NBER WORKING PAPER SERIES

THE STENCH OF FAILURE:
HOW PERCEPTION AFFECTS HOUSE PRICES

Kristle Cortés
Mandeep Singh
David H. Solomon
Philip Strahan

Working Paper 30760
http://www.nber.org/papers/w30760

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2022

We thank Sam Hartzmark, Jon Reuter, Kelly Shue, Tarun Ramadorai, David Miles, Elise Payzan-LeNestor, and seminar participants at the City Futures Centre (UNSW), University of Melbourne, Boston College and Imperial College London for valuable feedback. We thank SIRCA for providing access to the CoreLogic data. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

The Stench of Failure: How Perception Affects House Prices
Kristle Cortés, Mandeep Singh, David H. Solomon, and Philip Strahan
NBER Working Paper No. 30760
December 2022
JEL No. G40,R3

ABSTRACT

In Australian real estate markets, about a third of properties are sold at auction. We show that properties that fail auctions sell later for a 2.6% discount. This effect increases for properties failing multiple auctions and when no bids are made. Consistent with a causal channel, the effect holds when auction failure is instrumented by the tendency of owners to anchor on nearby better properties (and thus set reserve prices too high). Prices cluster just below salient round numbers, and the discount fades over time, inconsistent with our effects reflecting unobserved property characteristics. We test for several mechanisms and conclude that most of the pricing discounts reflect stigma, which reduces potential buyers' willingness to pay.

Kristle Cortés
UNSW Business School
School of Banking and Finance
Office 348, Level 3, Central Wing
Gate 2, High Street
University of New South Wales
Kensington 2052, Sydney New South Wales
Australia
kristle.cortes@unsw.edu.au

Mandeep Singh
Imperial College London
15 Prince's Gardens
London SW7 1NA
United Kingdom
m.singh@imperial.ac.uk

David H. Solomon
Boston College
140 Commonwealth Ave
Fulton Hall Room 330
Chestnut Hill, MA 02467
david.solomon@bc.edu

Philip Strahan
Carroll School of Management
324B Fulton Hall
Boston College
Chestnut Hill, MA 02467
and NBER
philip.strahan@bc.edu

1 Introduction

Most people have a deep-seated fear of public embarrassment. It is difficult to explain in purely economic terms the widespread horror felt at the idea of throwing a birthday party that nobody comes to or freezing up during a public speech. Social failure can affect the judgment of others through a process of stigma. Negative opinions can become self-reinforcing if people worry that association with something unpopular will cause the negative assessment to spill over to them. Social failure can also be demoralizing for those at the center of it, leading to despondency and a reduction in effort.

We show that the public failure of the sale process leads to lower subsequent property prices. Our setting is the Australian real estate market, where roughly one-third of properties are sold in a discrete-in-time auction. Importantly, about 17.0% of auctions carry a discrete category of failure when the highest bid fails to reach the seller's (undisclosed) reserve price, the minimum price they deem acceptable. This category of discrete and highly visible failure contrasts with negotiated property sales, known as private treaty sales in Australia, when sellers post an asking price and wait an unspecified amount of time for bids. The "failure" labeling sounds embarrassing to the seller and provides a sharp classification likely to be recalled by potential subsequent buyers. In a private treaty setting, if a property lingers on the market, this embarrassment is less dramatic, there is no clear and agreed cutoff for what counts as "too long", and the action of removing a property from the market is mostly invisible.[1]

We argue that the effects of auction failure have a significant psychological component that is not explained by fundamentals. This "failure cost" is a form of sentiment (Baker & Wurgler, 2006), but an explicitly social one, where traders react to other traders (Hirshleifer, 2020). On one side, a demoralized seller may bargain less hard and relent during subsequent negotiations. On the other, the negative judgment of buyers may create stigma, a vague perception that there must be "something wrong" with the

[1] Discussion with real estate agents suggests that private treaty sales which linger on the market also bring stigma to a property, but this gradual effect is difficult, or perhaps impossible, to isolate empirically.

property (even if one cannot say what it is). Both pathways predict that a failed auction will lower the subsequent sale price, regardless of the specific reason for the failure. Importantly, while auction failures sound like bad news, it is unclear what inference should be formed on underlying valuations because reserve prices are not publicly disclosed. While auction failure may occur because buyers place low values on the property, which could be informative in a common value setting (Milgrom & Weber, 1982), it can equally occur because the seller places *too high* a value on the property, which ought to be at least weakly positive information. In other words, the overall updating between buyer and seller should not obviously lead to a different final price compared to an otherwise identical house sold by private treaty.

We first show that properties listed to sell at auction, relative to those listed to sell via private treaty, receive on average higher prices, consistent with Frino et al. (2010). Importantly, and new to the literature, the higher expected prices from auctions come with greater risk. The average benefit of an auction combines a 1.2% increase in price for successful auctions (relative to properties sold under a private treaty) with a 2.6% *reduction* in the price for those that fail auctions (also relative to the private treaty). Since the overall success probability equals 83.0%, auction sales do indeed bring sellers higher expected prices (83.0%$\times$1.2% – 17.0%$\times$2.6% = 0.6%), but expose them to the stigma (downside risk) of failure. The benefit to auction sellers perhaps reflects buyers bidding too aggressively (such as under the winner's curse), leading to higher prices conditional on auction success. These baseline results are robust to a large number of fixed effects that capture time and location (neighborhood), as well as time- and location-varying controls for amenities such as size, number of bedrooms, number of bathrooms, et cetera.

The main alternative to psychology is unobservable property trait(s) that result in a lower value and a higher chance of auction failure. On observable traits, failed auctions have somewhat more amenities (e.g., number of bedrooms) than successful auctions, which does not suggest worse quality properties. But even if the properties were worse quality on some unobserved dimension, auction failure, and lower eventual prices are not mechanically linked simply by properties being worse than our fixed effects imply. A lower-quality property should not be more likely to fail an auction if both the buyer and the seller *agree it is lower quality*. Auction failure instead occurs because of a *difference* in valuation between the seller and potential buyers. The chief endogeneity concerns are unobserved factors that lead to a greater disagreement *and* lower valuations on average.

To establish a direct channel from failed auctions to low subsequent pricing, we explore the idea that sellers may form biased judgments from comparable property prices when setting their reserve prices. Owners of slightly worse properties in a neighborhood may optimistically anchor on the sale prices nearby, based on a general sense of what "properties in my neighborhood" have recently fetched. If anchoring on slightly better (or more expensive) properties causes the sellers to have reserve prices that are too high, this will cause them to fail auctions at a higher rate. We measure this effect using properties with either a low (below 10^{th} percentile) predicted hedonic price that month or a low score on the number of amenities (e.g., number of rooms).

Importantly, both metrics depend on other properties sold in the same neighborhood in the prior 12 months. Hence, two otherwise identical properties can have different values for the instruments, depending on properties sold nearby in the recent past. Our regressions hold each property's amenity bundle constant and exploit variation in a property's relative amenity bundle compared to its neighbor. Thus, we can rule out the possibility that the results reflect unobserved heterogeneity of the property under auction. Both instruments predict a higher chance of auction failure. Properties with low predicted prices are 1.4 percentage points more likely to fail auctions (an 8.2% increase). Properties with low amenity value are almost 2.2 percentage points more likely to fail auctions (a 12.9% increase). Since both instruments depend on sales of other properties, they reflect quasi-random variation; neither instrument should be correlated with unobserved heterogeneity in property quality (the source of possible bias in the OLS framework), once the average effects of the amenity levels are controlled for.

We find that properties with either *low predicted price* or *low amenity value* sell for lower prices if they were initially listed for an auction than sold under a private treaty. Since a seller's reserve price matters in either sale method, we allow both instruments to affect prices generally under both mechanisms, and we focus on the incremental (i.e., interactive) effect for properties initially listed at auction. Our identification strategy relies on two assumptions: 1) absent any psychological effects from failing an auction, the instruments would have the same effect on the transaction prices for properties, regardless of whether sold under auction or private treaty; and 2) our instruments are uncorrelated with unobserved heterogeneity in property quality.

We then explore heterogeneity across different forms of auction failures. Properties with multiple failed auctions receive lower eventual prices than properties with just one failed auction. We also find evidence that auctions that fail without receiving bids have lower prices than other auction failures. Auction failure also has worse effects in "hot" property markets, when failure is less common. In other words, repeated and embarrassing failures experience even lower subsequent prices.

Our results so far are consistent with both a seller discouragement channel and a buyer stigma channel. Sellers may also need to sell quickly after auction failure for liquidity reasons, or may list the property at auction to try to sell it faster (though the risk of failure could be reduced by listing a low reserve price). To test these possibilities, we examine the length of time between auction failure and eventual sale. Stigma, being a social perception without a concrete basis, will fade over time as the pool of potential buyers turns over and is replaced by others with less memory of the event. By contrast, if our results come from unobserved property characteristics that are both bad and disagreement-inducing (e.g. a shared driveway, proximity to the town dump), the effect should not obviously diminish over time. Second, seller discouragement, unlike stigma, is predicted to worsen as more time passes since the auction failure. Third, liquidity constraints ought to matter most immediately following failure, when it becomes clear that the initially sought high auction price has not materialized.

We find the strongest price reductions for properties that eventually sell within a month of the auction failure, with the effect being reduced to zero for properties that sell more than six months after failing. This finding is strongly consistent with the idea of gradually fading effects of stigma, but hard to reconcile with either seller discouragement or fixed omitted characteristics of properties driving our results. But importantly, at extremely short horizons - the weekend of the auction failure itself - the effect reverses. The auction discount is about three percentage points smaller if a property sells on the weekend of the failed auction (almost all auctions happen on Saturday), compared to the next few weeks. These often represent an ex-post negotiation between the highest bidder and the seller. Since these buyers themselves most likely bid at the auction, and thus publicly committed to a previous willingness to pay, they are less susceptible to stigma reducing their bids from the previous amounts. This small discount suggests a small role for liquidity effects unless one believes that the tendency to cave (in a complicated liquidity story) only begins several days after auction failure.

To provide further evidence of a psychology channel, we study the tendency of properties to sell just below salient round-number thresholds like multiples of $50,000. Properties which fail an auction are 6.6 percentage points more likely to sell just below (within $1000) round numbers than just above, relative to private treaty sales. These findings are not just a result of lower sale prices in general, as we show no effect around non-salient thresholds. Since these thresholds are likely psychologically important to both buyer and seller, we interpret this result as auction failure leading to sellers losing the subsequent bargaining game over small but psychologically salient price differences. This is consistent with a seller discouragement channel, where auction failure makes sellers bargain less hard in subsequent negotiations. It could also occur if stigma causes buyers to bargain harder over small, salient differences.

Our concept of stigma is related to information cascades (Bikhchandani et al., 1992), whereby individuals deciding sequentially may rationally choose to ignore their signals in favor of the existing consensus. Reacting to auction failure is less obviously a rational inference about others' signals, as the main information is about valuation *disagreement* rather than levels. The gradual fading of stigma and moderate price effects also appear different than the fragile and rapid shifts between equilibria in Bikhchandani et al.

(1992). Our idea of stigma also differs from the use of the term in Besbris et al. (2015) for neighbourhood effects like local crime or poverty on real estate valuations. We would define (and control for) these characteristics as part of property fundamentals.

Our results relate to papers on sentiment in housing markets. Much of this has focused on the role of market-level irrational beliefs in the 2008 financial crisis (Shiller, 2007; Chinco & Mayer, 2016; Kaplan et al., 2020; Chodorow-Reich et al., 2021). At the property level, Bhattacharya et al. (2020) document price effects for "haunted" properties due to murders, suicides, and other unnatural deaths, both on the immediate property and surrounding ones. We build on this work by showing how traders react to each other, rather than just irrationally responding to the same underlying cues or events.

We also contribute to the literature on auction design. Seminal work such as Vickrey (1961) and Milgrom & Weber (1982) show that various auction mechanisms (English, Dutch, first and second-price sealed) are predicted to produce equivalent expected revenue for the seller in independent private value settings. Empirically, auction types can matter for expected revenue (Coppinger et al., 1980; Miller, 2014), although the reasons for this are not well understood. We show that investors can over-extrapolate signals about other buyers' beliefs during the auction process, which can affect prices and expected revenue calculations. Our results also show the importance of setting the right listing price, as overly optimistic sellers fail auctions more frequently and obtain worse prices when the home finally sells. We also shed light on why some people do not list their properties for auction - auctions have a higher average sale price, but also higher volatility from lower prices after failure. The risk of stigma also suggests that psychological costs and social failure may motivate some people to avoid auctions.

Closest to our paper is Beggs & Graddy (1997), who argue that paintings that fail at auction sell for lower prices. Relative to their work, we are able to identify the effects of auction failure not only relative to successful auctions, but also to private treaties (i.e. if the asset had not been listed for auction at all).[2] Finally, we also isolate the effect of

[2]In a different context, Gargano & Giacoletti (2022) show that the average log price differential between auction and private treaty sales declines after introducing policies designed to deter selling agents from advertising 'too low' listing price. Although this paper does not study failed auctions,

auction failure from plausibly exogenous reasons unrelated to asset fundamentals.

2 Australian Real Estate Auctions

Real estate auctions have been common in Australia for several hundred years. Figure 1 reports monthly averages for the number of auctions (Figure 1a) and their total monetary value (Figure 1b), compared to similar data for private treaty sales, over our sample (2007:M1 to 2019:M12).

[Insert Figure 1 Here]

Figure 2 reports the share of sales at auction in the top panel (Figure 2a), and their failure rate in the bottom panel (Figure 2b). Early on, the number and value of auctions and private treaties are similar ($\approx$ 50.0% share each), whereas the auction share varies between 30.0% and 40.0% of the sales starting in 2011. The auction failure rate varies over time and ranges between 10.0% and 40.0%. We report the figures without the month of January when real estate markets become very thin as many take vacation. In our regression below, we do include all months, but we have estimated them without the small number of January transactions and find similar results.

[Insert Figure 2 Here]

Auction rules vary somewhat across the states in Australia, but they follow a similar pattern. Bidding is done via open outcry under the direction of a professional auctioneer. Auctions routinely occur at the property location itself, starting at a specific date and time advertised publicly (on the website providing listing services) well before the auction. Bidders must register with the state before the auction, and false or 'dummy' bids are illegal. Bids are made publicly, and if the highest bid exceeds the seller's confidential reserve price, the property is sold "under the hammer". Bids are firm

it suggests that setting a reservation price which is 'too high' - which is the idea behind both of our instruments - is bad for sellers.

commitments, and a winning bidder is required to post a 10.0% deposit immediately. Sometimes, a seller may negotiate a sale before the scheduled auction, which we would classify as a successful outcome. If the highest bid is less than the reserve price (the auction is "passed in", or "fails"), the seller has the option to negotiate subsequently with the highest bidder. As we do not have the timestamps of exact agreements, we classify the sale as being a failed auction as long as there was a failed auction reported in the data and the sale occurred at some point later. If the seller successfully negotiates a deal with the highest bidder, we classify this as an instance of auction failure.

Neither the number of bidders nor their actual bids are observable in our data. Also, the seller's reserve price is not observable to us (or to bidders). In 83.0% of cases, a property sells successfully at its first auction. Of these, 61.0% are sold under the hammer, meaning that the highest bid exceeded the seller's reserve price at the auction. In the other 39.0%, the property sells by negotiation before the scheduled auction. We consider both cases as successful auctions. In 17.0% of the cases, a property fails its auction. Most properties that fail during their first attempt at auction subsequently sell under a private treaty, and these subsequent sales typically occur within six months of the initial failure. In a small number of cases (about 3.0%), properties are sold in a subsequent auction.

3 Data, Methods, and Results

3.1 Data Description

In this study, we use data for the states of New South Wales and Victoria from the Domain Group and CoreLogic.[3] Our sample of properties initially listed for auction are from domain.com.au, which is one of Australia's major websites providing real-estate-related services, such as selling, renting, investing, financing, and insurance and

[3] Melbourne (capital of Victoria) and Sydney (capital of New South Wales) are the major auction markets in Australia. According to CoreLogic, in the quarter ending March 2022, these two cities accounted for approximately 78.3 percent of total real-estate-related auctions in Australia, while being only around 58% of the population. It follows that despite focusing on two of the seven Australian states, our sample captures a significant fraction of real-estate auction activity in Australia. It also implies thin auction activity in the rest of the Australian states.

utilities, and is one of the brands owned by the Domain Group.[4] To capture the whole real estate market, we combine the Domain dataset with the CoreLogic dataset that contains all properties sold initially under a private treaty. Corelogic is provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA) and is Australia's largest independent property and analytics data platform. Hence, by combining these data, we capture all (eventually) successful real estate transactions in both Australian states.

We subdivide the data in two ways. First, we split transactions into those listed under auction and those listed as a private treaty (i.e., Domain sample versus CoreLogic sample). Second, we split transactions initially listed at auction into four mutually exclusive categories: (1) initial auctions that succeed and sell under the hammer; (2) initial auctions that succeed but sell via negotiation before the auction; (3) initial auctions that fail and sell subsequently in a successful auction; (4) initial auctions that fail and sell subsequently in a private treaty. Panel A of Table 1 describes the first cut of the data based on auction versus private treaty; Panel B splits the auction sample into successful (1 and 2 above) versus failed auctions (3 and 4 above). In the regressions below, we introduce indicator variables for each of the four possible outcomes for the sample of auction transactions.

[Insert Table 1 Here]

Overall, about one-third of all sales in New South Wales and Victoria starts with an attempted auction. Amenities are somewhat lower in the auction sample relative to the private treaty sample (Panel A), although prices are substantially higher in the auction sample. For example, properties initially listed for an auction have an average of 3.0 bedrooms and 1.6 bathrooms; the mean log price is 13.6. Properties initially listed for a private treaty have an average of 3.2 bedrooms and 1.7 bathrooms; the mean log price is 13.4. These differences are statistically significant due to the massive sample

[4] According to Nielsen Digital Content Ratings, between January and March 2021, the Domain app was launched 19.2 million times. The website is used by approximately 8.4 million people over the same period, about a third of Australia's population.

size. Figure 3 reports a simple comparison of how the average (log) price differential between homes that attempt an auction (Domain) compared with those that do not (CoreLogic) varies with the auction failure rate.[5] Each point on the graph represents the mean from each year-month in our sample. Consistent with auction failure reducing prices, we see a declining relationship (slope = -0.15; R^2 = 3.7%), which is significant at the 5% level. That is to say, in months with higher auction failure rates, auctions outperform private treaty sales by a smaller amount. This plot of the raw data has the virtue of simplicity, but it does not account for substantial differences in home attributes across the two samples.

[Insert Figure 3 Here]

Comparing characteristics by auction outcome, amenities are better for failed auctions than successful ones, while price patterns are the reverse (Panel B). Specifically, on average, properties that fail at auction have 3.2 bedrooms, compared to 3.0 bedrooms for successful auctioned properties. However, despite the higher amenities, properties that fail at auction sell for $78,000 less at the mean (log price of 0.1 less).

3.2 Method and Results

We start with three core models. First, we report OLS regressions linking (log) transaction prices to the initial sales mechanism (auction versus private treaty), focusing on the effects of the auction outcome on the final sales prices. Second, we focus on the set of transactions that began at auction (i.e., the Domain sample) and model a failure indicator as the outcome. This model represents a 'first-stage', with the aim of finding variables that increase the probability of failure but are not correlated with unobservable property quality. Third, we link these proxies for an auction failure to prices, using the sample of all transactions, to identify the effects of failing an auction on transaction prices.

[5] We drop January months from the figure, as this month has very few transactions, which do not represent typical behavior in this market, as noted earlier.

We then explore how the impact of auction failure varies across different property types and market conditions. In our last set of tests, we use bunching around salient thresholds to provide further evidence that psychological factors have their greatest impact following failed auctions.

3.2.1 Linking Sales Prices to Auction Outcomes

We report baseline OLS models of the log transaction price as follows:

$$\ln P_i = \beta_1 \text{Listed For Auction}_i + \beta_2 \text{Failed Auction}_i + \text{Fixed Effects} + \epsilon_i \tag{1}$$

In equation (1) the variable *Listed For Auction*$_i$ equals one for properties initially listed under auction; *Failed Auction*$_i$ equals one for properties that fail at least one auction in their auction campaign. In equation (1), the omitted category is properties initially listed under private treaty. As such, β_1 measures the difference in prices between successful auctions relative to private treaty sales; β_2 measures the difference in prices between successful auctions versus failed auctions; and the sum of these two coefficients represents the difference between failed auctions versus private treaty sales.

To remove variation in property fundamentals, we estimate the models with time- and location-specific effects, as well as effects capturing property amenities: the number of bedrooms, the number of bathrooms, property type (apartment/units and houses), and a set of three fixed effects from lot size bins based on terciles. We alter our absorption of these effects, starting by entering the fixed effects separately, then interacting all of the amenity effects with location, and then interacting all of these with both location and year. Doing so allows us to assess the stability of our coefficient as we vary the degree of variance removed by observables. Standard errors are clustered by postcode and time (year$\times$month).

We also estimate models with four indicator variables representing each of the possible auction outcomes enumerated above, as follows:

$$
\begin{aligned}
\ln P_i = & \beta_1 \text{Successful Auction, Negotiated}_i + \beta_2 \text{Successful Auction, Under Hammer}_i + \\
& \beta_3 \text{Failed Auction, Private Treaty}_i + \beta_4 \text{Failed Auction, Subsequent Auction}_i + \\
& \text{Fixed Effects} + \epsilon_i
\end{aligned} \tag{2}
$$

Again, the omitted category is properties initially listed under a private treaty, and each includes the same (varying) sets of fixed effects. So, these coefficients compare the possible auction outcomes relative to private treaty sales.

The first three columns of Table 2 report results for estimating equation (1), where our coefficient of interest is β_2, the pricing discount from a failed auction. We then introduce indicators for the four possible auction outcomes in the next three columns (equation (2)). From the first row, we see that properties which list for auction, overall, sell for prices about 1.2% higher than those listed as a private treaty (column (3)). This coefficient estimate has very large statistical and economic significance. The model suggests that failed auctions sell for 3.8% lower prices than successful auctions overall (coefficients from the third column, second row), and about 2.6% (=1.22-3.81) lower prices than properties listed under private treaty.[6]

[Insert Table 2 Here]

The incremental effect of failing an auction varies little as we expand the granularity of the fixed effects (moving from column (1) to (3)). According to Oster (2019), the scope for omitted variables bias on the coefficient of interest (β_2 in equation (1) above) is proportional to the difference in the estimated coefficient (between a saturated and unsaturated model), multiplied by the ratio of unexplained variance to the change in explained variance (again, between the two models). Intuitively, if increasing the

[6]We have also estimated these models using just the Domain sample, which allows us to control for broker fixed effects for a subset of about 40 percent of these transactions. This sample delivers a somewhat larger effect of auction failure of around -5.0%. This helps rule out the possibility that sellers experience both a higher rate of auction failure and a lower subsequent price due to mismanagement of the transaction by a 'bad broker'.

number of explanatory variables substantially has a small effect on the coefficient estimate, then the scope for an omitted variables bias is small. Oster (2019) argues that a proportionality factor, denoted by δ, of 1 is a conservative assumption, as this factor depends on the importance of the included variables to the excluded variables in explaining auction failure. Using the estimates from columns (1) and (3) of Table 2, the scope for omitted variables bias thus equals the following expression:

$$\begin{aligned} &(\beta_2^{\text{Saturated}} - \beta_2^{\text{Unsaturated}}) \times \frac{1 - R^2_{\text{Saturated}}}{R^2_{\text{Unsaturated}} - R^2_{\text{Saturated}}} \times \delta = \\ &(-0.0381 - (-0.0377)) \times \frac{1 - 0.9142}{0.8345 - 0.9142} \times 1 = 0.0004 \end{aligned} \tag{3}$$

The estimate in equation 3 suggests a very limited role for unobservable variables to play in explaining our baseline result.

The last three columns of Table 2 disaggregate the auction outcomes into two kinds of success and two kinds of failure. These results suggest that both types of successful outcomes -– sold under negotiation before the auction date or sold under the hammer – fetch higher prices of roughly similar magnitude (0.9% for pre-negotiated sales and 1.4% for auctions sold under the hammer) compared to private treaty. And, when auctions fail, the subsequent sales methods -– auction or private treaty -– also fetch lower prices of roughly similar magnitude (2.6% and 2.4%). Given this similarity, we do not focus on these sub-categories in the results that follow.

3.2.2 Understanding Auction Failures

Auction failures occur when the seller's reserve price exceeds the maximum amount bid. So, auctions fail when the seller mis-values their property and sets an unrealistic reserve price. Alternatively, auctions may fail because buyers find something wrong with the property, which could undermine our preferred interpretation. In other words, subsequent valuations may be low because potential buyers learn about the underlying value of a property from bidders. For this endogeneity problem to be significant, two conditions would have to be met: (1) potential buyers would have to learn about valuation from the actions of other bidders, and (2) sellers would also have to learn about the value of the property from bidders (otherwise they would have adjusted their reserve prices downward to facilitate the original auction). We view both of these conditions as unlikely in our setting; sellers inherently know more than buyers (they have been living in the property), and all potential buyers have symmetric access to the common information (unlike many other settings).

Nevertheless, we allay this concern by building an auction failure model, which captures cases in which the seller is likely to set an unrealistically high reserve price for reasons *having nothing to do with the property itself*. The key idea is that of anchoring (Kahneman, 1992). When property owners are forming estimates of what they think their property is worth, if they observe that other nearby properties sell for high prices, they are likely to somewhat anchor on such recent amounts and thus overvalue their own property.[7] While it is possible for buyers to be doing the same, there are reasons to predict that this should affect sellers more and thus increase the probability of failure. Sellers are necessarily more concerned with the neighborhood their property is located in and so are more likely to be anchoring on specifically nearby properties relative to buyers, who potentially are considering a wider range of potential locations. If each party also partly engages in motivated reasoning (Kunda, 1990), then sellers are likely to interpret such high prices of nearby properties in an optimistic light (whereas for buyers, their motivation goes in the opposite direction). For this reason, we expect properties that are likely to be below recent sales to be more likely to have excessively high seller valuations relative to buyers and thus be more likely to fail at an auction.

We estimate a first-stage model linking auction failure to instruments for the seller's reserve price, specified as follows:

$$\text{Failed Auction}_i|\text{For Auction Listing}_i = \gamma_1 \text{Low Predicted Price}_i + \text{Fixed Effects} + v_i \tag{4a}$$

$$\text{Failed Auction}_i|\text{For Auction Listing}_i = \gamma_1 \text{Low Amenity Value}_i + \text{Fixed Effects} + v_i \tag{4b}$$

In equation (4a), our instrument, *Low Predicted Price*, is an indicator set to one for

[7] Andersen et al. (2022) provide a structural model to quantify reference dependence and loss aversion in the Danish property market and use a seller's previous purchase price as the reference point.

properties whose predicted prices lie in the lower 10$^{\text{th}}$ percentile of the distribution of other properties sold in the same neighborhood during the past year. The model used to construct predicted prices comes from a hedonic pricing regression model, described in detail in the appendix. With this model, we effectively control for housing amenities and generate variation in the instrument based on different local price trends over the preceding 12 months.

In equation (4b), our instrument, *Low Amenity Value*, equals an indicator set to one for properties with three key amenities lying on average one standard deviation or more below the mean, again based on the distribution of properties sold in the same neighborhood during the prior 12 months. The amenities we use are the number of bedrooms, the number of bathrooms, and the area. *Low Amenity Value*, to speak loosely, equals one for "the worst house on the block", which we argue is likely to be over-priced by the seller if they have a tendency to form value estimates in part by anchoring on nearby sale prices.[8] We estimate these models on the Domain sample using a linear probability model (due to the high dimensionality of the fixed effects, non-linear models like logit and probit are infeasible). We cluster by postcode and time (year$\times$month), as before, to build standard errors.

Our instruments are built to capture the variation in a seller's reserve price that reflects their anchoring on those recent sales, which they are most likely to remember. Hence, we compare a given property's price or amenity bundle to sales made within the same neighborhood during the prior 12 months. If recent sales have been declining in price, or if recently sold properties have had high amenity bundles, then we argue that sellers are likely to over-reach in setting their reserve price. The instrument *Low Predicted Price* focuses on pricing trends, whereas the variable *Low Amenity Value* ignores price information and focuses just on the amenity bundle. Since the two are looking at completely different types of variation, both can work independently to help capture a

[8]We recognize that buyer's agents with experience will understand the impact of amenities on price and may advise their clients to avoid over-pricing. However, agents compete for business with each other, which puts pressure on them to cater to the listing preferences of their clients, who ultimately bear the cost of mispricing the property.

seller's reserve price. Figure 4 plots the monthly average of the two instruments. As expected, *Low Predicted Price* displays substantial time variation (since it is driven by pricing trends); in contrast, *Low Amenity Value* displays almost no time variation (and no trend whatsoever).

[Insert Figure 4 Here]

We argue that these instruments are plausibly uncorrelated with unobservable property quality because their variation depends on transactions of other properties. For example, consider the instrument *Low Amenity Value*. For the sake of clarity, assume that we look at just a single amenity (the number of bedrooms). Now, imagine two similar properties: three-bedrooms, two-baths, each located in the same suburb-postcode. One property sells in January 2007 and the other in November 2007 (so they are in the same suburb-postcode-year). For the first sale, we look back to transactions in the same suburb-postcode from January 2006 to December 2006 and observe 10 transactions of 4-bedroom properties and 2 transactions of 3-bedroom properties. For this sale, we would set *Low Amenity Value* equal to 1 (because this property is more than one standard deviation below the mean number of bedrooms in the comparison group). For the second sale, we look back from November 2006 to October 2007 in the same suburb-postcode and observe 10 transactions of 3-bedroom properties and 2 transactions of 4-bedroom properties. For this sale, *Low Amenity Value* equals 0 (since most of the transactions in the look-back period are of the same, 3-bedroom type). When examining price effects, however, we control for the average effects of the amenity variables (e.g. number of bedrooms) on property prices under both sale methods, leaving the variation coming from the other nearby properties.

The key for identification: the variation of our instrument (after absorbing the fixed effects) depends on the specific set of other transactions used to construct the comparison group; a property's amenities are themselves captured by the fixed effects in the regression (see equations (4a) and (4b) above). The instrument works to move auction outcomes by influencing a seller's reserve price, based on the argument that sellers will tend to anchor on recent sales nearby. In the example above, the seller of the first home would be more likely to set an overly optimistic reserve price because recent sales came from better (and hence more expensive) homes than theirs. This will raise the likelihood of an auction failure.

[Insert Table 3 Here]

Table 3 reports the baseline estimation for equations (4a) and (4b), as well as a model including each instrument together. As in our earlier regressions, we report results with a relatively parsimonious set of fixed effects and widen the explained space of variation by interacting the fixed effects, both with each other as well as with the location and year effects. Both variables are strongly predictive of auction failure. For example, properties surrounded by those that have recently sold for high prices (*Low Predicted Price* = 1) are 1.4% to 1.6% more likely to fail at auction (columns (1) and (2)). These are properties in neighborhoods that have experienced declining prices over the past 12 months (controlling for amenities). Similarly, properties with a low amenity bundle relative to recent nearby sales (*Low Amenity Value* = 1) also fail about 2.4% more often (column (4)). Both effects remain similar when we include both measures together (columns (5) and (6)), which makes sense because they capture different kinds of variation, as explained above.

3.2.3 Linking Sales Prices and Reserve Prices: Auctions versus Private Treaty

If failed auctions lower subsequent valuations (as opposed to capturing property fundamentals), then sellers with high initial reserve prices ought to receive lower prices if they attempt an auction. Thus, we can test for the effects of auction failure without conditioning on actual auction outcome using the two instruments, *Low Predicted Price* and *Low Amenity Value*, because we have shown that each helps predict auction failure. Since both instruments vary due to the sale of other nearby properties (once we capture heterogeneity with the fixed effects), this avoids the potential bias of using actual auction failure to predict the ultimate sales price. This reduced-form strategy links property prices to the same set of amenities and fixed effects as in the OLS framework. However, we replace the auction outcome (failure) indicator with the instrument and its interaction with the auction indicator, as follows:

$$\ln P_i = \delta_1 \text{Auction}_i + \delta_2 \text{Auction}_i \times \text{Low Predicted Price}_i + \delta_3 \text{Low Predicted Price}_i + \text{Fixed Effects} + v_i \tag{5a}$$

$$\ln P_i = \delta_1 \text{Auction}_i + \delta_2 \text{Auction}_i \times \text{Low Amenity Value}_i + \delta_3 \text{Low Amenity Value}_i + \text{Fixed Effects} + v_i \tag{5b}$$

As in equation (4a) and (4b) above, we estimate these models with parsimonious and granular fixed effects, and we estimate them separately and together. The effect of an over-optimistic reserve price (captured by *Low Predicted Price* and *Low Amenity Value*) can differ for private treaty transactions relative to those that start at an auction because mis-valuation by sellers may reduce prices generally. We argue that the cost of mis-valuation is greater for properties that start at auctions because these properties, as we have shown, fail more frequently and thus face the additional cost of both buyer stigma (which lowers future buyers' willingness to pay) and seller discouragement (which lowers the seller's willingness to hold out for high prices).

[Insert Table 4 Here]

Table 4 reports these results. Compared to the OLS approach, varying the set of fixed effects has a substantial impact on the effects of the instruments. This makes sense because our identification strategy relies on capturing variation in the instrument from other sold properties; when we do not adequately control for local amenities and price trends, we lose this interpretation. As expected, both instruments for the seller's reserve price correlate strongly with low sales prices for both private treaty and auction cases, with substantially larger costs to the seller for the auction sample. The incremental effect for *Low Predicted Price* is -0.8% and the incremental effect of *Low Amenity Value* is -2.7% (column (6)).

3.2.4 Heterogeneous Effects of Auction Failure

To establish that psychological factors explain why auction failures lead to lower prices, we explore heterogeneity across property types and market conditions. To do so, we first interact the effects of the auction indicators with an indicator equal to one for "hot" markets (i.e., when the recent trends in prices have been strong); in the second set, we distinguish apartments/units from other property types.[9] Auction failure is less common in both cases. Psychological effects of failure ought to matter most when auctions are most likely to succeed since in these cases a failure is especially salient. Hence, the failure discount would tend to be highest both in hot markets and for apartments, both of which fail at rates below the unconditional average.

Overall, the results in Table 5 indicate a substantial pricing discount across all market conditions and property types. Yet the negative and significant interactions suggest that the cost of failing an auction is higher for sellers of apartments/units and for those that fail during hot markets. This latter result supports our interpretation that auction failures are costly for psychological reasons because failing an auction when real estate markets are hot would be especially notable and embarrassing to the seller, thus making the "stench of failure" worse. Apartment units, due to their relative homogeneity, tend to be well understood by both buyers and sellers and thus are less likely than other properties to fail at auction.[10] This result is consistent with the idea that when failure is less common, it is likely to be more salient, and thus have larger effects.

[Insert Table 5 Here]

As shown in Panel B of Table 1, the average property, which fails an auction is

[9] We define '*hot market*' as a dichotomous variable that equals 1 if the average time between the listing date and final sale date for a postcode-year-quarter triplet is below the cross-sectional median value.

[10] Among *for auction* listings, on average, apartments/units fail auctions around 15.6% of the time, versus 17.7% of the time for houses.

ultimately sold 1.7 months later (SD = 2.0 months). In our data, 2.0% of properties that have failed at auction fail at least one additional time before ultimately selling (usually under a private treaty). In addition, about 4.0% of the failed auctions receive no bids whatsoever – as opposed to most failed auctions, which fail because the highest bid falls below the seller's reserve price. We expect these no bids to experience even lower prices.

To help separate the effects of the buy-side stigma of an auction failure from sell-side discouragement, we focus on the amount of time that passed since the bad news (auction failure). Stigma ought to fade with time, as a new set of borrowers enters the market. In contrast, discouragement ought to increase with time, as the seller's frustration mounts. Hence, stigma predicts a declining discount, while discouragement predicts the opposite.

To test these ideas, we augment equation (1). We capture these effects first individually and then all of them together in one model. The most complete of these models follows:

$$\begin{aligned}\ln P_i =&\beta_1 \text{Auction}_i + \beta_2 \text{Failed Auction}_i + \beta_3 \text{Multiple Failed Auction}_i + \beta_4 \text{No Bid}_i + \\ &\sum \beta^k \mathbb{I}^k(\text{Time Since Most Recent Failure}) + \text{Fixed Effects} + \epsilon_i\end{aligned} \tag{6}$$

In the parsimonious approach, we interact the number of months since failure with the failed auction indicator. In the full model, we instead introduce $\mathbb{I}^k$(*Time Since Most Recent Failure*), which are seven non-overlapping indicator variables that turn to one for failed auctions based on the time (number of months) between the last failure and the sale of a property. According to our arguments, properties with multiple failed auctions sell for less than those with a single failure, and stigma fades with time (so $\beta^{\text{1-month}} < \beta^{\text{2-month}} < \cdots$).

Table 6 reports estimates of several variants on equation (6). These models expand the possible outcomes from auctions by testing the pricing effects of multiple auction failures (2.0% of the time); failures that receive no bids at all (4.0% of the time); and the amount of time that elapses from an auction failure to ultimate sale (1.7 months on average). From the first two columns of Table 6, auctions that fail more than once receive even lower prices, by an additional 1.1% to 1.6% percent over that of single failed auction cases. As in the earlier models, the magnitude of this additional downside is not very sensitive to how much variation we remove with the fixed effects. Columns (3) and (4) show that failed auctions, which receive no bid receive lower prices by a bit less than 1.0%, although this effect is only marginally statistically significant.

[Insert Table 6 Here]

[Insert Figure 5 Here]

In the last four columns of Table 6, we introduce *time since most recent failure*, as well as indicator variables based on this time (to allow the effect to enter non-linearly). In Figure 5, we present a distributional plot of time between the most recent failure and subsequent sales (including only to properties that fail their auctions). Most of the properties sell within the first two months following a failed auction, and the distribution thins out after that. Approximately 3.0% of properties that fail an auction end up selling on the same day and about 2.5% on the next day.[11] Since most auctions occur on Saturdays, we presume that most of the transactions that close over that weekend occur in negotiation between the seller and the high bidder.

The results in columns (7) and (8) of Table 6 show that the stigma cost of failure decays with time. In these models, the omitted category represents properties that sell on the day of the auction failure. These specifications (as in equation (6)) suggest that stigma worsens after failure, then decays monotonically with the subsequent waiting time. We think this pattern is consistent with our interpretation that the price discounts represent stigma; and this pattern is inconsistent with unobserved heterogeneity in house quality, which would not be expected to depreciate monotonically.

[11] Properties sold on 'day zero' serve as the reference group in columns (7) and (8) of Table 6.

These results suggest a trade-off between waiting and selling immediately after a failure. If sold soon after the failure, the seller pays a high cost in monetary terms. In contrast, if they wait, allowing the effects of stigma to dissipate, the downside is implicit in the cost of carrying the property. Based on the coefficients from column (8), a (single) failed auction sold within one month of failure experiences a pricing discount of 3.4% (=1.21-3.31-1.33) compared to a private treaty sale; in contrast, waiting at least six months reduces this discount to a small (and marginally significant, with a p-value = 0.10) premium of 0.8% (=1.21-3.31+2.93) which is not statistically significant at the 5% level. So, the monetary downside can be reduced effectively to zero by waiting. These two costs are roughly equivalent. For example, assuming an interest rate of 4.0%, the monthly payment on a $500,000 property is about $2,400. So, the interest cost of holding a property for six months comes to about $15,000 or 3.0% of the value.[12]

[Insert Figure 6 Here]

While Table 6 suggests stigma fades with time, sell-side liquidity concerns may also affect the time patterns. For example, liquidity constrained sellers may take low offers to move a property quickly. To calibrate the size of this effect, we disaggregate the effects of time-to-sale further in Figure 6. We separately estimate the size of the failure discount on the weekend of auction failure (when the property is sold to one of the original bidders), and then in each subsequent week following the failure (when new buyers emerge). This decomposition purges stigma from the effects observed during the failure weekend since these buyers actually attended the auction. The results show that the failure discount is small on the auction weekend itself, compared to the following weeks, suggesting a small effect from liquidity constraints. For example, the failure discount rises from about 2% on the failure weekend to 5% during the subsequent week. After which, the discount fades monotonically (consistent with Table 6). These results help mitigate the concern that the decline in the failure discount represents a 'fire-sale'

[12]This simple comparison ignores other costs of holding a property, such as taxes and depreciation, as well as other possible benefits, such as the implicit rent or utility value to the owner (who may or may not continue to live in the property).

effect, as this effect ought to be greatest (and most precisely estimated) immediately following the failure.[13]

3.2.5 Bunching around salient thresholds

In our last set of results, we explore additional evidence linking auction failure to psychological mechanisms by studying the role of clustering around salient round numbers. A long literature in psychology and marketing has documented the existence of left digit effects, where consumers perceive prices just below important thresholds as being disproportionately lower, such as $1.99 seeming saliently lower than $2 (Thomas & Morwitz, 2005). In our data, home sales cluster around increments of $50,000 (see Figure 7a). Because both buyers and sellers are likely of similar sophistication in these markets, these parties will have opposing incentives to sell on each side of these salient round numbers. In this respect, prices disproportionately falling *just below* round number thresholds after auction failures is evidence of sellers losing a bargaining game over price differences that are more important psychologically than economically.

[Insert Figure 7 Here]

We consider this question in Figure 7b and Table 7. Here, we study only the set of houses that sell either just above or just below (but not equal to) multiples of $50,000. In columns (1) and (2), we consider only being $1,000 above or below, and in columns (3) through (10), we examine larger increments of $2,000 through $5,000. The dependent variable is thus a dummy variable equal to one if the house sold within the threshold amount below the $50,000 multiple, and zero if it sold within the threshold amount above the multiple (with all other observations being dropped). The independent variables of interest are the auction indicator and the auction failure indicator, with the private treaty as the comparison group. Figure 7b reports the effect most simply, plotting the raw data. As in the earlier regressions, we control for year-month, and property characteristics fixed effects in odd-numbered columns. The interactions of property

[13] We have also produced a version of Figure 6 which includes only auctions which occur on a Saturday, which comprises about 80% of the auctions. This figure looks very similar to the one reported below.

characteristics and year replace property characteristics fixed effects in even-numbered columns.

[Insert Table 7 Here]

The results show that sales after auction failure are much more likely than other sales to close at prices slightly below round numbers. For prices within $1,000, auction failure is associated with a 21.8% higher probability of being just below the threshold (with a t-statistic of 11.6) without interacted fixed effects and 6.1% higher probability with interacted fixed effects (with a t-statistic of 3.3, even with only 21,517 observations and many fixed effects), compared to successful auctions. Compared to private treaties, failed auctions fall below the salient thresholds 6.6% to 2.2% more frequently (summing the two coefficients). Increasing the bands around the prices lowers the magnitude a bit, but leaves the effect highly significant. Attenuation occurs as we include more outcomes, which are less obviously "just below" or "just above" round numbers.

Table 8 introduces interaction effects for the property type and market condition, using the sample from a $2,000 bandwidth. In hot markets (but not for apartments), we find a much larger degree of bunching below the thresholds after failed auctions, further supporting our thesis. Failing an auction in hot markets is unusual and, thus especially discouraging for sellers. As such, sellers are much more likely to lose out in subsequent bargaining with future buyers.

[Insert Table 8 Here]

One concern with this analysis is that the results may just reflect a general tendency for auction failure to lead to lower prices. The drop in coefficients as the bands are expanded does not immediately suggest this mechanism, but it is nonetheless important to rule it out. To do this, in Table 9, we perform 100 versions of the same regressions as columns (3) and (4) of Table 7, for numbers ranging from $1,000 to $100,000 (with an increment of $1,000). As a result, we are now testing whether prices falling just below salient round number thresholds is more likely than falling just below other non-salient thresholds. Because the number of observations varies in each regression, the significance of the coefficients is not directly comparable. Still, the magnitudes across each digit threshold reveal where auction failure leads to greater tendencies to reduce prices slightly.

[Insert Table 9 Here]

Given there are 100 regressions, the ordering of the salient thresholds acts as a kind of p-value – if the price reduction were uniform across thresholds, there would be no reason to expect the round cutoffs to show the largest effects. The only complication in interpreting results as p-values is that there are multiple round number thresholds whose ordering is not always obvious. Is it more salient to be above 10 than 25, for instance? Nonetheless, the general prevalence of round numbers as having the largest coefficients is a good, even if slightly informal, test of the importance of round numbers versus others.

In Table 9, we report the ten largest coefficients. All of them are round numbers – 10, 20, 30, 40, 50, 55, 70, 90, 95, 100. This finding presents strong evidence that auction failure leads to not only lower prices but also prices just below psychologically salient thresholds. This result is difficult to reconcile with auction failure simply representing the rational pricing of bad but disagreed-on traits in an omitted variable framework.

The results in Tables 7, 8 and 9 further support the claim that the psychology of failure makes auctions risky for sellers. The perceived embarrassment from failed auctions encourages buyers to push harder to be below a round threshold and leads dis-spirited sellers to accept this outcome. Thus, the evidence points towards auction failure having effects that are considerably psychological in nature, not just economic.

4 Discussion

While not the central focus of the paper, our results also help shed light on the question of why some people choose to sell at auction versus via private treaty. As a baseline result, on average, auctions lead to higher prices; based on column (3) of Table 2, expected prices at auction are 0.6% higher than a private treaty.

One view is that it represents a selection effect, whereby auctioned properties are better on some unobservable dimension. This is hard to rule out entirely, but on the dimensions of amenities that we can observe, private treaty sales actually score better. Even if this were the case, it would still leave open the puzzle of why different mechanisms exist in the first place. That is, if the difference in the sale price is entirely due to unobservable traits, and has nothing to do with the sale mechanism, then why does the market persist with such different structures?

The next alternative is that it represents a mistake by some sellers. That is, not everyone understands that they could get higher expected revenue at auction, so simply use the traditional sale method. This is difficult to rule out. The level of sophistication of housing market participants is likely to vary considerably. There is also evidence in other contexts of mistakes like the disposition effect (Genesove & Mayer, 2001), where owners whose house has dropped in value will list their house far above market prices in order to try not to realize a loss. On the other hand, sellers are also advised by real estate agents who likely have more skill. The fact that sellers shop around for agents likely limits the ability of agents to de-bias sellers inclined to make mistakes. Whether or not the trade-off between an auction and a private treaty is being optimally made, our results nonetheless suggest some important costs that make auctions not a straightforwardly dominant choice. Most importantly, we show that auctions also carry more risk. While higher prices are obtained from a successful auction, the downside of lower prices due to the stigma of failure means that risk-averse agents may choose to take the safer option.

Perhaps most intriguingly, to the extent that stigma is indeed about negative impressions formed from social failure, it also suggests that auction failure may have additional psychological costs to sellers. That is, failing the auction in front of all of your friends may impose an additional embarrassment cost that deters some sellers from choosing the auction method. To the degree that people differ in both their risk aversion (in the standard sense), as well as their aversion to social stigma, it is probably not surprising that a sizable minority (about a third) try the auction method first.

Finally, our results also raise a number of possible angles for future research regarding the impact of stigma and fear of social failure in economic decisions. In particular, where there is a large and focal event in which failure may be embarrassing and value-destroying, this may shade participants towards conservatism. One such example is underpricing in initial public offerings (IPOs). It has long been known that IPOs have large average first-day returns, which suggests that firms going public are leaving money on the table by not pricing their issues higher (Ritter, 1987; Loughran & Ritter, 2004; Ljungqvist, 2007, among others). Early explanations focused on agency conflicts between underwriters and firms (Baron, 1982), IPOs are also underpriced when investment banks take themselves public (Muscarella & Vetsuypens, 1989).

While there are a number of other economic theories of what firms may gain from IPO underpricing,[14] the embarrassment of having to pull an IPO, or even just the embarrassment of dropping a large amount in early trading, may form a non-trivial additional component. Indeed, when Facebook conducted its IPO according to the best advice of corporate finance and left no money on the table, the resulting large price drop in the first several days was widely characterized in the media as an embarrassment and a failure of the IPO process. If firm owners are risk averse over perceptions of such a large and important event in a firm's life, or worry about what negative returns may do to subsequent investor confidence due to stigma, this may explain why even sophisticated investment banks choose to underprice their IPOs. Identifying whether such stigma effects are present, both in this instance and in other cases of high-profile

[14]These include risk (Ritter, 1984), litigation risk (Lowry & Shu, 2002), aftermarket liquidity (Ellul & Pagano, 2006), and others.

public events, is an interesting angle for future research.

5 Conclusion

In standard economics, people understand their own willingness to pay. Certainly, for goods with substantial consumption value, learning that others value an item less is not typically assumed to change one's own expected utility from the item. In the case of financial investments and common value items, however, the opinions of others may carry more weight, which may affect inferences about resale value. Knowing that the buyer's bids were actually low, for example, may reduce valuation. Knowing that the seller's reserve price is high creates the opposite inference.

This paper presents evidence that auction failure is bad news, generating stigma which ultimately lowers prices. It is worse for repeated failures and failures that occur without bids, but these effects gradually wear off over time. Inferences about the distribution of willingness to pay seem unable to explain our findings, partly because the cost of failure decays and partly because sellers who are most likely to over-reach do worse (not better) when they attempt an auction. Stigma – the vague sense that perhaps there might be something wrong with the property -– can explain our findings. Auction failures create an embarrassing but temporary "bad smell" around the property itself. Our results raise the possibility that willingness to pay may have a larger socially determined component than previously thought.

References

Andersen, S., Badarinza, C., Liu, L., Marx, J., & Ramadorai, T. (2022). Reference dependence in the housing market. *American Economic Review*, *112*(10), 3398-3440.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance*, *61*(4), 1645-1680.

Baron, D. P. (1982). A model of the demand for investment banking advising and distribution services for new issues. *Journal of Finance*, *37*(4), 955-976.

Beggs, A., & Graddy, K. (1997). Declining values and the afternoon effect: Evidence from art auctions. *Rand Journal of Economics*, 544-565.

Besbris, M., Faber, J. W., Rich, P., & Sharkey, P. (2015). Effect of neighborhood stigma on economic transactions. *Proceedings of the National Academy of Sciences*, *112*(16), 4994-4998.

Bhattacharya, U., Huang, D., & Nielsen, K. M. (2020). Spillovers in prices: The curious case of haunted houses. *Review of Finance*, *25*(3), 903-935.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, *100*(5), 992-1026.

Chinco, A., & Mayer, C. (2016). Misinformed speculators and mispricing in the housing market. *Review of Financial Studies*, *29*(2), 486-522.

Chodorow-Reich, G., Guren, A. M., & McQuade, T. (2021). The 2000s housing cycle with 2020 hindsight: A Neo-Kindlebergerian view. *NBER Working Paper*(w29140).

Coppinger, V. M., Smith, V. L., & Titus, J. A. (1980). Incentives and behavior in English, Dutch and Sealed-Bid auctions. *Economic Inquiry*, *18*(1), 1-22.

Ellul, A., & Pagano, M. (2006). IPO underpricing and after-market liquidity. *Review of Financial Studies*, *19*(2), 381-421.

Frino, A., Lepone, A., Mollica, V., & Vassallo, A. (2010). The impact of auctions on residential sale prices: Australian evidence. *Australasian Accounting, Business and Finance Journal*, *4*(3), 3-22.

Gargano, A., & Giacoletti, M. (2022). Cooling auction fever: Evidence from the housing market. *Available at SSRN: https://ssrn.com/abstract=3561268*.

Genesove, D., & Mayer, C. (2001). Loss aversion and seller behavior: Evidence from the housing market. *Quarterly Journal of Economics*, *116*(4), 1233-1260.

Hirshleifer, D. (2020). Presidential address: Social transmission bias in economics and finance. *Journal of Finance*, *75*(4), 1779-1831.

Kahneman, D. (1992). Reference points, anchors, norms, and mixed feelings. *Organizational Behavior and Human Decision Processes*, *51*(2), 296-312.

Kaplan, G., Mitman, K., & Violante, G. L. (2020). The housing boom and bust: Model meets evidence. *Journal of Political Economy*, *128*(9), 3285-3345.

Kunda, Z. (1990). The case for motivated reasoning. *Psychological Bulletin*, *108*(3), 480.

Ljungqvist, A. (2007). IPO underpricing. *Handbook of Empirical Corporate Finance*, 375-422.

Loughran, T., & Ritter, J. (2004). Why has IPO underpricing changed over time? *Financial Management*, 5-37.

Lowry, M., & Shu, S. (2002). Litigation risk and IPO underpricing. *Journal of Financial Economics*, *65*(3), 309-335.

Milgrom, P. R., & Weber, R. J. (1982). A theory of auctions and competitive bidding. *Econometrica*, 1089-1122.

Miller, J. J. (2014). From English to first-price sealed bid: An empirical assessment of the change in auction type on experienced bidders. *Review of Economic Perspectives*, *14*(2), 105-127.

Muscarella, C. J., & Vetsuypens, M. R. (1989). A simple test of Baron's model of IPO underpricing. *Journal of Financial Economics*, *24*(1), 125-135.

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, *37*(2), 187-204.

Ritter, J. R. (1984). The "hot issue" market of 1980. *Journal of Business*, 215-240.

Ritter, J. R. (1987). The costs of going public. *Journal of Financial Economics*, *19*(2), 269-281.

Shiller, R. J. (2007). Understanding recent trends in house prices and home ownership. *NBER Working Paper*(w13553).

Thomas, M., & Morwitz, V. (2005). Penny wise and pound foolish: the left-digit effect in price cognition. *Journal of Consumer Research*, *32*(1), 54–64.

Vickrey, W. (1961). Counterspeculation, auctions, and competitive sealed tenders. *Journal of Finance*, *16*(1), 8-37.

Table 1: **Summary Statistics**

This table presents summary statistics of key variables. In Panel A, we divide the complete sample into Domain and CoreLogic samples. '*Domain Sample*' is the set of properties initially listed for sale via *Auction*. '*CoreLogic Sample*' is the set of properties initially listed for sale via *Private Treaty*. In Panel B, we present summary statistics for the Domain sample, split into two groups. The *Failed Auction* (*Successful Auction*) group is a set of properties that clear the market after (without) failing an auction. '*Below* 10^{th} *Percentile Hedonic Price Indicator*' is a dichotomous variable that equals 1 (0 otherwise) if the hedonic price of a property is below the 10^{th} percentile of hedonic prices of comparable properties sold in the past 12 months. '*Low Amenity Indicator*' is a dichotomous variable that equals 1 (0 otherwise) if the average standardized score, based on three amenities (bedrooms, bathrooms, and lot size), of a property is more than 1 standard deviation below the mean, where the mean and standard deviation of these amenities are estimated using comparable properties sold in the past 12 months. Here, the comparable properties are those located in the same suburb-postcode and are of the same type (house or unit/apartment). '*Failed Auction Indicator*' equals 1 if a property listed *For Auction* records either *Passed-In* or *No Bids* type event before clearing the market. The sample period spans 13 years, starting in 2007:M1 and ending in 2019:M12.

Panel A: Auctions Vs. Private Treaties

	Domain Sample (N = 433,782)		**CoreLogic Sample (N = 830,723)**	
	Mean	**SD**	**Mean**	**SD**
Selling Price (in AUD '000s)	959	606	775	550
Ln(Selling Price)	13.61	0.56	13.39	0.56
Below 10^{th} Percentile Hedonic Price Indicator	0.08	0.27	0.08	0.27
Low Amenity Indicator	0.04	0.21	0.04	0.20
Area (in m^2)	915.71	1,593.06	1,150.21	2,422.16
Number of Bedrooms	3.04	0.99	3.23	0.95
Number of Bathrooms	1.64	0.72	1.72	0.71
Failed Auction Indicator	0.17	0.38	0.00	0.00

Panel B: Auctions Only (Domain Sample)

	Failed Auction (N = 74,937)		**Successful Auctions (N = 358,845)**	
	Mean	**SD**	**Mean**	**SD**
Selling Price (in AUD '000s)	895	604	973	606
Ln(Selling Price)	13.53	0.58	13.63	0.55
Below 10^{th} Percentile Hedonic Price Indicator	0.09	0.29	0.08	0.26
Low Amenity Indicator	0.04	0.19	0.05	0.21
Area (in m^2)	1,004.05	1,831.51	897.26	1,537.97
Number of Bedrooms	3.24	1.04	3.00	0.97
Number of Bathrooms	1.78	0.77	1.61	0.71
No Bid Indicator	0.04	0.20	0.00	0.00
Multiple Auction Failure Indicator	0.02	0.12	0.00	0.00
Time between Most Recent Auction Failure and Sale (in Months)	1.68	2.01	0.00	0.00

Table 2: **Prices and Auction Outcomes**

This table presents results from tests relating to the property prices and various auction outcomes. In columns (1)-(3), the key independent variables are *Listed For Auction* and *Failed Auction*. '*Listed For Auction*' is a dichotomous variable that equals 1 if a property is listed for auction. '*Failed Auction*' equals 1 if a property listed *For Auction* records either *Passed-In* or *No Bids* type event before clearing the market. In columns (3)-(6), the key independent variables are four indicator variables that represent the possible outcomes related to *for auction* listings relative to private treaty listings. The sample period spans 13 years, starting in 2007:M1 and ending in 2019:M12. The standard errors are clustered by postcode and time (year×month), and t-statistics are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Ln(Selling Price)					
𝟙.Listed For Auction	0.0053*	0.0165***	0.0122***			
	(1.6636)	(7.8400)	(7.0321)			
𝟙.Failed Auction	-0.0377***	-0.0360***	-0.0381***			
	(-16.0015)	(-19.4325)	(-24.4859)			
𝟙.Listed For Auction, Sold Prior Via Private Treaty				0.0048	0.0163***	0.0089***
				(1.3807)	(6.7642)	(4.8320)
𝟙.Listed For Auction, Sold At Auction				0.0056*	0.0167***	0.0143***
				(1.7653)	(7.7781)	(7.9508)
𝟙.Failed Auction, Sold Later Via Private Treaty				-0.0327***	-0.0196***	-0.0260***
				(-9.0397)	(-8.2744)	(-12.6311)
𝟙.Failed Auction, Sold Later At Auction				-0.0213***	-0.0154***	-0.0240***
				(-3.2949)	(-3.0420)	(-4.7125)
R^2	0.8345	0.8832	0.9142	0.8345	0.8832	0.9142
N	1,264,505	1,264,505	1,264,505	1,264,505	1,264,505	1,264,505
Suburb×Postcode, Area Group, Bedrooms, Bathrooms, Property Type FE	Yes	No	No	Yes	No	No
Suburb×Postcode×Area Group×Bedrooms×Bathrooms×Property Type FE	No	Yes	No	No	Yes	No
Suburb×Postcode×Area Group×Bedrooms×Bathrooms×Property Type×Year FE	No	No	Yes	No	No	Yes
Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: **Auction Failures – Role Of Reservation Price**

This table presents the results of a linear probability model linking auction failures and seller's reservation price. The dependent variable is a dichotomous variable that equals 1 if a property failed to sell at its initial auction and equals 0 otherwise. In this table, we proxy a seller's reservation price by two instruments. The first,'*Below* 10^{th} *Percentile Hedonic Price Indicator*', is an indicator variable that equals 1 (0 otherwise) if the hedonic price of a property is below the 10^{th} percentile of hedonic prices of comparable properties sold in the past 12 months. The second, '*Low Amenity Indicator*', is a dichotomous variable that equals 1 (0 otherwise) if the average standardized score, based on three amenities (bedrooms, bathrooms, and lot size), of a property is more than 1 standard deviation below the mean, where the mean and standard deviation of these amenities are estimated using comparable properties sold in the past 12 months. Here, the comparable properties are those located in the same suburb-postcode and are of the same type (house or unit/apartment). These results are based on observations corresponding to *for auction* listings sample. The sample period starts in 2007:M1 and ends in 2019:M12. The standard errors are clustered by postcode and time (year×month), and t-statistics are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Failed Auction Indicator ∣ For Auction Listing					
𝟙.Below 10^{th} Percentile Hedonic Price Indicator	0.0160***	0.0147***			0.0153***	0.0143***
	(6.0986)	(4.5661)			(5.7366)	(4.4459)
𝟙.Low Amenity Value Indicator			0.0086***	0.0238***	0.0046	0.0227***
			(2.8234)	(3.5826)	(1.4795)	(3.4324)
R^2	0.0991	0.3046	0.0991	0.3046	0.0992	0.3046
N	433,782	433,782	433,782	433,782	433,782	433,782
Suburb×Postcode, Area Group, Bedrooms, Bathrooms, Property Type FE	Yes	No	Yes	No	Yes	No
Suburb×Postcode×Area Group×Bedrooms×Bathrooms×Property Type×Year FE	No	Yes	No	Yes	No	Yes
Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: **Prices and Reservation Prices – Auctions Versus Private Treaty Sales**

This table presents results linking property prices with reservation prices. The dependent variable is the log of the selling price of a property. In this table, we proxy a seller's reservation price by two instruments. The first, '*Below* 10^{th} *Percentile Hedonic Price Indicator*', is an indicator variable that equals 1 (0 otherwise) if the hedonic price of a property is below the 10^{th} percentile of hedonic prices of comparable properties sold in the past 12 months. The second, '*Low Amenity Indicator*', is a dichotomous variable that equals 1 (0 otherwise) if the average standardized score, based on three amenities (bedrooms, bathrooms, and lot size), of a property is more than 1 standard deviation below the mean, where the mean and standard deviation of these amenities are estimated using comparable properties sold in the past 12 months. Here, the comparable properties are those located in the same suburb-postcode and are of the same type (house or unit/apartment). The sample period starts in 2007:M1 and ends in 2019:M12. The standard errors are clustered by postcode and time (year×month), and t-statistics are presented in parentheses. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Ln(Selling Price)					
𝟙.Listed For Auction	0.0022	0.0055***	0.0007	0.0060***	0.0032	0.0062***
	(0.7605)	(3.4670)	(0.2199)	(3.5932)	(1.0994)	(3.9040)
𝟙.Below 10^{th} Percentile Hedonic Price Indicator	0.0015	-0.0538***			-0.0087***	-0.0543***
	(0.4379)	(-26.3015)			(-2.7697)	(-25.8927)
𝟙.Listed For Auction × 𝟙.Below 10^{th} Percentile Hedonic Price Indicator	-0.0558***	-0.0127***			-0.0432***	-0.0080***
	(-10.2335)	(-5.1838)			(-7.7566)	(-2.9900)
𝟙.Low Amenity Value Indicator			0.0573***	-0.0656***	0.0570***	-0.0628***
			(8.5133)	(-14.5683)	(8.5813)	(-13.9627)
𝟙.Listed For Auction × 𝟙.Low Amenity Value Indicator			-0.0692***	-0.0303***	-0.0512***	-0.0275***
			(-9.2599)	(-8.0046)	(-6.6591)	(-6.6627)
R^2	0.8345	0.9144	0.8346	0.9142	0.8348	0.9145
N	1,264,505	1,264,505	1,264,505	1,264,505	1,264,505	1,264,505
Suburb×Postcode, Area Group, Bedrooms, Bathrooms, Property Type FE	Yes	No	Yes	No	Yes	No
Suburb×Postcode×Area Group×Bedrooms×Bathrooms×Property Type×Year FE	No	Yes	No	Yes	No	Yes
Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: **Auction Failure, Hot Markets and Property Types**

This table presents results from robustness tests relating to the property prices and various auction outcomes. The dependent variable is the log of the selling price of a property. '*Listed For Auction*' is a dichotomous variable that equals 1 if a property is listed for auction. '*Failed Auction*' equals 1 if a property listed *For Auction* records either *Passed-In* or *No Bids* type event before clearing the market. '*Hot Market*' is an indicator variable that equals 1 (0 otherwise) if the average time between the listing date and final sale date for a postcode-year-quarter is below its median value for that year-quarter. '*Unit*' is a dichotomous variable that equals 1 for apartment/unit type properties. The sample period starts in 2007:M1 and ends in 2019:M12. The standard errors are clustered by postcode and time (year×month), and t-statistics are presented in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Ln(Selling Price)					
𝟙.Listed For Auction	0.0014	0.0087***	0.0023	0.0081***	0.0215***	0.0064***
	(0.3854)	(4.4857)	(1.0608)	(5.9831)	(7.2595)	(3.9993)
𝟙.Failed Auction	-0.0330***	-0.0328***	-0.0335***	-0.0351***	-0.0381***	-0.0322***
	(-11.8337)	(-15.9022)	(-15.8547)	(-21.3173)	(-14.6125)	(-15.8582)
𝟙.Listed For Auction × 𝟙.Hot Market	0.0046	0.0066***			0.0037	0.0037**
	(1.5128)	(3.1554)			(1.4382)	(2.4733)
𝟙.Failed Auction × 𝟙.Hot Market	-0.0082***	-0.0070***			-0.0127***	-0.0061***
	(-3.0909)	(-2.9349)			(-4.5436)	(-2.6127)
𝟙.Listed For Auction × 𝟙.Unit			0.0265***	0.0216***	-0.1101***	0.0155**
			(3.6438)	(3.6310)	(-7.5328)	(2.0665)
𝟙.Failed Auction × 𝟙.Unit			-0.0046	-0.0139***	0.0410***	-0.0100**
			(-1.3446)	(-4.4851)	(5.2722)	(-2.0719)
R^2	0.8365	0.9187	0.8549	0.9143	0.8357	0.9143
N	1,264,505	1,264,505	1,264,505	1,264,505	1,264,505	1,264,505
Suburb×Postcode, Area Group, Bedrooms, Bathrooms, Property Type FE	Yes	No	Yes	No	Yes	No
Suburb×Postcode×Area Group×Bedrooms×Bathrooms×Property Type×Year FE	No	Yes	No	Yes	No	Yes
Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: **Stigma and Eventual Time to Sale**

This table presents results from additional tests relating to the property prices and various auction-related outcomes. The dependent variable is the log of the selling price of a property. '*Listed For Auction*' is a dichotomous variable that equals 1 if a property is listed for auction. '*Failed Auction*' equals 1 if a property listed *For Auction* records either *Passed-In* or *No Bids* type event before clearing the market. *Multiple Auction Failure* equals 1 (0 otherwise) if a property fails an auction more than once before clearing the market. '*No Bid*' is an indicator variable that equals 1 (0 otherwise) if a property receives *no bids* at its auction and fails an auction. The sample period starts in 2007:M1 and ends in 2019:M12. The standard errors are clustered by postcode and time (year×month), and t-statistics are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable: Ln(Selling Price)							
1.Listed For Auction	0.0053*	0.0122***	0.0053*	0.0122***	0.0052	0.0121***	0.0052	0.0121***
	(1.6636)	(7.0322)	(1.6657)	(7.0383)	(1.6378)	(6.9861)	(1.6452)	(6.9974)
1.Failed Auction	-0.0374***	-0.0379***	-0.0373***	-0.0378***	-0.0502***	-0.0478***	-0.0280***	-0.0331***
	(-16.0322)	(-24.2920)	(-15.4581)	(-23.9628)	(-22.6080)	(-32.7611)	(-6.3416)	(-8.3548)
1.Multiple Auction Failure	-0.0161**	-0.0107*					-0.0144**	-0.0093
	(-2.3289)	(-1.6772)					(-2.0395)	(-1.4412)
1.No Bid			-0.0089	-0.0089*			-0.0122	-0.0118**
			(-1.1102)	(-1.8114)			(-1.5633)	(-2.4306)
Time Between Most Recent Failure and Sale					0.0076***	0.0060***		
					(10.9914)	(11.6986)		
1.Time Between Most Recent Failure and Sale$_{\in(0,\,1]\text{ Months}}$							-0.0195***	-0.0133***
							(-4.3118)	(-3.1626)
1.Time Between Most Recent Failure and Sale$_{\in(1,\,2]\text{ Months}}$							-0.0158***	-0.0066
							(-3.0847)	(-1.4310)
1.Time Between Most Recent Failure and Sale$_{\in(2,\,3]\text{ Months}}$							-0.0002	0.0046
							(-0.0369)	(0.9197)
1.Time Between Most Recent Failure and Sale$_{\in(3,\,4]\text{ Months}}$							0.0098	0.0113*
							(1.3868)	(1.9434)
1.Time Between Most Recent Failure and Sale$_{\in(4,\,5]\text{ Months}}$							0.0120	0.0133**
							(1.5578)	(1.9827)
1.Time Between Most Recent Failure and Sale$_{\in(5,\,6]\text{ Months}}$							0.0199***	0.0189***
							(2.6502)	(2.8981)
1.Time Between Most Recent Failure and Sale$_{>6\text{ Months}}$							0.0404***	0.0293***
							(5.7253)	(4.8104)
R^2	0.8345	0.9142	0.8345	0.9142	0.8346	0.9142	0.8346	0.9142
N	1,264,505	1,264,505	1,264,505	1,264,505	1,264,505	1,264,505	1,264,505	1,264,505
Suburb×Postcode, Area Group, Bedrooms, Bathrooms, Property Type FE	Yes	No	Yes	No	Yes	No	Yes	No
Suburb×Postcode×Area Group×Bedrooms×Bathrooms×Property Type×Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: **Prices, Round Numbers and Auction Outcomes**

This table presents results for a regression model in which the dependent variable is a dichotomous variable that equals 1 (0) if the selling price of a property is some threshold amount below (above) 50K multiples. This threshold amount is one, two, three, four, and five thousand Australian dollars in columns (1)-(2), (3)-(4), (5)-(6), (7)-(8), and (9)-(10), respectively. The independent variable, *Failed Auction*, is a dichotomous variable that equals 1 (0 otherwise) if a property fails the first listed auction event. The standard errors are clustered by postcode and time (year×month), and t-statistics are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable: Below x50K									
1.Listed For Auction	-0.1518***	-0.0385***	-0.1178***	-0.0489***	-0.0806***	-0.0344***	-0.0531***	-0.0217***	-0.0474***	-0.0316***
	(-15.0480)	(-5.7283)	(-15.2984)	(-7.4770)	(-14.5186)	(-6.1870)	(-10.5686)	(-4.1735)	(-14.1779)	(-9.1486)
1.Failed Auction	0.2175***	0.0610***	0.1780***	0.1018***	0.1212***	0.0760***	0.0838***	0.0505***	0.0759***	0.0568***
	(11.5609)	(3.2912)	(15.4670)	(6.9874)	(13.2503)	(6.5824)	(9.1727)	(4.5072)	(12.1219)	(7.8118)
R^2	0.1823	0.6904	0.0987	0.5668	0.0697	0.5074	0.0527	0.4820	0.0257	0.3673
N	21,517	21,517	44,781	44,781	62,720	62,720	74,744	74,744	185,875	185,875
Suburb×Postcode, Area Group, Bedrooms, Bathrooms, Property Type FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Suburb×Postcode×Area Group×Bedrooms×Bathrooms×Property Type×Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Threshold around ×50K	± 1K	± 1K	± 2K	± 2K	± 3K	± 3K	± 4K	± 4K	± 5K	± 5K

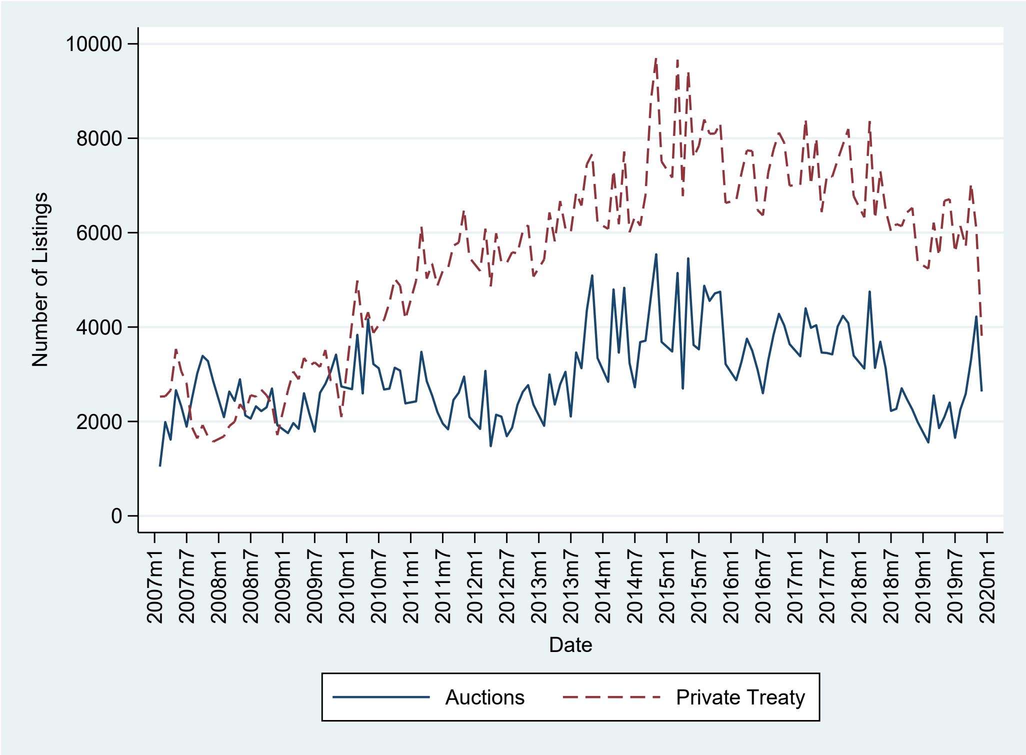
Table 8: **Prices, Round Numbers, Hot Markets and Property Types**

This table presents results for a regression model in which the dependent variable is a dichotomous variable that equals 1 (0) if the selling price of a property is up to 2,000 Australian dollars below (above) 50K multiples. The independent variables are *listed for auction* and *failed auction*. *Failed Auction*, is a dichotomous variable that equals 1 (0 otherwise) if a property failed an auction during the first listed event. *Hot Market* is an indicator variable that equals 1 (0 otherwise) if the average time between the listing date and final sale date for a postcode-year-quarter is below its median value for that year-quarter. *Unit* is a dichotomous variable that equals 1 for apartment/unit type properties. The sample period starts in 2007:M1 and ends in 2019:M12. The standard errors are clustered by postcode and time (year×month), and t-statistics are in parentheses. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

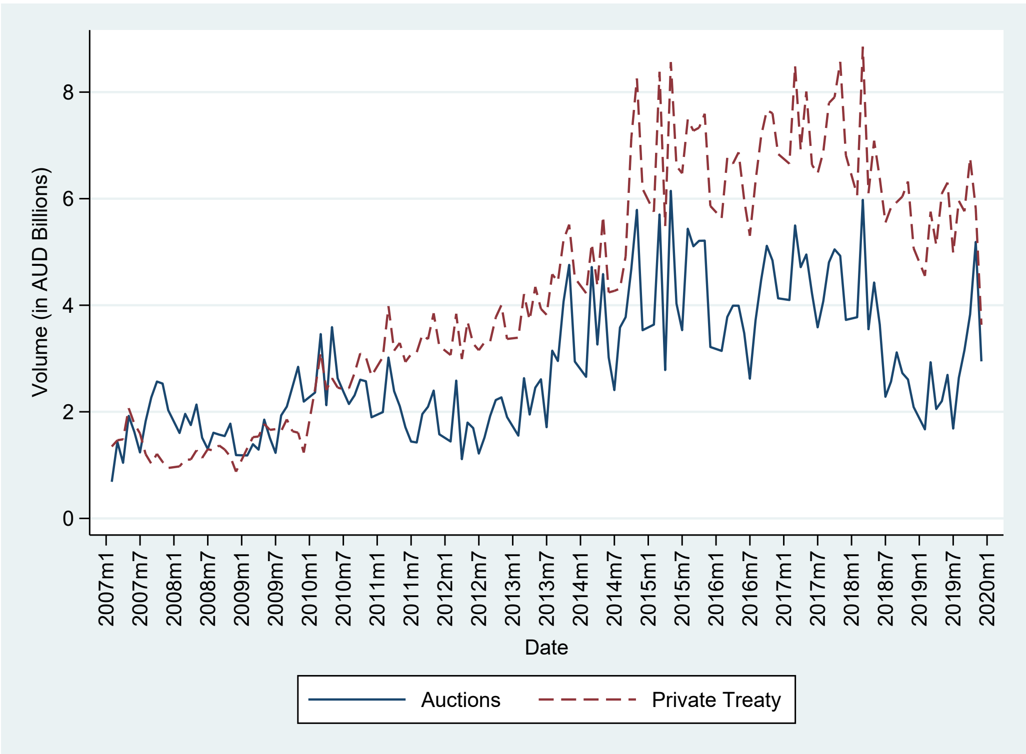
	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Below x50K					
𝟙.Listed For Auction	-0.1058***	-0.0272***	-0.1053***	-0.0371***	-0.1019***	-0.0310***
	(-11.9190)	(-3.5002)	(-13.3894)	(-5.6876)	(-11.3883)	(-3.7052)
𝟙.Failed Auction	0.1473***	0.0467**	0.1730***	0.0972***	0.1440***	0.0664***
	(8.8886)	(2.3543)	(12.5639)	(6.6089)	(7.7315)	(3.3005)
𝟙.Listed For Auction × 𝟙.Hot Market	-0.0234**	-0.0325***			-0.0187**	-0.0148
	(-2.4556)	(-2.9368)			(-2.1274)	(-1.3682)
𝟙.Failed Auction × 𝟙.Hot Market	0.0654***	0.0854***			0.0731***	0.0740**
	(2.6686)	(2.8450)			(2.8472)	(2.2883)
𝟙.Listed For Auction × 𝟙.Unit			-0.0402***	-0.0869***	-0.0205	-0.0733**
			(-2.8932)	(-3.9999)	(-1.1567)	(-2.3337)
𝟙.Failed Auction × 𝟙.Unit			0.0120	0.0178	0.0089	0.0033
			(0.4113)	(0.3171)	(0.2089)	(0.0388)
R^2	0.1255	0.6163	0.1171	0.5738	0.0991	0.5677
N	44,693	44,693	44,781	44,781	44,693	44,693
Suburb×Postcode, Area Group, Bedrooms, Bathrooms, Property Type FE	Yes	No	Yes	No	Yes	No
Suburb×Postcode×Area Group×Bedrooms×Bathrooms×Property Type×Year FE	No	Yes	No	Yes	No	Yes
Year×Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: **Prices, Round Numbers and Auction Outcomes – Robustness**
This table presents results for a regression model in which the dependent variable is a dichotomous variable that equals 1 (0) if the selling price of a property is 2,000 Australian dollars below (above) a number represented by k (in AUD '000s) that ranges between 1 and 100. Here, k represents the ending digits on the selling price (in AUD '000s) rounded to the nearest thousand. For brevity's sake, we present the top ten coefficient estimates ranked by their economic significance. The independent variables are *listed for auction*, and *failed auction*. *Failed Auction*, is a dichotomous variable that equals 1 (0 otherwise) if a property failed an auction during the first listed event. All regression specifications include Suburb×Postcode, Area Group, Bedrooms, Bathrooms, Property Type, and Year×Month fixed effects. The standard errors are clustered by postcode and time (year×month). Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Rank	k	$\hat{\beta}_{\mathbb{1}.\text{Failed Auction}}$	t-stat	N	R^2
1	50	0.1807***	(12.1720)	22,238	0.1260
2	100	0.1700***	(10.3208)	22,543	0.1338
3	20	0.1483***	(7.9712)	21,370	0.1036
4	40	0.1433***	(8.2850)	21,452	0.0896
5	30	0.1290***	(7.5858)	20,390	0.0922
6	90	0.1288***	(6.9256)	20,701	0.0912
7	95	0.1055***	(4.3629)	13,919	0.1039
8	10	0.1019***	(5.7803)	21,067	0.0805
9	55	0.0977***	(4.9915)	17,321	0.0852
10	70	0.0940***	(5.1892)	20,729	0.0911

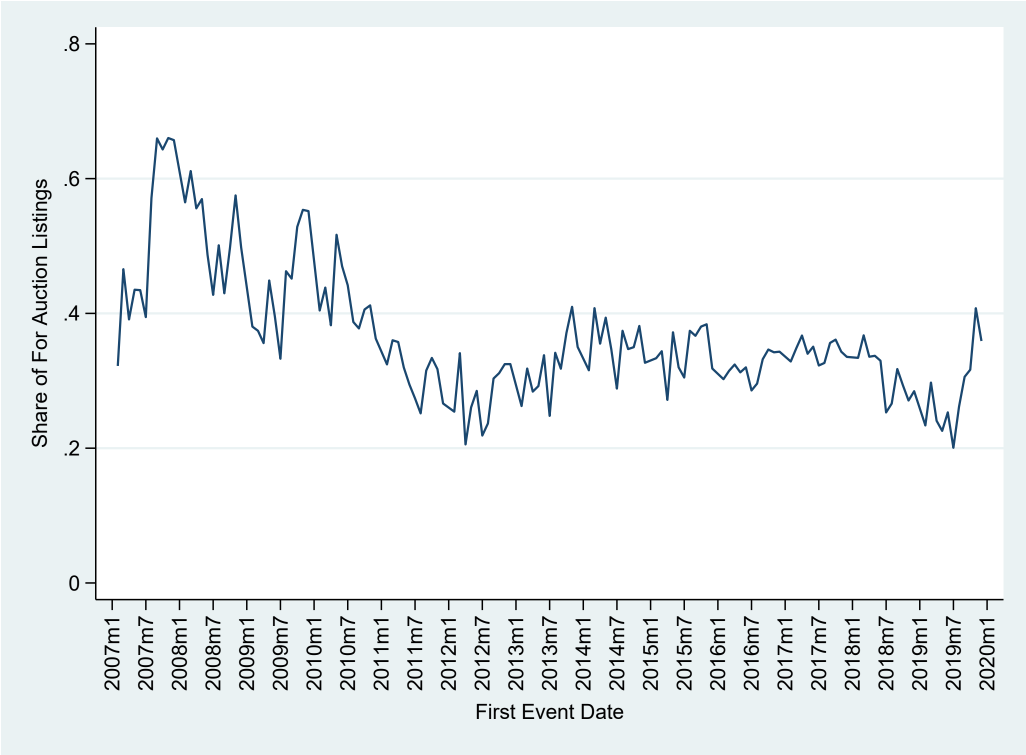


(a) Number of Listings

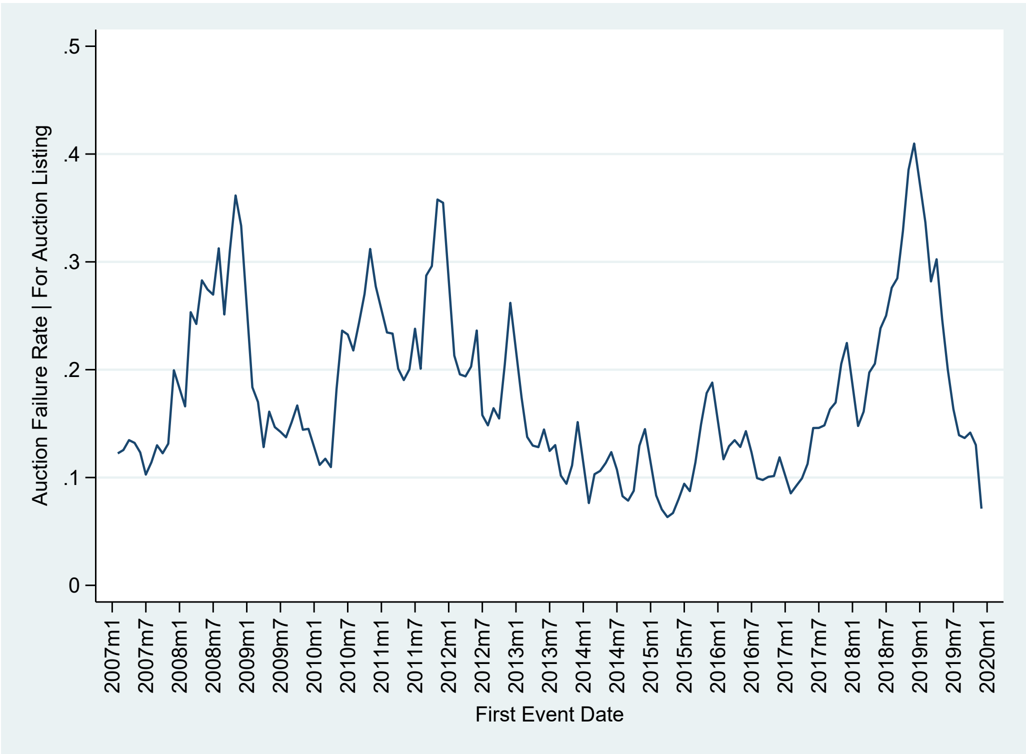


(b) Volume of Listings

Figure 1: This figure presents time-series of aggregate number (Panel (a)), and amount (Panel (b)) of property sales under two selling methods: auctions and private treaty. The sample period is from 2007:M1 to 2019:M12.



(a) Share of For Auction Listings



(b) Auction Failure Rate

Figure 2: In Panel (a), the figure presents the share of *for auction* listings relatively to all *for sale* listings. In Panel (b), the figure presents the auction failure rate, conditional on a property listed *for auction*. The sample period is from 2007:M1 to 2019:M12.

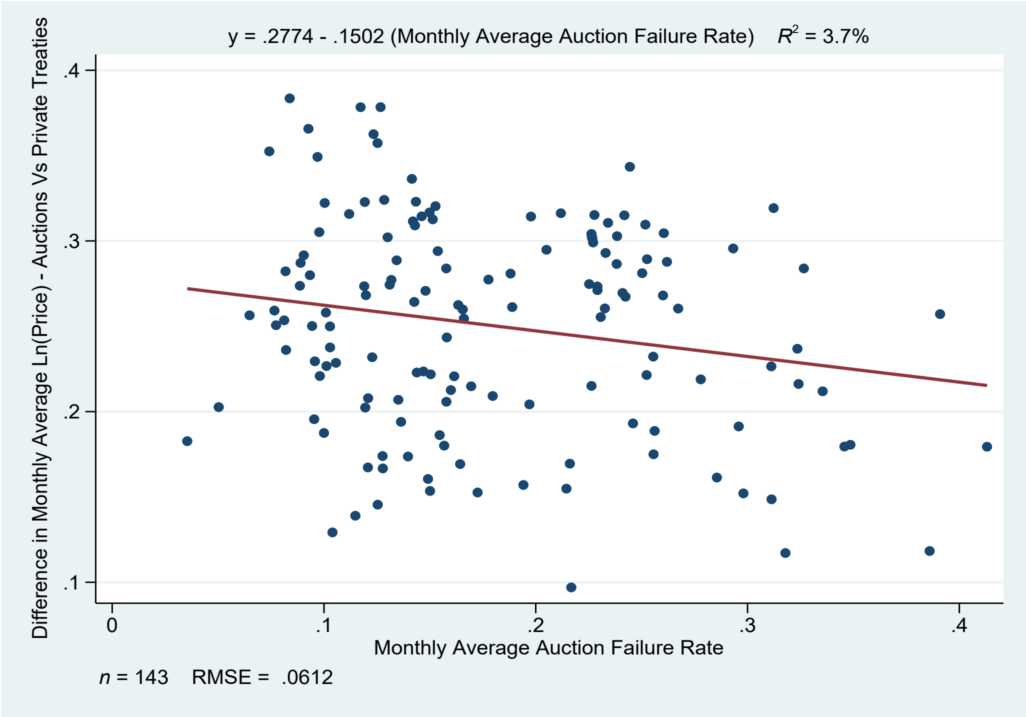
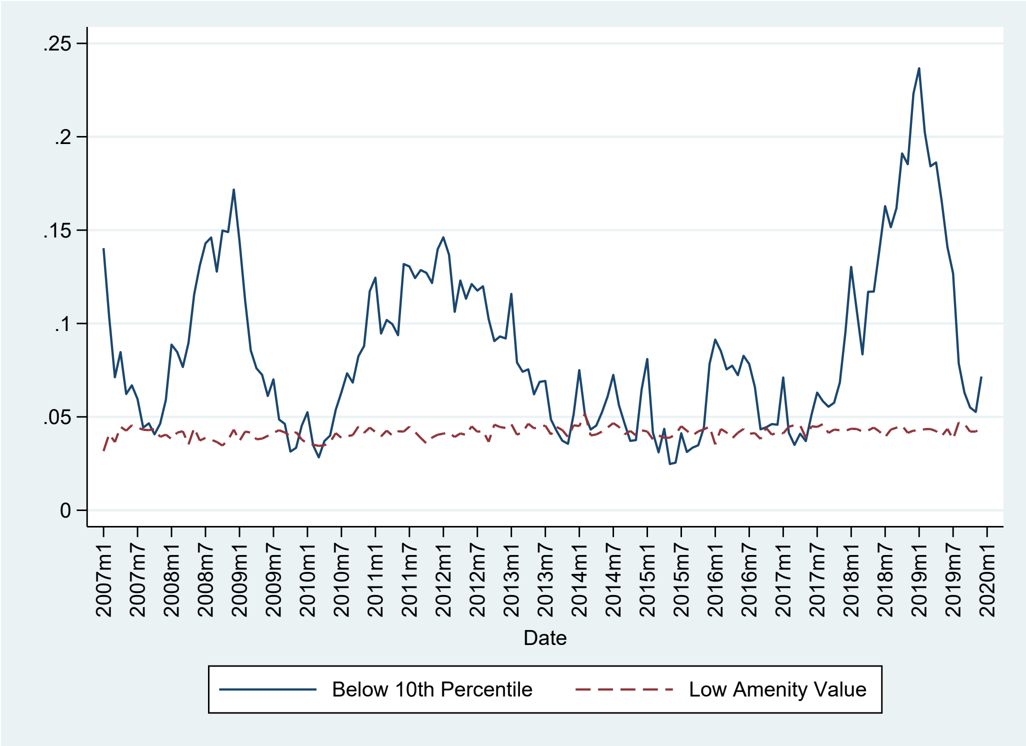
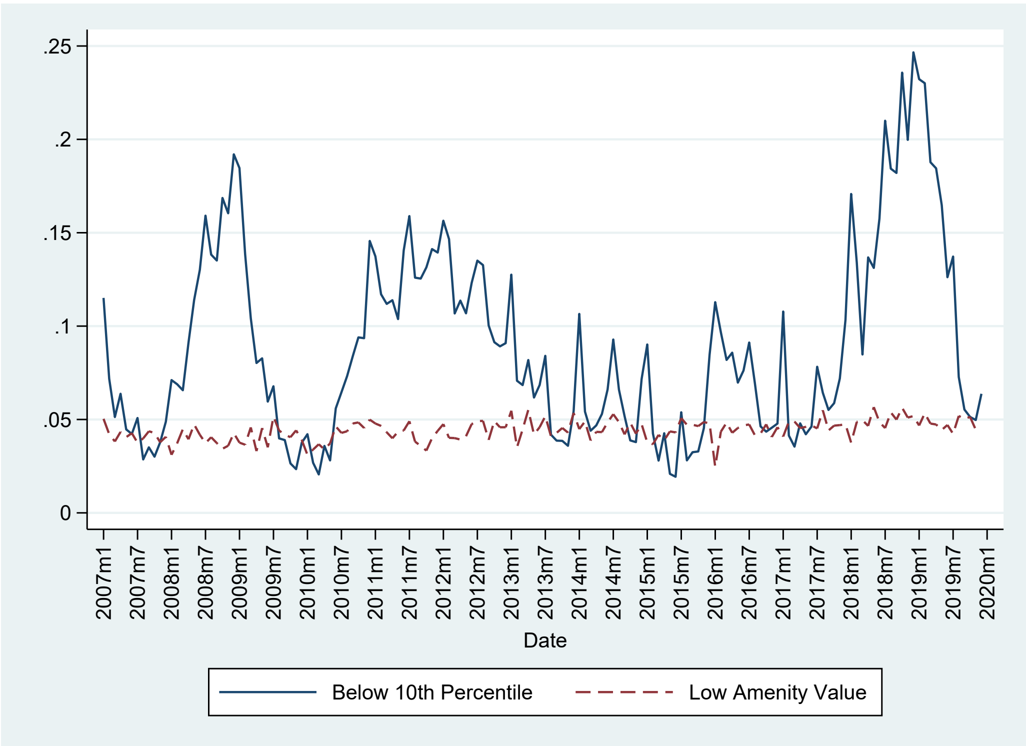


Figure 3: The figure presents a plot of monthly average auction failure rate and the difference in monthly average of log price of properties sold via auctions and that of properties sold via private treaty. The sample period is from 2007 to 2019.



(a) Full Sample



(b) Domain Sample Only

Figure 4: The figures present a time-series of cross-sectional averages of *Below* 10^{th} *Percentile Hedonic Price Indicator* and *Low Amenity Value Indicator*. In Panels (a) and (b), the cross-sectional averages of two indicators are based on the full sample, and Domain Sample, respectively. The sample period is from 2007:M1 to 2019:M12.

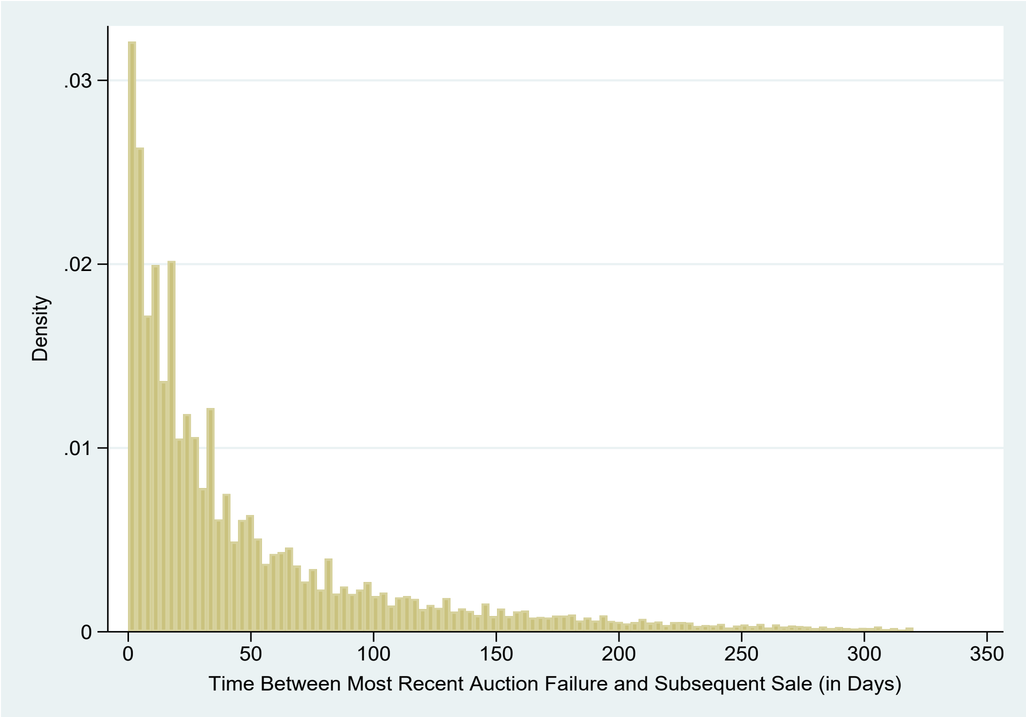
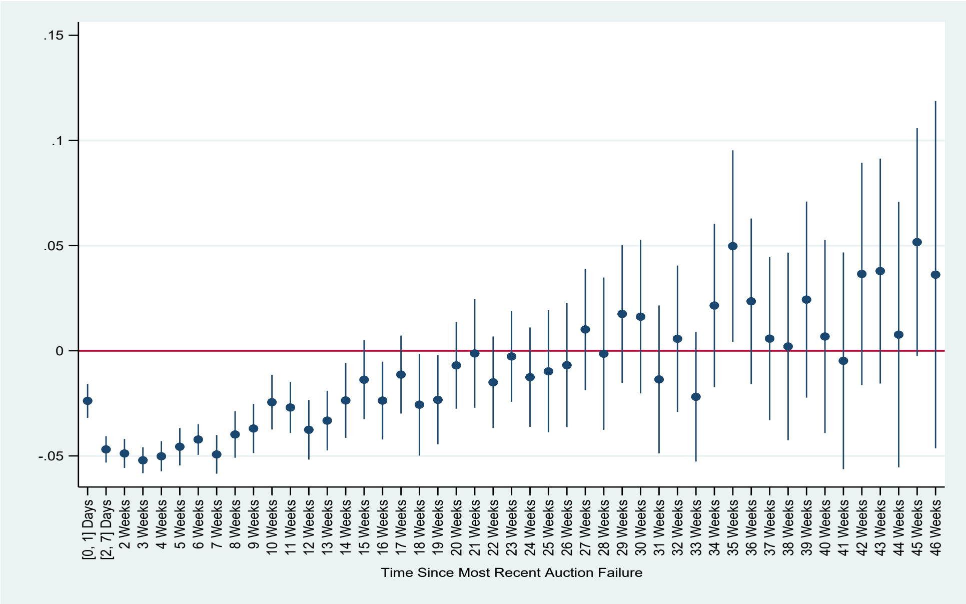
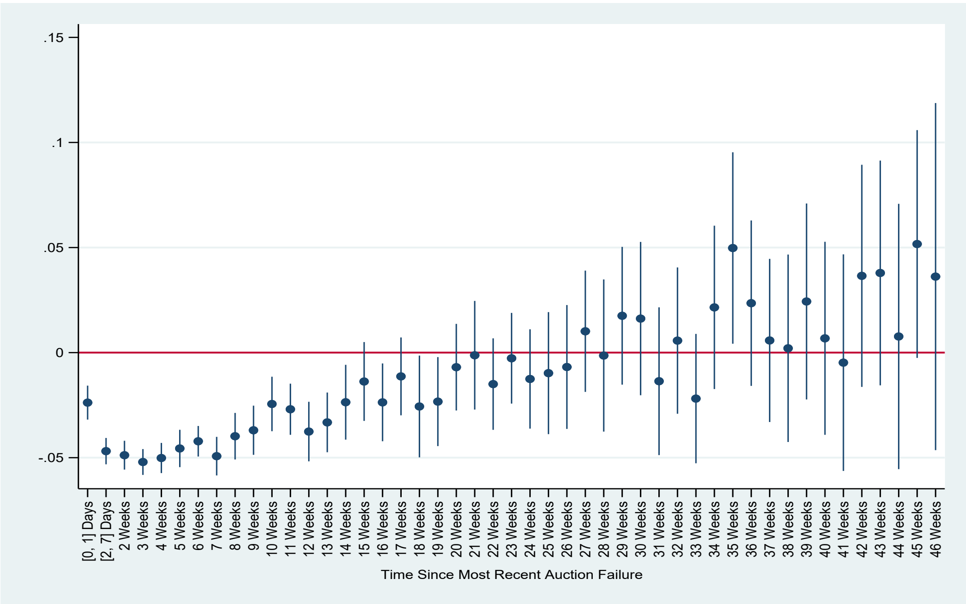


Figure 5: The figure presents the distribution of time difference (in days) between the most recent auction failure and subsequent sale, conditional on a property failing an auction. The sample period is from 2007:M1 to 2019:M12.

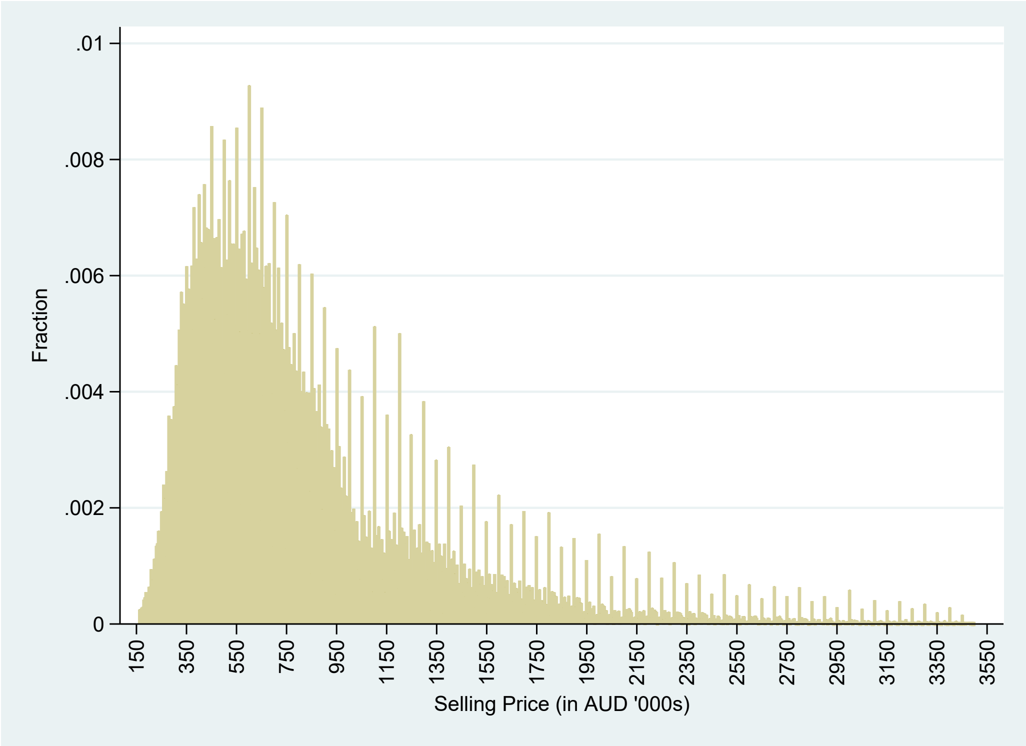


(a)

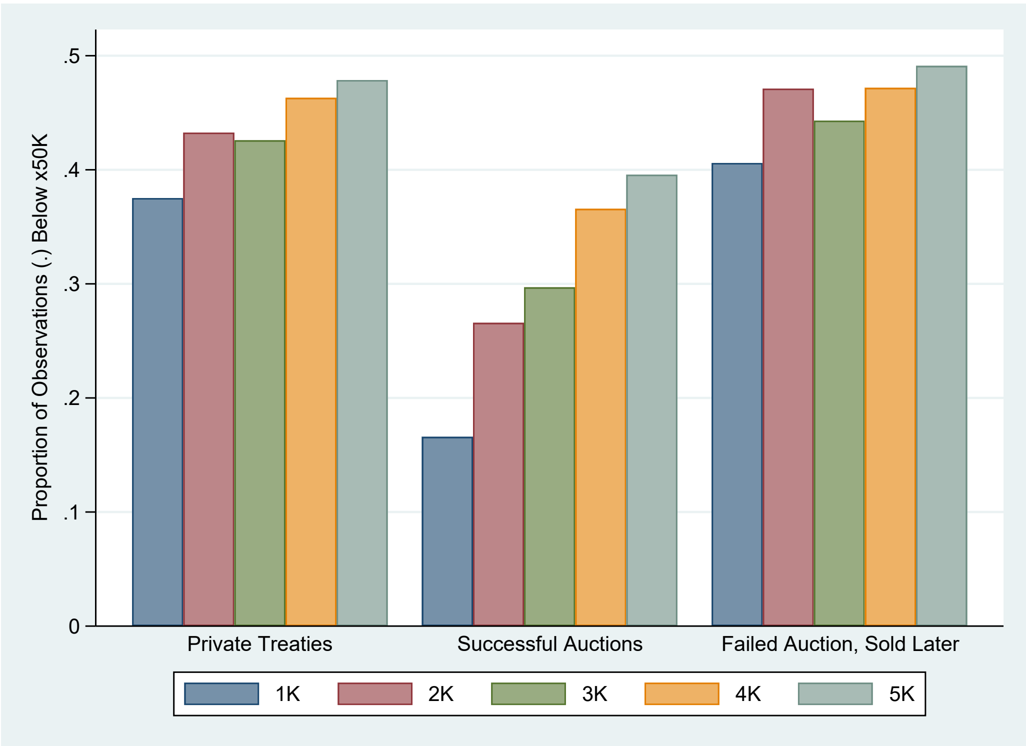


(b)

Figure 6: The figure presents coefficient estimates from a regression test in which the dependent variable is the log of the selling price of a property. The plotted coefficients correspond to dichotomous variables based on the time between the most recent auction failure and the subsequent sale of a property. For brevity's sake, we do not present a coefficient estimate for *listed for auction* that equals 1 (0 otherwise) if a property is listed for an auction. The reference set of observations corresponds to private treaty sales. The sample period is from 2007:M1 to 2019:M12. In Panel (a), the regression specification includes suburb×postcode, area group, bedrooms, bathrooms, property type, and year×month fixed effects. In Panel (b), the regression specification includes suburb×postcode×area group×bedrooms×bathrooms×property type, and year×month fixed effects. The standard errors are clustered by postcode and time (year×month).



(a) Selling Price



(b) Proportion of Observations Below $\times$50K

Figure 7: The figure presents a histogram of selling prices, rounded to the nearest thousand, in Panel (a), and the proportion of observations below $\times$50K by event type in Panel (b). The sample period is from 2007:M1 to 2019:M12.

Appendix

The Stench of Failure: How Perception Affects House Prices

Kristle R. Cortés
UNSW Business School, University of NSW

Mandeep Singh
Imperial College Business School, Imperial College London

David H. Solomon
Carroll School of Management, Boston College

Philip E. Strahan
Carroll School of Management, Boston College, and NBER

Appendix A: Hedonic Pricing Model

To calculate the expected price $\hat{P}$ for each property in our sample, we estimate a 4-year rolling window hedonic pricing model using our sample of sold listings. The model predicts the log of selling price for property i in year-month t as follows:

$$\ln(\mathrm{P}_{it}) = \mathbf{\Gamma}'\mathbf{X_{it}} + \mathbf{\Psi} + u_{it}$$

where $\mathbf{X_{it}}$ is a vector of property characteristics: number of bedrooms, number of bathrooms, area, a dichotomous variable for property type (unit/apartment or house) and the presence of parking. $\mathbf{\Psi}$ are the Suburb$\times$Postcode$\times$Year$\times$Month fixed effects. These fixed effects allow us to control for local trends in property prices. The rolling-window design of the hedonic regression is useful as it allows the marginal prices of characteristics of a property to vary over time.

In the table below, we present summary statistics of R^2 based on 168 (156) months, starting in 2006:M1 (2007:M1) and ending in 2019:M12. The average R^2 of 79.4 percent

Sample Period	Mean	SD	Min	Max
2006:M1 - 2019:M12	0.7947	0.0151	0.7476	0.8200
2007:M1 - 2019:M12	0.7930	0.0143	0.7476	0.8129

indicates a high degree of accuracy. Next, we describe the use of the expected property price $\hat{P}$ to estimate *Below* 10^{th} *Percentile Hedonic Price Indicator*.

For each property i sold in year-month t, we estimate the following quantity:

$$\hat{P}_{it}^{10^{\text{th}}} = \mathfrak{P}_{10}\left[\{\hat{P}_{i't'}\}_{t'=t-1}^{t-12}\right]$$

where $\mathfrak{P}_{10}$ is an operator selecting the 10^{th} percentile of quantity inside $[\cdot]$, and $\{\hat{P}_{i't'}\}_{t'=t-1}^{t-12}$ represents the set of hedonic prices of all *other* properties, indexed by i', sold in the location (suburb-postcode) of property i in the past 12 months. In the last step, we construct the *Below* 10^{th} *Percentile Hedonic Price Indicator* as follows:

$$\text{Below } 10^{th} \text{ Percentile Hedonic Price Indicator}_{it} = \begin{cases} 1 \text{ if } \hat{P}_{it} < \hat{P}_{it}^{10^{\text{th}}} \\ 0 \text{ otherwise} \end{cases}$$