relationship like what we document. 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. In the uniform distribution case, the auction price equals the average signal plus the gap between the first order and second order bid statistics, divided by the number of bidders. For large numbers of bidders, the percentage change in price per additional unit of valuation will become close to a, the same as for private-treaty prices.

G. Backward Looking Price Formation and Publicity

Auction results are quickly published in newspapers and auction company websites (negotiated prices may be available only after a quarter or more); their drama and visibility may make them additionaly salieent. If buyers and sellers use past transactions to form valuations,[31] the greater saliency of auction prices couild explain the Granger causality pattern we observe.

However, price formation that focuses on recent auction prices also generates auction price momentum as large as that for negotiated prices. To see this, write

$$a_t = \delta z_t + (1-\delta)\, a_{t-1} + \varepsilon_t^a \tag{13}$$

$$p_t = \delta z_t + (1-\delta)\, a_{t-1} + \varepsilon_t^p \tag{14}$$

This models prices as a convex combination of the current state and the lagged auction price, plus a temporary shock. Using the same δ in both equations posits common use of historical information across sale mechanisms. First differencing,

$$\Delta a_t = \mu + \delta m(\delta)\, \eta_t + m(\delta)\, \Delta\varepsilon_t^a \tag{15}$$

$$\Delta p_t = \mu + \delta\left(1 + (1-\delta)\, m(\delta)\, L\right)\eta_t + (1-\delta)\, m(\delta)\, \Delta\varepsilon_{t-1}^a + \Delta\varepsilon_t^p \tag{16}$$

where $m(\delta) = (1-(1-\delta)\, L)^{-1}$. For equation (15) to be consistent with the auction data, δ must be close to 1 .[32] However, for $\delta \approx 1$, private-treaty price growth should also lack autocorrelation. This is inconsistent with our evidence.

Can asymmetry in the use of historical information rescue this argument? In

[31] This may be due to (a) availability of appraisals, which rely on past transactions (Quan and Quigley (1991)) ; (b) prices being revealing about the state of the market; and (c) backward looking (Case and Shiller, 1988) or informationally rigid (Coibion and Gorodnichenko (2015)) expectations.

[32] Otherwise, auction price growth is a linear combination of two (independent) infinite moving average prices and so could be approximated by a low-order autoregressive process – i.e. would be significantly autocorrelated. To see this clearly, set $\varepsilon_t^a = 0$ before first differencing (13). The result is an AR(1) process in auction price growth whose persistence is decreasing in δ.

principle, yes. If only sellers condition on past auction prices, we have

$$
\begin{aligned}
a_t &= \beta z_t + \varepsilon_t^a \\
p_t &= (1-\psi)\, z_t + (1-\delta)\, \psi z_t + \psi \delta a_{t-1} + \varepsilon_t^p \\
l_t &= (1-\delta)\, z_t + \delta a_{t-1} + \varepsilon_t^l
\end{aligned}
$$

The only substantive difference from the preferred model is that sellers condition on lagged auction prices rather than the unobserved permanent component itself. Assuming sellers use past auction prices is consistent with our previous findings. Estimates of this model are reported in Columns (3) and (4) of Table 10. The results are similar to the preferred model, including the estimates of relative bargaining strength and the weight on past auction prices.

IV. Conclusion

Housing market dynamics differ dramatically from those of perfect asset models and so have proved difficult to model. Particularly challenging has been the widely documented high positive autocorrelation of housing price growth. Working in an environment with an unusually high auction share, we find a much lower autocorrelation in auction prices than negotiated sales, which other markets use near exclusively. We argue that the larger weight that auction prices put on buyer valuations points to seller valuations as the source of the autocorrelation. We argue, further, that seller valuations appear to lag buyer valuations, and provide supporting evidence for this claim in the behaviour of list prices and the Phillips curve like relationship between the auction clearance rate and price growth.

Indeed, recent calibration studies have incorporated seller sluggishness in order to generate positive price growth autocorrelation. However, why sellers update values more slowly than buyers in response to new shocks is unclear. We primarily suspect the asymmetric nature of the matching process, for the reasons given in the Introduction. These explanations require further theoretical elaboration, and additional empirical verification, which should further our understanding of housing market dynamics. This paper also examplifies how our understanding of sale mechanisms can be used to uncover the propagation of price shocks over time.

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V. Online Appendix

A. *Accounting for failed transactions*

This section generalizes Section IV.A's discussion of how a seller reserve and overlapping buyer and seller distributions – which are necessary to account for not all meetings of buyers and sellers ending in a sale – affect the preferred model's ability to account for our core empirical results on Granger causality and momentum. We consider generalisations of the buyer and seller distributions and alternative models of the seller reserve to those used in that section.

Let the valuation of a given home to a potential buyer in the market at time t be $z_t + b$ where z_t is common to all buyers, while b is specific to the buyer-home pair and is drawn from the Generalized Pareto distribution with cdf $F(x) = 1 - (1-x)^{c_B}$. Likewise, let the valuation of a given home to the seller be $\kappa + (1-\alpha) z_t + \alpha z_{t-1} + s$, where s is specific to the seller and is drawn independently from distribution $F(y) = 1 - (1-y)^{c_S}$, and κ is a constant. As before, $z_t = \mu + z_{t-1} + \eta_t$, with η_t white noise. Then the expected negotiated price is

$$p_t = z_t - \alpha\psi\eta_t + E_{b,s}\left[(1-\psi)\, b + \psi s \;\middle|\; b \geq s + \widetilde{\kappa} - \alpha\eta_t\right]$$

where the expectation is taken with respect to the joint distributions of b and s. The expectation is conditioned on the buyer valuing the property more than the seller. $\widetilde{\kappa} \equiv \kappa - \alpha\mu$ captures the degree of non-overlap in the supports of the distributions of buyer and seller valuations.

Let $b^{(j)}$ indicate the jth highest value among the buyer-specific components of buyer valuations. The expected price at auction, conditional on sale, is

$$a = z_t + \mathcal{H}(\eta_t) \tag{17}$$

where the function $\mathcal{H}$ varies according to how the auction price is modelled. In the first two scenarios, the seller chooses their reserve price non-strategically, setting it equal to their valuation. In the first scenario, the reserve price is not announced, and the bidders do not 'jump-bid' in order to exceed it; a transaction takes place then when the second highest bidder value exceeds the seller valuation, and

$$\mathcal{H}(\eta_t) = E_{b,s:N}\left[b^{(2)} \;\middle|\; b^{(2)} \geq s + \widetilde{\kappa} - \alpha\eta_t\right]$$

In the second scenario, the seller reserve is announced, so that price is the maximum of the second highest buyer value and the reserve price, and a transaction takes place if the highest bidder value exceeds the seller valuation; thus

$$\mathcal{H}(\eta_t) = E_{b,s:N}\left[\max\left(b^{(2)}, s\right) \,\middle|\, b^{(1)} \geq s + \widetilde{\kappa} - \alpha\eta_t\right]$$

In the third scenario, the seller sets an optimal reserve price. Here, we need to take a stand on what sellers know about the buyer distribution. We assume that sellers know the shape of the buyer distribution but set the optimal reserve price as if the buyer common component were equal to their own, so that

$$\mathcal{H}(\eta_t) = E_{b,s:N}\left[\max\left(b^{(2)}, r(s)\right) \,\middle|\, b^{(1)} \geq s + \widetilde{\kappa} - \alpha\eta_t\right]$$

where $r(s) \equiv \frac{1+c_B(s+\widetilde{\kappa})}{1+c_B}$. First-differencing (17), and then taking a linear approximation of each price around a non-stochastic steady state, and ignoring constant terms, we have

$$\begin{aligned}
\Delta a_t &\approx \eta_t - \alpha q^a (\eta_t - \eta_{t-1}) \\
\Delta p_t &\approx \eta_t - \alpha (\psi + q^p)(\eta_t - \eta_{t-1})
\end{aligned}$$

where $q^a \equiv H'(0)$ and $q^p \equiv \frac{\partial E_{b,s}\left[(1-\psi)b+\psi s \middle| b \geq s+\widetilde{\kappa}+x\right]}{\partial x}_{|x=0}$. As before, the two series are cointegrated since a linear approximation of the difference between auction and private-treaty prices is stationary

$$a_t - p_t = \alpha\left[\psi - (q^a - q^p)\right]\eta_t$$

There is also a VECM representation, as before

$$\begin{aligned}
\Delta a_t &= \frac{q^a}{\psi - (q^a - q^p)}(a_{t-1} - p_{t-1}) + (1 - q^a\alpha)\eta_t \\
\Delta p_t &= \frac{\psi + q^p}{\psi - (q^a - q^p)}(a_{t-1} - p_{t-1}) + (1 - \alpha(\psi + q^p))\eta_t
\end{aligned}$$

Unlike the model in which all transactions are consummated, here each series Granger causes the other. Also, now both series display positive momentum, and

not only private-treaty prices

$$Cov\left(\Delta a_t, \Delta a_{t-1}\right) = \left(1 - q^a \alpha\right) q^a \alpha Var\left(\eta_t\right)$$
$$Cov\left(\Delta p_t, \Delta p_{t-1}\right) = \left(1 - \left(\psi + q^p\right)\alpha\right)\left(\psi + q^p\right)\alpha Var\left(\eta_t\right)$$

Unconsummated transactions thus rob our preferred model of its stark predictions for Granger causality and momentum. Quantitatively, however, those predictions can still hold. The relative behaviour of the two price indices depends on the ratios $r_1 \equiv \frac{q^a}{\psi+q^p-q^a}$ and $r_2 \equiv \frac{q^a}{\psi+q^p}$. If these are small, the combination of auctions weighting buyer valuations more heavily and a lagging seller valuation will continue to predict an auction price momentum substantial smaller than the private-treaties. It will also predict that the contribution of private-treaty prices to predicting auction prices is small relative to that of lagged auction prices to predicting private-treaty prices.

The ratios depend on the buyer and seller distributions, the number of bidders and ψ. Examining the two terms analytically is intractable, in large part due to the need to work with the second order statistic. However, simulations that assume equal bargaining power (consistent with our estimates in Table 10) and are calibrated by choosing a value of $\widetilde{\kappa}$ to fit the observed fraction of auctions that end in a sale, yield small ratios for a wide range of distribution shapes and for a sufficient number of bidders.

Figures 5 shows the ratios r_1 and r_2 for each scenario with three distributions cases: uniform $[c_B = c_S = 1]$, $[c_B = 2, c_S = 0.5]$ (right-skewed buyer, left-skewed seller) and $[c_B = 0.5, c_s = 2]$ (left-skewed buyer, right-skewed seller). We also report the empirical counterpart for r_2 based on $Cov\left(\Delta a_t, \Delta a_{t-1}\right)/Cov\left(\Delta p_t, \Delta a_{t-1}\right)$, as taken directly from the data.

Figure 5 highlights that with sufficiently many bidders (typically six is enough), all three scenarios can replicate the r_2 ratio observed in the data. That is, the autocorrelation in auction prices is small relative to their information content for private-treaty prices. Thus, even when allowing for unconsummated transactions, the results are still consistent with the main text's findings. This is also supported by the fact that r_1 is typically close to zero in the simulations, consistent with an insignificant coefficient on the adjustment parameter in the auctions equation, α_a,

from Table 5. Figure 6 further highlights that q^a is small, below 0.3 with six or more bidders, which guarantees the condition $\alpha q^a < 1$ (Section IV.E) for sellers only having a small overall effect on auction prices.

B. Asymmetry in the Lead/Lag Relationship

Table 11 shows correlations between auction price and private-treaty price growth, that condition on the previous direction of price changes (in levels or relative to the sample average). The top panel presents the correlation of past auction price growth with current private-treaty price growth, when past auction prices are rising in levels (or by more than their mean); the bottom panel presents the correlation of past private-treaty price growth with current auction price growth, when past private-treaty prices are falling (rising less than their mean). Column 1 reports the unconditional correlations using the entire sample.

From the first column, we see that, as expected, the top correlation is much greater than the bottom (auction prices Granger cause private-treaty prices but the reverse is not true). In the next two columns, we see that auction price growth does predict private-treaty price growth when auction prices are rising (the top panel), but that private-treaty price growth does not predict auction prices when private-treaty prices are falling or rising by less than their mean (the bottom panel). The absence of predictability using private-treaty prices, when previous price growth is negative (or rising less than usual), does not favour a model with asymmetry in the lead-lag relationship.

Table 11—Conditional Correlations: Auction and Private-treaty Prices

	$\rho(\Delta p_t, \Delta a_{t-1})$	$\rho(\Delta p_t, \Delta a_{t-1}) \mid \Delta a_{t-1} > 0$	$\rho(\Delta p_t, \Delta a_{t-1}) \mid \Delta a_{t-1} > \overline{\Delta a_t}$
Sydney	0.51	0.41	0.31
	(81)	(51)	(41)
Melbourne	0.59	0.63	0.58
	(77)	(54)	(36)
	$\rho(\Delta p_{t-1}, \Delta a_t)$	$\rho(\Delta p_{t-1}, \Delta a_t) \mid \Delta p_{t-1} < 0$	$\rho(\Delta p_{t-1}, \Delta a_t) \mid \Delta p_{t-1} < \overline{\Delta p_t}$
Sydney	0.11	-0.05	-0.10
	(81)	(24)	(39)
Melbourne	0.33	-0.39	0.13
	(77)	(19)	(44)

Note: 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 private-treaty prices.

As an alternative structural check, we also estimate non-linear models that explicitly allow for a kinked response in auction prices, conditioning on the direction of the change in the permanent component in price relative to its mean.[33] Retaining the assumption that the response in private-treaty prices to shocks is symmetric, as suggested by the theoretical discussion above, the non-linear model for the auction price is

$$\Delta a_t = \mu + \beta^+ \eta_t I\left(\eta_t \geq 0\right) + \beta^- \eta_t I\left(\eta_t < 0\right) + \varepsilon_t^a - \varepsilon_{t-1}^a$$

where $I\left(.\right)$ is a binary indicator function taking a value of one when the condition in its argument is satisfied and zero otherwise. The second model we consider allows both for asymmetry and lagged diffusion of shocks in the auction price

$$\begin{aligned}\Delta a_t = \mu &+ \left(1-\gamma^+\right)\eta_t I\left(\eta_t \geq 0\right) + \gamma^+ \eta_{t-1} I\left(\eta_{t-1} \geq 0\right) \\ &+ \left(1-\gamma^-\right)\eta_t I\left(\eta_t < 0\right) + \gamma^- \eta_{t-1} I\left(\eta_{t-1} < 0\right) + \varepsilon_t^a - \varepsilon_{t-1}^a\end{aligned}$$

For each model, estimation is undertaken jointly with private-treaty prices (Equation 11) and list prices (Equation 12), which assist in providing conditional identification of the unobserved permanent shock, η_t.

The results in Table 12 suggest there is little evidence in support of an asymmetric response in auctions prices to shocks in the permanent trend. Across all models, the contemporaneous point estimates for the response to a positive shock (β^+ or $1-\gamma^+$) are less than the response to a negative shock (β^- or $1-\gamma^-$). This is the opposite prediction to that implied by asymmetry and lagged diffusion of shocks across the buyer distribution, which predicts a stronger response to positive shocks than for negative. Accounting for the uncertainty around the point estimates, the null hypotheses of no asymmetry in the response to shocks ($\beta^+ = \beta^-$ and $\gamma^+ = \gamma^-$) cannot be rejected in either city. Overall, there is little evidence of lagged diffusion of shocks through the buyer distribution.

C. Robustness of the Empirical Findings

This section addresses the robustness of our core empirical findings to: (a) measurement of the hedonic indices; (b) selection of the sales mechanism; and (c) whether other housing characteristics, either observed or unobserved, could explain

[33] Similar results are obtained allowing for kinked effects around zero growth rather than mean growth.

Table 12—Asymmetry in the Response of Auction Prices to Shocks

	Contemporaneous asymmetry		Asymmetry and lagged diffusion	
	β^+	β^-	γ^+	γ^-
Sydney	0.73	1.58	0.48	-0.09
	(0.08,1.32)	(0.47,2.13)	(-0.08,0.91)	(-0.78,0.44)
Melbourne	1.07	1.12	0.56	0.42
	(0.67,1.60)	(0.62,1.58)	(-1.17,1.25)	(-0.72,1.31)
p-values	$H_0 : \beta^+ = \beta^-$		$H_0 : \gamma^+ = \gamma^-$	
Sydney	*0.17*		*0.27*	
Melbourne	*0.84*		*0.87*	

Note: Point estimates are computed using two-step maximum likelihood; bootstrapped percentile confidence intervals (at 95 per cent in parenthesis) and p-values (in italics) are reported; Melbourne data are adjusted for seasonality prior to estimation.

them. For brevity, we focus on in-sample results.

Measurement

To address whether measurement could be a concern, we revisit the in-sample Granger causality tests using data without attribute controls – specifically, the number of bedrooms, bathrooms and log size. We also revisit them using repeat-sales instead of hedonic indices, which effectively difference out unobserved time-invariant characteristics of homes.[34] Table 13 shows that our results are robust to the omission of attributes, and to using alternative repeat-sales indices. As such, our main findings do not appear to be sensitive to the measurement approach taken.

Table 13—In-Sample Causality Robustness: Varying Hedonic Controls and Repeat-Sales

Null hypothesis	Sydney (hedonic)	Sydney (repeat-sales)	Melbourne (hedonic)	Melbourne (repeat-sales)
$a_t \overset{GC}{\nrightarrow} p_t$	24.76***	15.62***	36.70***	24.16***
	(0.00)	(0.01)	(0.00)	(0.00)
$p_t \overset{GC}{\nrightarrow} a_t$	4.12	8.39	2.15	3.02
	(0.53)	(0.14)	(0.71)	(0.55)

Note: Using Toda and Yamamoto's (1995) testing approach. All tests include seasonal controls; the lag structure is unchanged from that used in the main text; p-values are reported in parentheses. For the hedonic indices only controls for the postcode and property type are included while the number of bedrooms, bathrooms and log size are omitted.

[34] It should be noted that a limitation of using repeat-sales is that they introduce scope for sample-selection bias since only multiple sales observations are used in their calculation. However, consistent with Hansen (2009), we find that the indices are comparable at the city-wide level, exhibiting similar price dynamics in terms of their leading and lagging properties, and in their average estimated growth rates.

Table 14 shows that for repeat-sales,the contribution of transaction level variance to the variance of quarterly growth is small.

Table 14—RMSE of Repeat-Sales Price Regressions

	RMSE	N	$\frac{RMSE}{\sqrt{N}}$	St. Dev.
		Sydney		
Auction	0.21	209	0.015	0.029
Private	0.23	6 166	0.003	0.017
		Melbourne		
Auction	0.22	334	0.012	0.033
Private	0.30	4 984	0.004	0.021

Note: RMSE is the root mean squared error of the corresponding regression; N is the average number of observations per quarter; and St. Dev. is the standard deviation of quarterly prices growth.

Selection of the sales mechanism

Another possible concern is that endogeneity in sellers' selection of the sales mechanism could be responsible for the differential time series properties of auctions and private-treaty prices. To address this, we first provide reduced-form and then structural evidence that does not support a selection explanation.

If selection is driving our findings, then one might expect that selection of the sales mechanism could itself have predictive information for prices. For example, if sellers are forward looking and auctions are more profitable in rising markets then one might expect the share of auctions in total sales to pick up before prices rise. Conversely, the share of private-treaties will increase when prices fall.[35] To examine if this true, we augment the benchmark VAR with a measure of the auction share – the ratio of all auctions held (successful and unsuccessful) to all sales events held (i.e. successful and unsuccessful auctions plus private-treaty sales) and the auction clearance rate. We include the latter to separately control for predictability through the sales mechanism chosen and predictability through clearance (the fact that buyer values update more quickly than sellers).[36]

Based on the evidence in Sydney (Table 15), the share of auctions held, as a proportion of all sales, is only useful for predicting the clearance rate and itself. It

[35] In addition, one might expect to the extent that both sellers and buyers are forward looking, and fully update their information in response to a common shock, the auction sales rate – the ratio of successful auctions to all auctions held – should not assist when predicting future price growth. This is true, for example, in Wang's (1993) dynamic model with endogenous selection.

[36] Without a control for the auction clearance rate, it is possible (likely) that auction incidence is correlated with the clearance rate and so omitting it could lead to spurious inference when buyers values update more quickly than sellers in response to shocks.

has no predictive content for future price formation as one might expect if selection is the explanation. Similar results are found in Melbourne where the auction share is also not informative for forecasting prices.

Table 15—Causality Tests with Auction Incidence and the Clearance Rate

H_0 : $\overset{GC}{\nrightarrow}$	Auction prices a_t	Clearance rate c_t	Private-treaty prices p_t	Auction incidence v_t
		Sydney		
a_t	0.48	0.00***	0.00***	0.00***
c_t	0.23	0.02**	0.00***	0.02**
p_t	0.53	0.02**	0.01***	0.03**
v_t	0.35	0.00***	0.37	0.00***
		Melbourne		
a_t	0.36	0.99	0.00***	0.35
c_t	0.03**	0.36	0.01**	0.04**
p_t	0.34	0.90	0.29	0.51
v_t	0.50	0.74	0.39	0.02**

Note: ***,** and * denote significance at 1, 5 and 10 per cent levels; $H_0 : \overset{GC}{\nrightarrow}$ denotes the null of non-causality from the row variable to the column variable; p-values are reported.

Taking a structural approach, we also undertake Granger causality tests using estimated price indices that adjust for endogenous selection of the sales mechanism. Specifically, we use a two-step Heckman estimator of the endogenous switching regression

$$a_{ijt} = \begin{cases} 1 \text{ if } x'_{ijt}\kappa \geq u_{ijt} \\ 0 \text{ if } x'_{ijt}\kappa < u_{ijt} \end{cases}$$

$$\ln p_{ijt} = \begin{cases} \sum_{t=0}^{T} \gamma_t^a D_{it} + \sum_{j=1}^{J} \beta_j^a PC_{ij} + \sum_{k=1}^{k} \theta_k^a C_{ikt} + \varepsilon_{ijt}^a \text{ if } a_{ijt} = 1 \\ \sum_{t=0}^{T} \gamma_t^p D_{it} + \sum_{j=1}^{J} \beta_j^p PC_{ij} + \sum_{k=1}^{k} \theta_k^p C_{ikt} + \varepsilon_{ijt}^p \text{ if } a_{ijt} = 0 \end{cases}$$

where γ_t^a and γ_t^p are the estimated selection-adjusted price indices for auctions and private treaties at time t. Assuming the selection and pricing residuals are joint normal (and correlated), the selection vector x'_{ijt} includes all variables in the price equation and a dummy variable for whether the property was ever previously auctioned successfully. If it is true that the current price of a property is statistically independent of the previous mechanism used to affect its sale, this variable assists in providing conditional identification of auction incidence.

Table 16 reports the share of auctions and private-treaties that were previously sold at auction: about 62 (58) percent of auctioned properties were previously sold through auction but only 6 (9) per cent of private-treaties were previously sold at auction for Sydney (Melbourne). Table 17 reports the in-sample causality findings using the selection-adjusted indices and the benchmark price indices estimated on the same sample.[37] Although controlling for selection does reduce the value of the test statistic when the null is that auction prices do not Granger cause private-treaty prices, and increases the value of the test statistic when the null is that private-treaty prices do not Granger cause auction prices, there is still clear evidence to reject the null that auction prices do not Granger cause private-treaty prices, but little evidence to reject the null that private-treaty prices do not Granger cause auction prices.

Table 16—Correlation Between d^a_{ijt} and a_{ijt}

	Auction previously chosen	No auction previously chosen	Total
		Sydney	
Auction	37,679	23,181	60,860
	(0.62)	(0.38)	
Private-treaty	31,983	534,199	566,182
	(0.06)	(0.94)	
Total	69,662	557,380	
		Melbourne	
Auction	77,842	56,123	133,965
	(0.58)	(0.42)	
Private-treaty	40,258	411,035	451,293
	(0.09)	(0.91)	
Total	118,100	467,158	585,258

Note: Proportions are in parentheses and are with respect to the row total. For example, of all auctions held, 62 per cent of them were previously auctioned at some point in the sample (within the sample of repeat-sales).

Using Real Prices

Here we show that our results are robust to the use of real house price indices rather than nominal. Using city-specific CPIs to deflate nominal prices in each city, Table 18 compares the autocorrelation coefficients in nominal and real (deflated) prices growth. The autocorrelation coefficients are similar across the two measures and there is less momentum in auction prices growth than there is in private-treaty

[37] The definition of d^a_{ijt} requires us to restrict the sample to repeat sales only.

Table 17—In-Sample Causality: Accounting for Endogenous Selection

Null hypothesis	Sydney (2step-HESM)	Sydney (Hedonic)	Melbourne (2step-HESM)	Melbourne (Hedonic)
$a_t \overset{GC}{\nrightarrow} p_t$	35.78***	51.58***	51.38***	48.86***
	(0.00)	(0.00)	(0.00)	(0.00)
$p_t \overset{GC}{\nrightarrow} a_t$	11.02	5.65	1.86	8.93
	(0.14)	(0.58)	(0.76)	(0.26)

Note: Using Toda and Yamamoto's (1995) testing approach; 2step-HESM stands for a two step-estimator of the Heckman Endogenous Switching model; all models estimated on the repeat-sales sample.

prices growth. Table 19 re-examines our key causality and efficiency findings using real prices: the results are qualitatively unchanged.

Table 18—Momentum in Real and Nominal Prices

Autocorrelation coefficient	Sydney		Melbourne	
	Nominal	Real	Nominal	Real
		Auction price growth		
Lag 1	-0.05	-0.01	0.44	0.41
Lag 2	0.09	0.10	0.25	0.26
Lag 3	0.10	0.10	0.00	-0.03
Lag 4	0.01	-0.04	-0.14	-0.16
		Private-treaty price growth		
Lag 1	0.13	0.12	0.40	0.30
Lag 2	0.22	0.21	0.43	0.39
Lag 3	-0.03	-0.04	0.05	0.00
Lag 4	-0.08	-0.12	0.07	0.05

Note: Autocorrelations based on nominal data are the same as those reported in Figure 2 and are reported using all attribute controls for Sydney on the sample 1992:I to 2012:IV and limited attribute controls for Melbourne on the sample 1993:I to 2012:IV. City-specific CPIs for Sydney and Melbourne are sourced from the Australian Bureau of Statistics, Catalogue 6401.0, Table 5.

Housing characteristics and location

Our final checks examine whether the causality findings could be explained by the location or types of homes sold, rather than the mechanism used to sell it. Auction prices might capture more timely information because they are more prevalent in locations that lead housing prices. For example, inner city prices could lead middle and outer city prices and auctions are more frequent in inner city areas.

To address this concern, we estimate 14 (10) pairs of sub-city hedonic indices for Sydney (Melbourne), one index for auctions and one for private-treaties in each sub-city district.[38] Using a panel-VAR framework, which allows for heterogeneous

[38] We use Statistical Area Level 4 localities as defined by the Australian Bureau of Statistics. They are

Table 19—In-sample Granger Causality Tests: Real Prices

	All controls	
Null hypothesis	Sydney	Melbourne
$a_t \overset{GC}{\nrightarrow} p_t$	68.89***	11.95**
	(0.00)	(0.02)
$p_t \overset{GC}{\nrightarrow} a_t$	8.67	4.33
	(0.12)	(0.36)
$E\left(a_t \mid \mathcal{I}_{t-1}^{a,p}\right) = a_{t-1}$	11.67	9.97
	(0.23)	(0.19)
$E\left(p_t \mid \mathcal{I}_{t-1}^{a,p}\right) = p_{t-1}$	78.84***	28.18***
	(0.00)	(0.00)

Note: ***, ** and * denote significance at 1, 5 and 10 per cent levels. $\overset{GC}{\nrightarrow}$ is a test for non-Granger causality; a_t is the real auction price, p_t the real private-treaty price and $\mathcal{I}_{t-1}^{a,p}$ is the information set at time $t-1$ (conditioning on lagged real auction and real private-treaty prices). All controls includes the property type and interactions with the number of bedrooms, the number of bathrooms, and the logarithm of the size of the property. For Melbourne this sample is restricted to 1997:IV onwards and includes controls for seasonality; p-values are in parentheses.

lagged diffusion and contemporaneous correlation in shocks across districts, we test whether the causality from auctions to private-treaty prices holds at this finer level of geographic disaggregation.[39] If location is the alternative explanation, we should not expect to find the same results to hold *within* sub-city districts.

Table 20 reports the results of panel-VAR Granger causality tests (Dumitrescu and Hurlin (2012)). They highlight that the null of non-causality from auction to private-treaty prices, within districts, is clearly rejected for both cities. There is little evidence to suggest that private-treaty prices similarly Granger cause auction prices, with the exception of perhaps Melbourne where there is a marginally significant p-value (0.09). However, this result is driven by several outer-city districts with very low district-specific auction shares (in the order of 1 to 2 per cent of all

areas with common socio-economic demographics and have 1200 (1350) private-treaty sales and 120 (220) auctions per quarter in Sydney (Melbourne) on average.

[39] The model panel-VAR is

$$\ln a_{j,t} = \sum_{k=1}^{K} \phi_{j,k}^{a} \ln a_{j,t-k} + \sum_{k=1}^{K} \phi_{j,k}^{p} \ln p_{j,t-k} + \varepsilon_{j,t}^{a}$$
$$\ln p_{j,t} = \sum_{k=1}^{K} \lambda_{j,k}^{a} \ln a_{j,t-k} + \sum_{k=1}^{K} \lambda_{j,k}^{p} \ln p_{j,t-k} + \varepsilon_{j,t}^{p}$$

for all sub-regions $j = 1, ..., J$ with $E\left(\varepsilon_t \varepsilon_\tau'\right) = \Sigma_\varepsilon$ for $t = \tau$ and $\mathbf{0}$ for $t \neq \tau$ $\left(\varepsilon_t \equiv \left[\varepsilon_t^a, \varepsilon_{,t}^p\right]', \varepsilon_t^a \equiv \left[\varepsilon_{1,t}^a ..., \varepsilon_{J,t}^a\right], \varepsilon_{,t}^p = \left[\varepsilon_{1,t}^p, ..., \varepsilon_{J,t}^p\right]\right)$. The null hypotheses are $p_t \overset{GC}{\nrightarrow} a_t$ ($H_0 : \phi_{j,k}^p = 0$ for all $j = 1, ..., J$ and $k = 1, .., K-1$) and $a_t \overset{GC}{\nrightarrow} p_t$ ($H_0 : \lambda_{j,k}^a = 0$ for all $j = 1, ..., J$ and $k = 1, ..., K-1$) with at least one non-zero element under the alternative in each case.

sales within a district), and that comprise a low share of total sales overall. These districts are heavily affected by small-sample noise in the underlying auction price estimates, which obscures the underlying relationship in price across mechanisms.[40] Restricting attention to districts where auctions comprise a minimum of 7.5 per cent of all sales (within the district) – thus mitigating the small sample concern – there is strong evidence to suggest auction prices Granger cause private-treaty prices, but no evidence to suggest that private-treaty prices are similarly informative.

Table 20—In-Sample Causality Conditioning on Sub-city Prices

Null hypothesis	Sydney		Melbourne	
	All districts	Min. auction share	All districts	Min. auction share
$a_t \overset{GC}{\nrightarrow} p_t$	4.27***	6.16***	4.14**	4.56***
	(0.01)	(0.00)	(0.02)	(0.01)
$p_t \overset{GC}{\nrightarrow} a_t$	8.71	4.95	2.81*	2.03
	(0.21)	(0.32)	(0.09)	(0.20)
No. of districts	14	6	10	6

Note: Test statistics are the $Z_{N,T}^{Hnc}$ test-statistic with residual bootstrapped p-values in parentheses to account for cross-locality error dependence (Dumitrescu and Hurlin (2012)). All districts denotes Statistical Area Level 4 localities in Sydney and Melbourne as defined by the Australian Bureau of Statistics and are based on the 2011 concordance (1270055006C183 Postcode to Statistical Area Level 4). Min. auction share restricts attention to districts where at least 7.5 per cent of successful sales are auctions.

Finally, conditioning on housing type, Table 21 revisits our in-sample causality findings using houses in lieu of auctions, and units (apartments) in lieu of private-treat sales. If houses are a better guide as to future market conditions, we would expect them to Granger cause unit prices, but that the reverse would not be true. The data are inconsistent with this hypothesis: in both cities there is bivariate causality between house and unit prices. In contrast, if we focus on within-group variation (either house sales or apartment sales), we still find unidirectional causality from auction to private-treaty prices by the type of home sold (Table 22).

VI. Cointegration Results

Table 23 reports results from bivariate and trivariate cointegration tests using Johansen's Likelihood Ratio (Trace) Test. At conventional levels of significance, all tests are consistent with the presence of a single common trend in price.

[40] This is also reflected in graphs of prices where auction prices still lead private-treaty prices, but the former's volatility obscures the presence of a leading relationship when testing for Granger causality. The same effect is also present in Sydney and is reflected in a thicker right tail of the test statistic distribution under the null that private-treaty prices Granger cause auction prices, than under the null that auction prices Granger cause private-treaty prices.

Table 21—In-Sample Causality: Do House Prices Lead Apartment Prices?

Null hypothesis	Sydney All-sales	Melbourne All-sales
$h_t \overset{GC}{\nrightarrow} u_t$	57.27***	42.86***
	(0.00)	(0.00)
$u_t \overset{GC}{\nrightarrow} h_t$	9.18*	74.10***
	(0.10)	(0.00)

Note: h_t denotes house prices and u_t apartment prices.

Table 22—In-Sample Causality Conditioning on The Type of Housing Sold

Null hypothesis	Sydney houses	Sydney apartments	Melbourne houses	Melbourne apartments
$a_t \overset{GC}{\nrightarrow} p_t$	60.20***	7.15***	30.81***	5.73**
	(0.00)	(0.01)	(0.00)	(0.02)
$p_t \overset{GC}{\nrightarrow} a_t$	5.31	0.30	2.00	2.30
	(0.38)	(0.59)	(0.74)	(0.13)

Note: Tests based on the apartments sample are restricted to 1997 onwards due to the small number of auctioned apartments prior to that date.

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Table 23—Johansen Trace Test Results

Variables	No cointegration	Null Hypothesis 1 cointegrating vector	2 cointegrating vectors
		Sydney	
s_t and a_t	20.20***	3.03	–
s_t and p_t	28.27***	3.14	–
a_t and p_t	21.39***	3.29	–
a_t, p_t and s_t	50.96***	20.62***	3.42
		Melbourne	
s_t and a_t	18.58**	0.92	–
s_t and p_t	23.70***	0.45	–
a_t and p_t	20.44***	0.89	–
a_t, p_t and s_t	63.70***	18.27**	2.28

Note: *** and ** denote rejection of the null at 1 and 5 per cent levels of significance. Tests are in-sample and based on Johansen's Trace Test statistic.

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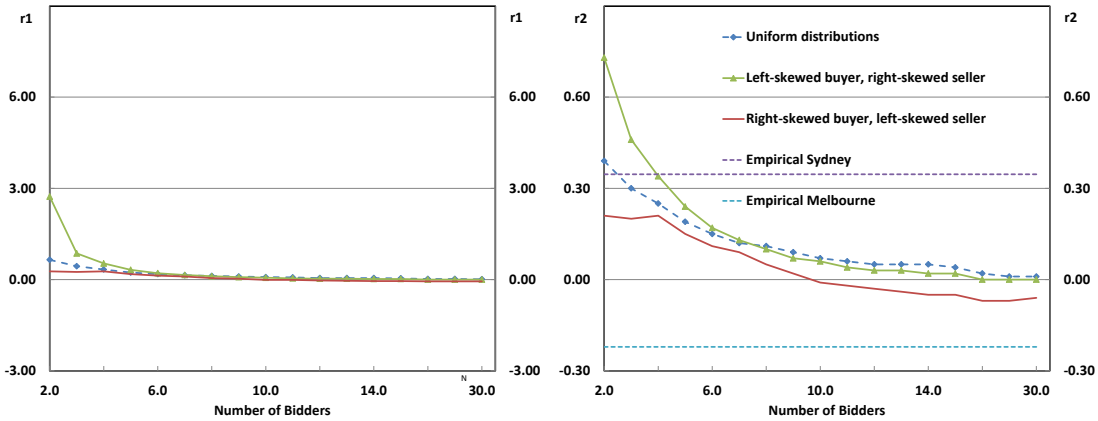
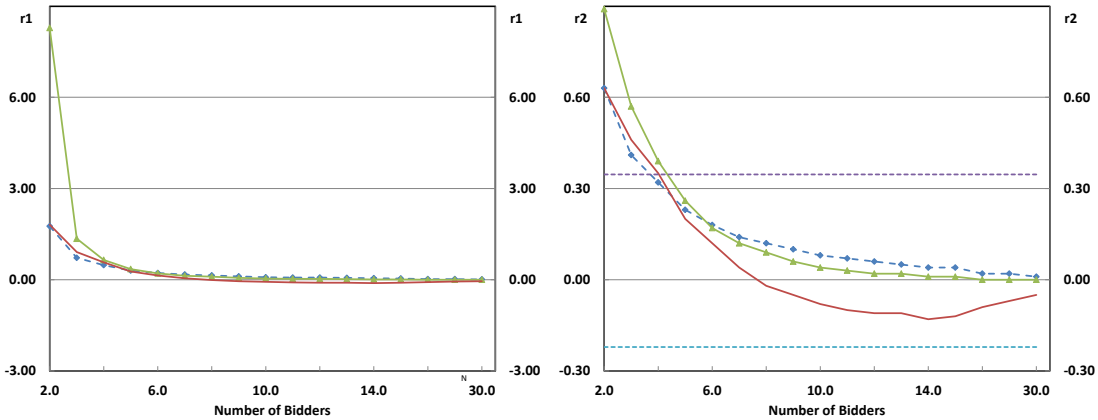
Scenario 1: Hidden Reserve Price



Scenario 2: Announced Reserve Price



Scenario 3: Optimal Announced Reserve Price

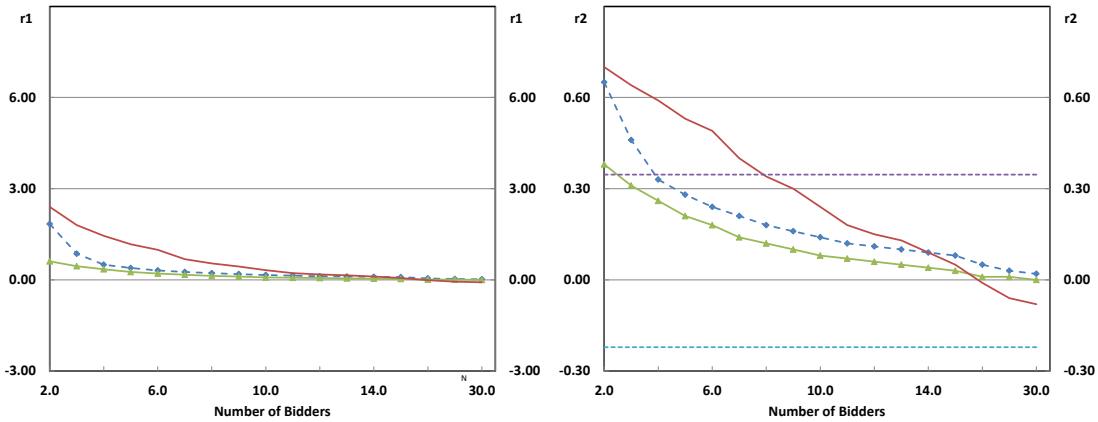
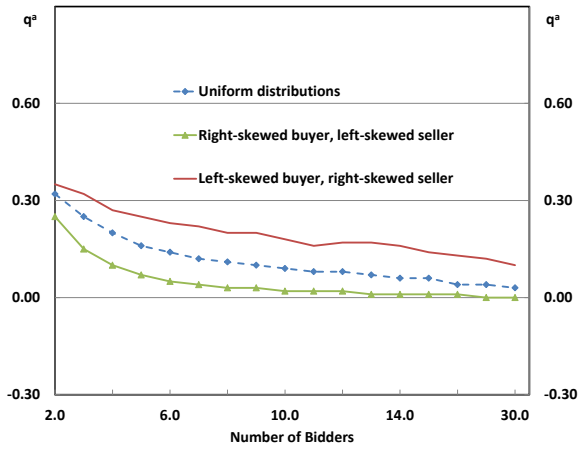


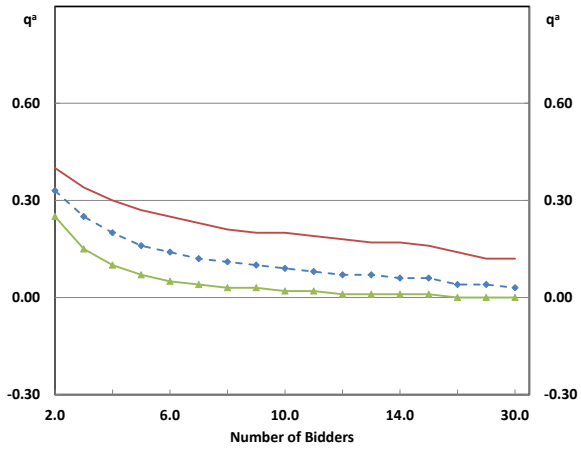
Figure 5. Comparison of Simulated and Empirical Price Ratios

Note: The empirical "r2" for Sydney and Melbourne are calculated using the ratio of $cov\left(\Delta a_t, \Delta a_{t-1}\right)/cov\left(\Delta p_t, \Delta a_{t-1}\right)$ based on a comparable sample from 1997:II to 2012:IV using the hedonic indices with all attributes (and their interactions with the property type) estimated.

Scenario 1: Hidden Reserve Price



Scenario 2: Announced Reserve Price



Scenario 3: Optimal Announced Reserve Price

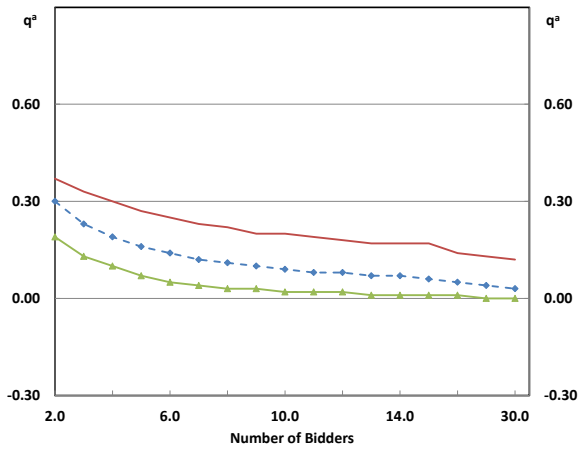


Figure 6. The Magnitude of q^a