# How Perception Affects House Prices: Evidence from Failed Auctions

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**Abstract**

In the Australian real estate market, about a third of properties are sold at auction. Properties that fail auctions sell later for a 1.3% discount. Consistent with a causal channel, the effect holds with property-level fixed effects and when auction failure is instrumented by adverse weather (rain). Prices cluster just below round numbers, and the discount fades over time, inconsistent with our effects reflecting unobserved property characteristics. The evidence suggests that there are behavioral factors affecting potential buyers' willingness to pay.

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# 1 Introduction

This paper studies the effects of auction failure on house prices. We provide the first solid evidence that 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 19% of auctions carry a distinct category of failure, when the highest bid fails to reach the seller's (undisclosed) reserve price, the minimum price acceptable to them. 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 "For Sale" or 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]

Our results suggest that auction failure is a more important component than much of the auction theory literature has considered. For instance, in Athey & Haile (2006), which aims to identify different standard auction models, the format of having any reserve price (the precondition for a failed auction) is modeled only where this is announced publicly, and the case of auction failure is not considered at all. The omission likely reflects the idea that failure is an uninteresting corner case of extreme disagreement, and does not have any important economic implications. In a simple willingness-to-pay setting, whether private valuation or common valuation, the seller simply keeps the item if they value it more than the bidders. In our setting, reserve prices are not revealed, auction failures are common, and people who fail auctions still generally want to sell their house. As such, they subsequently list it under a different sale mechanism, or auction it again. We document that these subsequent sales come with lower prices, even when those failures happen for exogenous reasons.

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

We argue that the pricing effects are causal. We identify the effects of auction failure in a sample of repeated sales, which allows us to control for property-specific fixed effects, as well as a large set of granular and time-varying effects for location and property amenities. Next, we proxy for auction failure using precipitation. Most auctions are held outdoors on the property in question. As we show, rainfall is a powerful predictor of failure. It does so both by raising the physical impediment to attending the auction (thus reducing the number of bidders) and also creating a negative psychological effect on attendees (thus reducing bidder aggressiveness). The literature shows the effects of adverse weather on human behavior, and we show that auctions fail more on bad weather days. A key component for our study is that while bad weather leads to increased auction failure, the weather on the day of the auction should not affect the subsequent sale on a later date, other than through its impact on failure likelihood; hence, the instrument passes the exclusion restriction. The results from a reduced-form model show that a price discount exists when using rain in lieu of auction failure.

Our results show that failing an auction has long-term price implications not explained by fundamentals. We argue that this 'failure cost' is a form of sentiment (Baker & Wurgler, 2006), but a social one where traders react to other traders (Hirshleifer, 2020). On the 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 property (even if one cannot tell what it is). Both pathways predict that a failed auction will lower the subsequent sale price, regardless of the specific reason for failure.

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 a buyer and a seller should not obviously lead to a different final price compared to an

otherwise identical house sold by a private treaty.

We first show that properties listed to sell at auction, relative to those listed to sell via private treaty, receive higher prices, consistent with Frino et al. (2010) and Hu & Lee (2020). Importantly, and new to the literature, the higher expected prices from auctions come with greater risk. The average benefit of an auction combines a 0.7% increase in price for successful auctions (relative to private treaty sales) with a 1.3% *reduction* in the price for those that fail auctions (also relative to private treaty sales). Since the overall success probability is 81.0%, auction sales do indeed bring sellers higher expected prices ($81.0\% \times 0.7\% - 19.0\% \times 1.3\% = 0.3\%$), but expose them to the 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.[2]

These baseline results are estimated off regressions with property-level fixed effects, using a sample of repeat sales (about a third of all sales), and suburb-by-time fixed effects to control for changing price levels of the surrounding area. The effects are robust to adding time- and location-varying controls for amenities like size, number of bedrooms, number of bathrooms, etc. This means that the same house that sells after a failed auction sells at a lower price (relative to other comparable nearby houses at that time) compared to the same house sold by private treaty at a different time. Failed auctions are still estimated to sell for significantly less than successful auctions even without property fixed effects, but their inclusion helps sharpen the identification.

The main alternative to auction failure having a causal effect on sale price is a selection process whereby some unobservable traits correlate with a higher chance of auction failure and a lower sales price. These could be traits of the property itself or traits of the owner. Property fixed effects rule out the most straightforward explanations based on stable property characteristics whereby certain houses are more likely to sell at auction or even fail at auction. While we control for changes in observable traits like adding another bedroom, other unobservable changes in the property (like a remodeling

[2] Hu & Lee (2020) use variation in weather and market hotness as shocks to sentiment and find a higher premium at successful auctions when sentiment is high.

that keeps the size and number of rooms the same) are harder to measure.

Another alternative is different types of sellers, which may affect various aspects of negotiation. These may include liquidity constraints or psychological differences in how they manage the sale process (but where auction failure merely correlates with these differences rather than causing a sale price decrease). By using rainfall to predict auction failure, we can rule out both concerns, as neither would plausibly be correlated with rain. Bad weather, which we measure both continuously and by focusing on large rainfalls, raises auction failure rates by more than 20 percent, compared to the unconditional rate. Consistent with this increased failure probability, auctions that occur on bad weather days receive lower prices. This approach is conceptually distinct from our baseline analysis because it does not condition on the outcome of the auctions.

Our results so far are consistent with two behavioral mechanisms, namely seller discouragement and buyer stigma. They may also arise under some versions of liquidity needs, where selling at auction or selling quickly after a failed auction may be a sign of needing a fast sale. This is neither the only way liquidity needs could work under auctions nor the simplest - an impatient seller could also reduce the risk of failure by setting a low reserve price, in which case auction failure would be associated with lower liquidity needs, not higher. Finally, the baseline results could come from omitted property traits that our fixed effects do not control for. In order to explain our results, the traits would need to both make the property worse and induce disagreement (so that buyer and seller do not simply agree on a lower price, in which case failure probability would not be unaffected). The rain instrument suggests these aspects are unlikely to be the entire explanation, but nonetheless may be contributing to the effects.

To partially distinguish between these possibilities, we examine the length of time between the auction failure and eventual sale. Under the main alternative of unobserved property characteristics, there is no clear reason to expect the effects to diminish over time. By contrast, stigma, 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. On the other hand, seller discouragement, unlike stigma, should

*worsen* as more time passes since the auction failure. Finally, 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 that the price discount from failing an auction decreases as time from failure passes. This does not support omitted characteristics as the explanation. Meanwhile, the diminishing effect over time is consistent with gradually fading stigma. It is less supportive of a seller discouragement channel, as sellers would need to be getting *less* discouraged over time, not more. Additional evidence consistent with stigma comes from the fact that delayed sales have the opposite effect for private treaties, where longer times since listing are associated with lower prices. Lacking a single event, the stigma-related perception of a failed process ought to grow over time under private treaty. The fact that the two sales types show opposite time-series patterns is also not easy to reconcile with simple liquidity explanations, as more impatient sellers would accept low offers for both types. Finally, liquidity explanations seem to imply a two-part process of setting normal or high reserve prices at auction and then caving afterward if the auction fails. But sales that occur within a day or two of a failed auction, when the need to cave ought to be the strongest, do not show significantly different prices relative to the time-decay effect. While it is hard to rule out sufficiently complicated liquidity explanations, the most obvious ones do not seem to explain our results.

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 8.2 percentage points more likely to sell just below (within $2,000) 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 to be 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 finding 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 but salient differences.

Finally, consistent with our psychology channel, the effects of auction failure are larger when the failure is more embarrassing, either due to having failed multiple auctions, or when there are no bids at all. Effects are also larger when failure is more surprising, either because it is during a hot market, or for units (which are generally more homogeneous, and thus ought to be better understood).

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 neighborhood 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 and Fortin et al. (2014) looks at the address and "lucky" versus "unlucky" numbers. Our paper provides evidence showing how traders react to each other, rather than just irrationally responding to the same underlying cues or events. The role of real estate agents is also explored in previous literature and finds there can be behavioral biases.[3] While we focus on exogenous reasons for auction failure, we also show that agent experience matters for the chances of this outcome.

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,

[3] Goldsmith-Pinkham & Shue (2023); Gilbukh & Goldsmith-Pinkham (2024); Levitt & Syverson (2008)

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. Our results also potentially explain 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.

Other papers look specifically at auction failures. For example 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. And McConnell & Saretto (2010) show in the market for auction rate securities (ARS) certain characteristics of the underlying asset can explain auction failure. In their setting the underlying securities are not unique (unlike houses) and would have a built-in cap in value, again, unlike houses.[4] Finally, we also isolate the effect of auction failure from plausibly exogenous reasons unrelated to asset fundamentals. Cortés et al. (2016) directly shows the role of weather on sentiment and we extend this logic to use rain as an instrument for auction failure.

# 2 Institutional Setting

## 2.1 Sell Side

Nearly all residential properties in Australia are sold through real estate agents. There are two primary sales methods: *Private Treaty*, where a sale is negotiated privately,

[4]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, it suggests that setting a reserve price that is 'too high' is bad for sellers.

and *Auctions*, which are discrete events where all potential bidders bid at a pre-specified location, date, and time. Determining a method of sale and setting an asking/reserve price is a collaborative effort between the seller and agent. While the seller has the ultimate say, they rely heavily on the agent's expertise based on market conditions and buyer behavior. When *auction* is chosen, the agent engages a professional auctioneer to conduct the auction.

Both methods share similar marketing strategies. In private treaty sales, buyers can place bids after attending at least one open house inspection. For auctions, the marketing campaign usually lasts for four weeks, followed by an on-premises auction.

Sellers have several avenues to enhance transparency and build buyer confidence. They generally provide a building and pest inspection report for houses or share the cost of strata reports for apartments. Sellers also engage a solicitor to prepare a contract of sale, which is shared with bidders upon request. On open house days, a seller's agent is present on the premises, displaying a contract of sale and other legal documents for visitors to inspect.

The auction, typically held at the property, is an English (Japanese Button) auction where an auctioneer increases the bid amount until only one bidder remains. If the highest bid exceeds the reserve price, the sale is binding and unconditional. Sometimes, a seller may negotiate a sale before the scheduled auction with a buyer, which we classify as a successful outcome. If not, the auction *passes in*, and the seller may negotiate with the highest bidder or attempt another sale later.[5] The auction outcome becomes public as the agent updates the listing status, and prospective buyers are informed if the property did not sell at auction.

## 2.2 Buy Side

A buyer begins by obtaining a home loan pre-approval to determine borrowing capacity and strengthen their position when making offers. Buyers can also hire a buy-side real estate agent, especially if they are time-poor, by signing an agency agreement.

[5] 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.

Like sellers, buyers engage a solicitor to review the contract of sale and ensure all disclosed information is understood.

Buyers shortlist properties based on preferred characteristics. For properties for sale, they attend at least one open house inspection, often more, and can arrange private inspections with the sell-side agent. Buyers conduct due diligence by arranging building and pest inspections, obtaining valuations, and purchasing building reports for apartments. They also share the contract of sale with their solicitor for advice on terms and conditions. These services are usually available for a small fee.

Satisfied buyers submit formal offers to the seller's real estate agent, including proposed price and conditions like subject to finance or inspection. The seller can accept, reject, or negotiate the offer, leading to potential counteroffers until an agreement is reached. Once accepted, the buyer pays a deposit (typically 10 percent of the property price) and arranges the remaining financing. The buyer's solicitor reviews the contract and ensures legal requirements, such as title search and regulatory compliance, are met.

Buying at an auction is similar to buying a property for sale, except that all due diligence must be completed before the auction. On auction day, buyers register, provide identification, and receive a bidder number. They bid in an English (Japanese Button) auction, with the highest bid above the reserve price winning. Auction sales are binding and unconditional, with no cooling-off period or additional conditions. The buyer immediately signs the contract and pays a deposit (usually 10 percent).

Post-exchange, the process is similar across both sale methods. As the settlement date approaches, the buyer conducts a final inspection to ensure the property's condition. On settlement day, the remaining purchase price is paid, and ownership is transferred.

## 2.3 Overview

The two methods of sale, private treaty, and auction, have co-existed 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). Our empirical work uses

the sample of repeat sales so we can capture property-level fixed effects; both the full sample of home sales and the repeat sales sample are reported in Figure 1.

[Insert Figure 1 Here]

Figure 2 reports the rate of sales that attempt an auction (top panel, Figure 2a) and their failure rate (bottom panel, Figure 2b) over time. Each panel graphs the rates for both the repeat sales and full samples. As shown, the auction share varies between 20% and 40% of the sales, and the auction failure rate varies over time and ranges between 10% and 40%. Notably, both series exhibit similar time series patterns for both repeat sales and full samples.[6]

[Insert Figure 2 Here]

With this empirical background, we explore key factors that determine sellers' decision-making process when choosing between auction and private treaty methods. In Panel A of Table A.1, we observe that property fixed effects, agent fixed effects, and time-varying factors at the location-property characteristics level explain a significant proportion of the variation in seller's decision to choose auction over private treaty as selling method. In Panel B, we present the incremental explanatory power from conditioning one's decision to sell via auction on fixed effects that plausibly drive the variation. Property fixed effects alone explain 62 percent of the variance in this decision. The time fixed effects contribute little, with less than 2 percent explained. In contrast, location-property characteristics account for 15 percent of the decision to sell via auction. Real estate agencies, leveraging specialized local knowledge, add an additional 5 percent. Finally, agents, who provide crucial advice to sellers, contribute an increment of 10 percent. Overall, our empirical findings align with conversations with sellers and agents and popular press that highlight the role of property, local market conditions, and agent expertise in influencing the decision to sell via auction or private

[6]We report the figures without January, when real estate markets become very thin as many take a vacation. In our regression models below, we include all months, but we also estimate those models without the small number of January transactions and find similar results.

treaty. In total, these factors explain 93 percent of the variation in sellers' choice of the method of sale, suggesting that seller-specific effects have a limited influence on our results via selection.

For auctions, 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% of cases (81% for the repeat sales sample), a property sells successfully at its first auction. Of these, almost two-thirds are sold under the hammer, meaning that the highest bid exceeded the seller's reserve price at the auction. In others, the property sells by negotiation before the scheduled auction. We consider both cases as successful auctions. In 17% of the cases (19% for repeat sales), 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%), 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.[7] Our sample of properties initially listed for an auction and a private treaty is 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 utilities, and is one of the brands owned by the Domain Group.[8] Our data capture all (eventually) successful real estate transactions in both Australian states. Because we observe each property's street address, we are able to identify the sample of repeat sales and absorb property fixed effects in our subsequent models.

[7] 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% 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 six Australian states, our sample captures a significant fraction of real-estate auction activity in Australia.

[8] 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.

We subdivide the data in two ways. First, we split transactions into those listed under auction and those listed as private treaties. Second, we split transactions initially listed at auction into two categories: (1) initial auctions that succeed under the hammer or sell via negotiation before the auction; (2) initial auctions that fail and sell subsequently in a successful auction or 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 versus failed auctions.

For each panel, we report summary statistics for the repeat sales sample and what we call the 'identifying sample'. This latter group drops repeat sales in which the property was sold always from auction or always under private treaty. We do this because these observations do not contribute to identification due to the presence of the property-level fixed effect.

[Insert Table 1 Here]

Overall, about one-fourth of all sales in New South Wales and Victoria starts with an attempted auction. Amenities are similar 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 about 2.92 bedrooms and 1.57 bathrooms; properties initially listed for a private treaty have an average of 2.97 bedrooms and 1.58 bathrooms. Despite this, the private treaty properties are substantially larger than those sold at auction; conversely, the private treaty properties sell for much lower prices. These difference occur because auctions rarely happen in areas with low population density, for example. However, as the last four columns of the table show, the price difference narrows substantially in the identifying sample, which includes only properties which are sold under both methods.

Table 1 also includes statistics for time-to-sale. For this variable, we code successful auctions as having zero time-to-sale since the property sold exactly when desired by the seller. For failed auctions, time-to-sale equals the number of months between the auction failure date and the ultimate sale. For private treaties, time-to-sale equals the

number of months from the listing date to the sale date.[9] Comparing sale methods, the time-to-sale is much shorter for auctions, suggesting that speed and certainty are key motivating factors for sellers opting to use auctions. Even for failed auctions, the time-to-sale averages 1.62 months, compared to more than 2.0 months for private treaties.[10]

Figure 3 reports a simple comparison of how the average (log) price differential between homes that attempt an auction and those that do not varies with the auction failure rate.[11] 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 = -0.42; $R^2$ = 43.1%), which is significant at the 1% 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 time series 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 3.1 bedrooms, compared to 2.9 bedrooms for successful auctioned properties. However, despite the higher amenities, properties that fail an auction sell on average for about $80,000 less (log price of about 0.1 less).

## 3.2 Method and Results

We start with three core models. First, we report OLS/fixed effects 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. These

[9] We drop transactions with time-to-sale greater than 500 days, which constitutes less than 1% of the sample.

[10] If we code time-to-sale as the difference between the listing date and the sale date for both types, auctions sell in 1.1 months on average (including both failed and successful auctions), still much lower than that observed for private treaty sales.

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

models always include property-level fixed effects. Second, we report models for properties that began at auction and model a failure indicator as the outcome. This model represents a 'first-stage' in which we show that the likelihood of failure increases as the weather deteriorates. Third, we link our proxies for bad weather to prices to identify the causal effect of failing an auction on transaction prices. These last two approaches constitute an alternative way to deal with unobserved heterogeneity; they are distinct from the first approach by not conditioning on the actual outcome of the auction.

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, $\beta_1$ measures the difference in prices between successful auctions relative to private treaty sales; $\beta_2$ 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 beyond property fixed effects, we include as a baseline suburb-by-time fixed effects to control for overall changes in the price level in the suburb over time. Property fixed effects obviate the need for detailed property characteristics controls since most will be fixed for the property. Nonetheless, in subsequent specifications, we include additional interactions of property characteristics

with our baseline suburb-by-time controls. We include property amenities like 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. By including these as interactions with suburb-by-time fixed effects, we not only allow for explicit amenity controls (in case amenities are changing within a property over time) but also allow for finer time controls (for instance, apartments/units in a given suburb have a different price path than houses). Adding these controls also 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).

Table 2 reports results for estimating equation (1), where our coefficient of interest is $\beta_2$, the pricing discount from a failed auction. We report the model with various sets of fixed effects, with the last column having the tightest specification. Here, we see that properties that list and sell successfully at auction receive prices about 0.72% higher than those listed as a private treaty (column (5)). This coefficient estimate has a large statistical significance. The model suggests that failed auctions sell for 1.98% lower prices than successful auctions overall and about 1.26% (=0.72-1.98) lower than properties listed under private treaty.

[Insert Table 2 Here]

The incremental effect of failing an auction varies only modestly as we expand the granularity of the fixed effects (moving from column (1) to (5)), suggesting that the combination of property and suburb-time fixed effects controls for much of the important variation in price (as seen in the baseline high $R^2$ in column (1) of 0.98). This finding also suggests that neither more granular time-by-location nor more amenity controls greatly impact the estimated effect of auction failure. To the extent that the coefficients vary across specifications, column 5 (with the most controls) has the largest point estimate.

[Insert Figure 4 Here]

One concern with the identification may be that property characteristics themselves vary over time. However, as shown in Figure 4, the observable characteristics (area, bedrooms, and bathrooms) of properties that sell via private treaty and auction over the sample period overlap significantly as the distributions are nearly identical. Random variation would pose no concerns, but if changes in amenities are systematically related to auction outcomes, then the property fixed effects may not go far enough. To assess this possibility, we have re-estimated these models with two alternative data subsets. First, we drop the properties that first sell under a private treaty and later attempt an auction (about 25,000 transactions); second, we drop the reverse cases - properties that first attempt an auction and later sell under a private treaty (about 36,000 transactions). If one were concerned that our results were arising because sellers were more likely to attempt an auction after improving their property (or conversely after it had declined in quality), then dropping each sample should show different estimated effects of auction failure. Instead, these models give very similar estimates for the failure discount (roughly 2%), as shown in Appendix Table A.2.

Oster (2019) suggests another way to assess the scope for omitted variables bias. She shows that the coefficient of interest ($\beta_2$ 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 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 $\delta$, 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 (5) of Table 2, the scope for omitted variables bias thus equals the following expression:

$$\begin{aligned}(\beta_2^{\text{Saturated}} - \beta_2^{\text{Unsaturated}}) \times \frac{1 - R^2_{\text{Saturated}}}{R^2_{\text{Unsaturated}} - R^2_{\text{Saturated}}} \times \delta = \\ (-0.0174 - (-0.0198)) \times \frac{1 - 0.9912}{0.9816 - 0.9912} \times 1 = 0.0022\end{aligned} \tag{2}$$

The estimate in equation (2) suggests a very limited role for unobservable variables to play in explaining our baseline result.

Do these effects represent selection? Most of the decision to sell a property at auction versus private treaty, as we explain in Section 2.3, stems from property, neighborhood, and market conditions (recall Table A.1). We capture all these effects with time-varying fixed effects in our core models. Nevertheless, differences in seller characteristics (which are unobservable), such as the desire for a fast sale, may raise selection concerns in interpreting how auction failures affect prices. To eliminate this possibility, we report the models from Table 2 without the private treaty transactions (see Table A.3). Because these regressions include property-level fixed effects, identification comes only from those repeat sale observations with (at least) one auction failure and one success – that is, properties in which both sellers chose to attempt an auction. This comparison suggests auction failure reduces prices by 1.4-1.6% (columns (4) and (5)), consistent with our argument. These effects are slightly smaller than the analogous ones from Table 2.

Finally, it is worth emphasizing that while our sample is 480K observations, the effective sample size for identifying the effects of auction failure is the smaller identifying sample of just under 120K observations that sell at least once under both methods. The remaining observations are useful, however, for estimating the controls in the equations. This is especially important when using fine combinations of interacted fixed effects, where the number of properties included in each bin ends up being a binding constraint on how fine these fixed effects can be. As a result, the additional observations help sharpen the identification strategy, even if they are not directly used to identify auction failure itself.

#### 3.2.2 Establishing Causality: Auctions that Fail due to Bad Luck

Auction failures occur when the seller's reserve price exceeds the maximum amount bid, which in turn depends on both the quality of the property as well as the number and disposition of bidders. So, auctions could fail if the seller over-values the property and sets an unrealistic reserve price. Or, auctions may fail if very few bidders arrive, or

if those who do arrive bid tepidly. If auctions fail because bidders (or bidder behavior) reveals something wrong with the property, however, our preferred interpretation would be invalid. For these endogeneity problems 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/or (2) sellers would 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 because sellers inherently know more than buyers (they have been living in the property), and because potential buyers have symmetric access to the common information (unlike many other settings).

To allay these concerns, however, we explore a setting in which auctions fail due to mere bad luck, based on variation in weather near the property. Poor weather can affect auction outcomes most directly by reducing the number of bidders who attend the auction.[12] In addition, bad weather has been shown to reduce sentiment and thus may lead a given number of bidders to bid less aggressively (Cortés et al., 2016). Both of these effects will raise the likelihood of auction failure, but neither is plausibly related to either a seller's or buyers' revisions in their subjective valuation of a given property. As such, if we see a property failing an auction due to bad weather, there is no reason why it ought to sell at a discount in a future transaction, unless the failure itself lowers that future price (our interpretation).

This discussion motivates an empirical specification, which first links auction failure to rainfall during the auction, and second links rainfall during auctions to pricing outcomes. Hence, we first report models with the following structure:

$$\text{Auction Failure}_i = \beta_1 \text{Rainfall}_i + \text{Fixed Effects} + \epsilon_i \tag{3}$$

Where equation (3) contains all transactions that initially attempt an auction. We

[12] In our analysis, we focus solely on auctions that were held and either succeeded or failed, thereby excluding any potential endogeneity related to auctions withdrawn due to anticipated rainfall. Moreover, the costs associated with holding an auction are typically non-refundable, which incentivizes sellers to proceed as scheduled.

capture rainfall with a continuous variable that equals Ln(1+rainfall in millimeters) or with a discrete indicator that equals one if rain exceeds 8 millimeters, which represents the upper $90^{th}$ percentile of the rainfall distribution. Next, we use all transactions and link the two rainfall measures to pricing outcomes, distinguishing between properties which attempt an auction with those that do not (i.e., with private treaty transactions). These reduced-form models take the following form:

$$\begin{aligned} \ln P_i = &\beta_1 \text{Listed For Auction}_i + \beta_2 \text{Rainfall}_i + \\ &\beta_3 \text{Listed For Auction}_i \times \text{Rainfall}_i + \text{Fixed Effects} + \epsilon_i \end{aligned} \tag{4}$$

We report these models in reduced form, rather than as a 2SLS model because auction failure is only possible for properties that attempt an auction in the first place (unlike those sold initially under the private treaty); we need to keep the private treaty observations in order to have a sufficient number of repeat transactions. Hence, we allow the effect of rainfall to differ, depending on whether or not an auction was attempted. The idea is to test whether rainfall matters only for properties that attempt an auction since these are the ones that face the risk of a discrete failure. Private treaty negotiations occur over an unspecified period of time and, hence, are not subject to the risk of unusually bad weather. As such, we expect $\beta_3$ to be negative, while $\beta_2$ ought to have no effect on pricing. The key advantage to this approach, relative to the results in Table 2, is that we do not condition on the outcome of the auction and, thus, are also not conditioning on any endogenous factors that auction failure may be associated with.

To measure precipitation, we use data from the National Oceanic and Atmospheric Administration (NOAA), whose Physical Sciences Laboratory maintains a library of gridded datasets. We use the CPC Global Unified Gauge-Based Analysis of Daily Precipitation, which provides daily mean precipitation with a grid size of 0.5-degree latitude x 0.5-degree longitude. Using shapefiles of Australian postcodes sourced from the Australian Bureau of Statistics, we map these grids into a polygon (each representing the map of a unique Australian postcode) and estimate the daily mean precipitation.

This procedure yields a daily time series of mean precipitation for all postcodes in our sample. We follow Met Office UK's classification of very heavy rain if the daily average precipitation amount is at least 8 millimeters. To map the rainfall by location-day into our transactions, we use the day of the (first) auction for all properties which attempt one, and we use the sale date for each private treaty transaction. For successful auctions, this auction date matches the sale date. However, for auctions that fail, this date corresponds to when the auction failed, as the actual sale happens later.

Table 3 reports estimates for equation (3); each of these models provides strong evidence that bad weather raises the odds of an auction failure. We report the models with property fixed effects, as in our baseline regressions, and vary the level of time-varying fixed effects. Since weather patterns vary across space, the models that include the full set of fixed effects return substantially better overall model fit, and these results yield a large quantitative effect of rain on failure. For example, the indicator variable model implies that high levels of rain increase the probability of failure by 4.39 percentage points, which is a 23% increase relative to the unconditional probability of failures (=19% - recall Table 1).

Table 4 shows that the higher likelihood of failure during rain leads to lower sale prices. While the direct effect of both the continuous and discrete measures has no pricing effects, rainfall during auctions leads to lower prices because bad weather raises the likelihood of failing the auction. Using the indicator variable model, high levels of rain are associated with about a 1% decline in the expected sales price, with very strong statistical significance. The effect is much larger in the model which controls for location by amenity by time fixed effects, which makes sense because these effects remove 'normal' weather variation from our measures. Areas that normally experience high levels of rain during, say, two or three months during the year would not be experiencing an adverse weather shock, for example.

Appendix Table A.4 provides another way to use rainfall to establish a causal effect of auction failure on property prices. Here, we return to the OLS/Fixed effects framework of Table 2 and simply leave out those transactions most likely to be related

to endogenous auction outcomes. To be specific, we first leave out failed auctions that occur on non-rainy days - that is, days in which rainfall is less than 8mm on the auction date (columns (1) and (2)). These are failures that are, in a sense, most surprising and thus most likely to be related to idiosyncratic (or errant) decisions by the seller. Second, we leave out successful auctions that occur on days with heavy rainfall (columns (3) and (4)) - again, a set of outcomes that seem likely to be due to mis-valuation by the seller. In both of these tests, the estimated effect of auction failure is negative and significant, with a somewhat larger magnitude (i.e., more negative) than what we estimated in the base model.

#### 3.2.3 What is the mechanism?

We have established that auction failures reduce prices and that this effect comes from non-fundamental factors. Three mechanisms could explain the effect. First, sellers who choose to list at auction may place an especially high premium on the speed of sale; such sellers may be more liquidity constrained than sellers choosing private treaty. As noted before, auctions sell faster than private treaty sales, even after an auction fails. Second, seller discouragement after failing an auction could limit their subsequent willingness to bargain or hold out for the highest price. Third, buy-side stigma may reduce the willingness to pay for a property after the public and embarrassing auction failure.

To help separate the effects of the buy-side stigma of an auction failure from sell-side discouragement and liquidity, we focus on the amount of time that has passed since the bad news (auction failure). For instance, Martel (2018) presents a model in which both sellers and buyers are unaware of an asset's true quality, with buyers receiving noisy signals upon inspection that influence purchasing decisions, resulting in a negative relationship between time-on-market and sale price and yielding simple, closed-form expressions for beliefs, prices, and rates of sale. In our setting, a seller is likely to be aware of a property's quality. However, stigma ought to fade with time as new buyers enter 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) by introducing time-to-sale as an additional explanatory variable. Because we combine properties listed for auction with those listed for private treaty, we can compare the effect of time-to-sale for the two listing types. In general, the impact of waiting time on pricing is complicated because it captures several effects. First, more patient sellers may fetch better prices because they are more likely to find the buyer with the highest willingness to pay. Second, waiting longer can generate stigma, as buyers observe that a property has been on the market for many months. The direct effect of time-to-sale can capture these effects. Hence, we can isolate the unique effect of auction failure with the interaction term as follows:

$$\begin{aligned} \ln P_i = &\beta_1 \text{Listed For Auction}_i + \beta_2 \text{Failed Auction}_i + \beta_3 \text{Time-to-Sale}_i + \\ &\beta_4 \text{Time-to-Sale}_i \times \text{Listed for Auction}_i + \text{Fixed Effects} + \epsilon_i \end{aligned} \tag{5}$$

Table 5 reports estimates of several variants on equation (5). 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 5, auctions that fail more than once receive even lower prices, by an additional 1.8% percent over that of single failed auction cases. Failed auctions that receive no bids receive lower prices by a bit less than 1.7%.

[Insert Table 5 Here]

The last three columns of Table 5 include time-to-sale, first by itself (column (3)), and then interacted with the auction failure indicator (columns (4) and (5)). Recall that this variable is coded as zero for the set of successful auctions since these properties sold on the 'optimal' day from a seller's point of view. The results show a sharp difference in the effect of time-to-sale for failed auctions. Unlike private treaty listings, for which price declines in time-to-sale, auction listings that fail an auction exhibit an increase in

price as more time elapses since auction failure. These results strongly support stigma but are hard to square seller discouragement, which would seem to increase, rather than diminish, over time. The regression shows not only that time-to-sale matters differently (more positively) for auction failures compared to private treaties but also that the total effect of waiting is positive, as the sum of the two coefficients is positive (=-0.0011+0.0022 = +0.0011). What about liquidity effects? We test for a 'fire sale' effect in column (5), where we add an indicator variable set to 1 for failed auctions that sell on the day of (typically Saturday) or the day after the auction has failed. This additional indicator suggests no such effect, as it signs positively. (In Section 3.2.6 below, we discuss liquidity effects in more detail.)

[Insert Figure 5 Here]

#### 3.2.4 Robustness Tests

We explore heterogeneity across property types and market conditions to establish the robustness of our core OLS/fixed effects results. 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 price trends have been strong).[13] Next, we distinguish apartments/units from other property types. Due to their relative homogeneity, apartments/units tend to be well understood by buyers and sellers and thus are less likely than other properties to fail at auction.[14] The psychological effects of failing an auction ought to matter most when auctions are most likely to succeed since a failure is especially salient in such a case. Hence, the failure discount would tend to be highest in hot markets and for apartments/units, both with auction failure rates below the unconditional average.

[Insert Table 6 Here]

[13] 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-month triplet is below the cross-sectional median value.

[14] Among *for auction* listings, on average, apartments/units fail auctions around 16.9% of the time, versus 19.6% of the time for houses.

Overall, the results in Table 6 indicate a substantial failure discount across all market conditions and property types, consistent with our earlier results. This discount, however, is larger when markets are booming, as the interaction between failure and market condition is negative and significant (column (1)). In the models estimated separately for units versus houses, the failure interaction is negative in both cases, but more so and only significantly for units. These results also suggest substantially higher price premiums for successful auctions when markets are hot. In fact, there is no premium (even a small discount) for successful auctions during non-hot markets (first row, columns (1) and (2)). In hot markets, both the upside (success) and the downside (failure) from auctions increase.

#### 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, as shown in Figure 6a, home sales cluster around increments of $50,000 (Backus et al., 2015). 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 6 Here]

We consider this question in Figure 6b 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 column (1), we consider only being $1,000 above or below, and in columns (2) through (5), we examine larger increments of $2,000 through $5,000. The dependent variable is

an indicator 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 and auction failure indicators, with the private treaty as the comparison group. Figure 6b reports the effect most simply, plotting the raw data. As in the earlier regressions, we control for year-month and the interactions of property characteristics and year fixed effects.

[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. The effect varies with the threshold. We prefer the specification using a $2,000 cutoff, which gives a large enough sample to pin down the fixed effects but does not get too close to other possible salient cutoffs (such as increments of $5,000). For prices within $2,000, auction failure is associated with a 21.4% higher probability of being just below the threshold compared to successful auctions. Compared to private treaties, failed auctions fall below the salient thresholds about 8.2% 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 that are less obviously 'just below' or 'just above' round numbers.

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 8, we perform 100 versions of the same regressions as columns (2) of Table 7, replacing the $50,000 threshold with different values ranging from $1,000 to $100,000 (studying increments of $2,000 on either side of each threshold). 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 8 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, if slightly informal, test of the importance of round numbers versus others. We report the ten largest coefficients in Table 8. All but one of them are round numbers – 10, 20, 35, 50, 60, 70, 75, 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 and 8 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, leading dis-spirited sellers to accept this outcome. Thus, the evidence points towards auction failure having considerable psychological effects, not just economic ones.

# 4 Discussion: Can selection explain our results?

Can selection explain our results in the absence of stigma? The most likely way involves a combination of liquidity needs, heterogeneity across sellers, and rule-of-thumb behavior. First, because they sell faster, auctions may be chosen by people who need to sell quickly. Such a simple model would not obviously generate our results,

because a seller who is especially constrained on time can increase the likelihood of a sale by setting a low reserve price. As a result, if going to an auction indicates a liquidity-based need to sell quickly, there must be some other reason why the reserve price is set too high (at least ex-post). Indeed, the ability to set a low reserve price as an additional lever for a liquidity-constrained seller complicates a lot of liquidity-based explanations (it does not make them impossible, or even implausible, but liquidity alone is not a parsimonious explanation).

One additional ingredient could be from overestimating the value of the house. On its own, this would explain auction failure, but would not explain why the house subsequently sells for a value that is too-low relative to similar houses. In other words, if the only drivers of responses after failure were informational, there would also need to be an overreaction to the failure of the auction (e.g., stigma), rather than just a reversion to the correct level. Meanwhile, there would need to be an additional source of heterogeneity to explain why the houses that sell quickly after a failed auction do so at much lower prices, whereas those that wait longer sell at higher prices. If the main response is information-driven from the failed auction, this prediction is difficult to generate without additional model components.

A more plausible version posits a two-part process where liquidity-constrained investors also care about the price at which they transact in a more complicated way. In this possibility, they first "shoot for the moon" by setting a high reservation price, hoping for optimistic bidders. Then, they plan to hold out for another day or two even after a failed auction hoping for a high price, but then plan to cave and sell at a more reasonable price, or even a discount, after this time. They must implement this two-part plan whether the auction fails due to bad weather, or fails for other reasons.

The two-part selling strategy seems more consistent with a rule-of-thumb heuristic, rather than an optimal equilibrium bidding strategy. The reason is that it generates additional variance in sales price, relative to setting a more moderate initial reserve price and having a lower chance of auction failure. It is possible that particular assumptions about the distribution of buyers might make it optimal in certain circumstances, but it

is not clear what these would be.

But if such a strategy occurs, it would potentially explain the baseline facts – choosing to list in a format that generally sells quicker, then selling at a discount if the auction fails. Meanwhile, there is an additional component needed to explain the variation over time after the auction failure – why some people cave quickly, while others wait and sell at a higher price. This could be because the ones who sell later are more patient, and willing to wait for a higher price. This combined version of investors who are liquidity constrained, but heterogeneously so, and who use a two-part selling heuristic, is also consistent with our results. The number of model components makes it less parsimonious, but given the assumptions, it is difficult to rule out.

Finally, the differences around round numbers suggest a willingness to concede over small price differences. This form of demoralization could occur separately from the liquidity channel – while caring about round numbers suggests a behavioral part of the price-setting process, it is not sharply tied to stigma to the exclusion of other theories.

Generating a full equilibrium explanation of why some sellers choose auctions and others do not is complicated by the fact that this dual system is rather unusual in a global sense. That is, if the facts to be explained are broadened to include the question of why Australian housing markets are structured so differently to other Western countries and why there is further variation across states in Australia, then it is less clear what economic forces drive these differences. In most other economic respects, Australian homes and home buyers do not look especially different from those in other countries. One answer for the existence of different selling forms is a form of historical path-dependence and familiarity. That is, auctions had a history in the early colonial days of Melbourne due to wool sales, and an initial level of familiarity with it in one setting grew into a more common practice elsewhere in housing that persists today, but one whose frequency varies by state and even by suburb. This kind of path-dependence has been argued to hold in other financial settings, such as the design of market indices in Hartzmark & Solomon (2022), even when economically superior alternatives are available. The current setting is less of a stretch for positing a partial form of path-

dependence, because the two selling forms have different economic consequences such that neither one clearly dominates the other, as we describe.

Finally, our results also raise a number of possible angles for future research regarding the impact of fear of social failure on 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), but 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,[15] the negative perception of having to pull an IPO, or even just 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 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 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

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

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 which ultimately lowers prices. It is worse for repeated failures and failures featuring no 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 failures due to mere bad luck lead to low subsequent prices. Stigma – the vague sense that perhaps there might be something wrong with the property -– can explain our findings. Our results raise the possibility that willingness to pay may have a larger socially determined component than previously thought.

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Table 1: **Summary Statistics**

This table presents summary statistics of key variables for the repeat sales sample. In Panel A, we divide the complete sample into two types of selling methods. '*Auctions*' is the set of properties initially listed for sale via *Auction*. '*Private Treaties*' is the set of properties initially listed for sale via *Private Treaty*. In Panel B, we present summary statistics for the Auctions 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. '*Failed Auction Indicator*' equals 1 if a property listed *For Auction* records either *Passed-In* or *No Bids* type event before clearing the market. '*Time to Sale*' is defined as the difference between the sale date and listing (auction failure) date for a private treaty (failed auction) sample. '*Time to Sale*' equals 0 for successful auctions sample. The number of observations differs for the '#' marked variables. The sample period spans 13 years, starting in 2007:M1 and ending in 2019:M12.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | **Repeat Sales Only** | | | | **Identifying Sample** | | | |
| **Panel A** | | | | | | | | |
| | **Auctions** | | **Private Treaty** | | **Auctions** | | **Private Treaties** | |
| | N = 129,019 | | N = 351,446 | | N = 58,451 | | N = 61,477 | |
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| Selling Price (in AUD '000s) | 877 | 498 | 586 | 352 | 808 | 459 | 703 | 437 |
| Ln Selling Price | 13.54 | 0.52 | 13.16 | 0.47 | 13.46 | 0.52 | 13.32 | 0.51 |
| Ln(1+Precipitation) | 0.58 | 0.90 | 0.62 | 0.92 | 0.62 | 0.92 | 0.59 | 0.89 |
| Rain (1 = Yes, 0 = No) | 0.09 | 0.29 | 0.08 | 0.28 | 0.09 | 0.28 | 0.08 | 0.27 |
| Ln(Area) | 6.34 | 0.83 | 6.63 | 0.86 | 6.43 | 0.85 | 6.46 | 0.85 |
| Number of Bedrooms | 2.92 | 0.91 | 2.97 | 0.92 | 2.91 | 0.88 | 2.92 | 0.88 |
| Number of Bathrooms | 1.57 | 0.64 | 1.58 | 0.61 | 1.57 | 0.62 | 1.57 | 0.63 |
| Failed Auction (1 = Yes, 0 = No) | 0.19 | 0.39 | 0.00 | 0.00 | 0.22 | 0.41 | 0.00 | 0.00 |
| Time to Sale (in Months)$^{\#}$ | 0.31 | 1.06 | 2.12 | 2.67 | 0.35 | 1.13 | 2.26 | 3.15 |
| **Panel B** | | | | | | | | |
| | **Failed Auctions** | | **Successful Auctions** | | **Failed Auctions** | | **Successful Auctions** | |
| | N = 24,444 | | N = 104,575 | | N = 12,612 | | N = 45,839 | |
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| Selling Price (in AUD '000s) | 810 | 480 | 893 | 500 | 744 | 442 | 825 | 463 |
| Ln Selling Price | 13.46 | 0.53 | 13.57 | 0.52 | 13.38 | 0.52 | 13.49 | 0.51 |
| Ln(1+Precipitation) | 0.67 | 0.97 | 0.61 | 0.91 | 0.66 | 0.96 | 0.61 | 0.91 |
| Rain (1 = Yes, 0 = No) | 0.11 | 0.31 | 0.09 | 0.28 | 0.10 | 0.31 | 0.08 | 0.28 |
| Ln(Area) | 6.40 | 0.82 | 6.32 | 0.83 | 6.49 | 0.85 | 6.42 | 0.85 |
| Number of Bedrooms | 3.10 | 0.94 | 2.87 | 0.90 | 3.07 | 0.90 | 2.87 | 0.87 |
| Number of Bathrooms | 1.67 | 0.66 | 1.55 | 0.63 | 1.66 | 0.64 | 1.55 | 0.62 |
| No Bid | 0.04 | 0.20 | 0.00 | 0.00 | 0.04 | 0.20 | 0.00 | 0.00 |
| Failed Auction Multiple Times | 0.01 | 0.12 | 0.00 | 0.00 | 0.01 | 0.11 | 0.00 | 0.00 |
| Time to Sale (in Months)$^{\#}$ | 1.62 | 1.96 | 0.00 | 0.00 | 1.61 | 1.96 | 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. 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. 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) |
|---|---|---|---|---|---|
| | Dependent Variable: Ln(Selling Price) | | | | |
| 𝟙.Listed For Auction | 0.0061*** | 0.0050*** | 0.0073*** | 0.0091*** | 0.0072*** |
| | (5.3286) | (4.5343) | (6.5479) | (7.6716) | (5.4208) |
| 𝟙.Failed Auction | -0.0174*** | -0.0149*** | -0.0183*** | -0.0211*** | -0.0198*** |
| | (-10.9719) | (-10.6942) | (-12.8222) | (-14.2586) | (-13.3176) |
| $R^2$ | 0.9816 | 0.9835 | 0.9870 | 0.9895 | 0.9912 |
| N | 480,465 | 480,465 | 480,465 | 480,465 | 480,465 |
| Property FE | Yes | Yes | Yes | Yes | Yes |
| Suburb×Year FE | Yes | No | No | No | No |
| Suburb×Property Type×Year FE | No | Yes | No | No | No |
| Suburb×Property Type×Bedrooms×Year FE | No | No | Yes | No | No |
| Suburb×Property Type×Bedrooms×Bathrooms×Year FE | No | No | No | Yes | No |
| Suburb×Property Type×Bedrooms×Bathrooms×Area Group×Year FE | No | No | No | No | Yes |
| Year×Month FE | Yes | Yes | Yes | Yes | Yes |

Table 3: **Auction Failures and Local Weather**

This table presents the results of a linear probability model linking auction failures and local weather. The dependent variable is a dichotomous variable that equals 1 if a property failed to sell at its initial auction and equals 0 otherwise. *Rain* is a dichotomous variable that equals 1 if the daily total surface precipitation is at least 8 millimeters and equals 0 otherwise. 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) |
|---|---|---|---|---|
| | Dependent Variable: Failed Auction \| For Auction Listing (1 = Yes, 0 = No) | | | |
| Ln(1+Precipitation) | 0.0080*** | | 0.0162*** | |
| | (3.0141) | | (3.7184) | |
| 𝟙.Rain | | 0.0261*** | | 0.0439*** |
| | | (2.7560) | | (2.8688) |
| $R^2$ | 0.5392 | 0.5394 | 0.7813 | 0.7818 |
| N | 66,198 | 66,435 | 66,198 | 66,435 |
| Property FE | Yes | Yes | Yes | Yes |
| Suburb×Property Type×Bedrooms×Bathrooms×Area Group×Year FE | No | No | Yes | Yes |
| Year×Month FE | Yes | Yes | Yes | Yes |

Table 4: **Prices and Local Weather – Auctions Versus Private Treaty Sales**
This table presents results linking property prices with local weather. The dependent variable is the log of the selling price of a property. *Rain* is a dichotomous variable that equals 1 if the daily total surface precipitation is at least 8 millimeters and equals 0 otherwise. 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) |
|---|---|---|---|---|
| | Dependent Variable: Ln(Selling Price) | | | |
| 𝟙.Listed For Auction | 0.0125*** | 0.0120*** | 0.0043*** | 0.0033*** |
| | (5.8750) | (5.8786) | (3.2722) | (2.6172) |
| Ln(1+Precipitation) | 0.0008 | | 0.0003 | |
| | (1.2822) | | (0.9390) | |
| 𝟙.Listed For Auction×Ln(1+Precipitation) | -0.0017* | | -0.0030*** | |
| | (-1.8281) | | (-4.7101) | |
| 𝟙.Rain | | 0.0029* | | 0.0008 |
| | | (1.7149) | | (0.8959) |
| 𝟙.Listed for Auction×𝟙.Rain | | -0.0047* | | -0.0098*** |
| | | (-1.7454) | | (-5.1640) |
| $R^2$ | 0.9724 | 0.9724 | 0.9912 | 0.9912 |
| N | 479,632 | 480,465 | 479,632 | 480,465 |
| Property FE | Yes | Yes | Yes | Yes |
| Suburb×Property Type×Bedrooms×Bathrooms×Area Group×Year FE | No | No | Yes | Yes |
| Year×Month FE | Yes | Yes | Yes | Yes |

Table 5: **Selling Price, Auction Failure and 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. '*Time to Sale*' is defined as the difference between the sale date and listing (auction failure) date for a private treaty (failed auction) sample. '*Time to Sale*' equals 0 for successful auctions 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) |
|---|---|---|---|---|---|
| | Dependent Variable: Ln(Selling Price) | | | | |
| 𝟙.Listed For Auction | 0.0071*** | 0.0072*** | 0.0052*** | 0.0051*** | 0.0051*** |
| | (5.4130) | (5.4559) | (3.9635) | (3.8268) | (3.8284) |
| 𝟙.Failed Auction | -0.0195*** | -0.0192*** | -0.0183*** | -0.0215*** | -0.0215*** |
| | (-13.0991) | (-12.5953) | (-12.3088) | (-12.2752) | (-12.0183) |
| 𝟙.Multiple Auction Failure | -0.0175* | | | | |
| | (-1.8372) | | | | |
| 𝟙.No Bid | | -0.0169*** | | | |
| | | (-2.7079) | | | |
| Time To Sale | | | -0.0010*** | -0.0011*** | -0.0011*** |
| | | | (-8.8182) | (-9.4338) | (-9.4333) |
| 𝟙.Failed Auction×Time To Sale | | | | 0.0022*** | 0.0022*** |
| | | | | (3.3950) | (3.3134) |
| 𝟙.Failed Auction × 𝟙.Time To Sale$_{\text{Day 0 or 1}}$ | | | | | 0.0010 |
| | | | | | (0.1927) |
| $R^2$ | 0.9913 | 0.9913 | 0.9913 | 0.9913 | 0.9913 |
| N | 480,465 | 480,465 | 477,381 | 477,381 | 477,381 |
| Property FE | Yes | Yes | Yes | Yes | Yes |
| Suburb×Property Type×Bedrooms×Bathrooms×Area Group×Year FE | Yes | Yes | Yes | Yes | Yes |
| Year×Month FE | Yes | Yes | Yes | Yes | Yes |

Table 6: **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-month is below its median value for that year-month. The sample period starts in 2007:M1 and ends in 2019:M12. To correctly estimate the differential effect of listed for auction and auction failure in hot relative to not-hot markets, all fixed effects are also interacted with the hot market indicator variable. 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) |
|---|---|---|---|
| | Dependent Variable: Ln(Selling Price) | | |
| | Property Type | | |
| | All | Houses | Units |
| 𝟙.Listed For Auction | -0.0067** | -0.0063* | -0.0098* |
| | (-2.3161) | (-1.9704) | (-1.9650) |
| 𝟙.Failed Auction | -0.0104*** | -0.0111*** | -0.0036 |
| | (-3.4580) | (-3.3108) | (-0.6941) |
| 𝟙.Listed For Auction × 𝟙.Hot Market | 0.0195*** | 0.0194*** | 0.0218*** |
| | (5.4459) | (4.6419) | (3.9853) |
| 𝟙.Failed Auction × 𝟙.Hot Market | -0.0080* | -0.0042 | -0.0202*** |
| | (-1.9403) | (-0.8685) | (-3.0588) |
| $R^2$ | 0.9921 | 0.9921 | 0.9919 |
| N | 480,465 | 353,187 | 127,278 |
| Property FE | Yes | Yes | Yes |
| Suburb×Property Type×Bedrooms×Bathrooms×Area Group×Year FE | Yes | Yes | Yes |
| Year×Month FE | 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), and (5), respectively. '*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. 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.

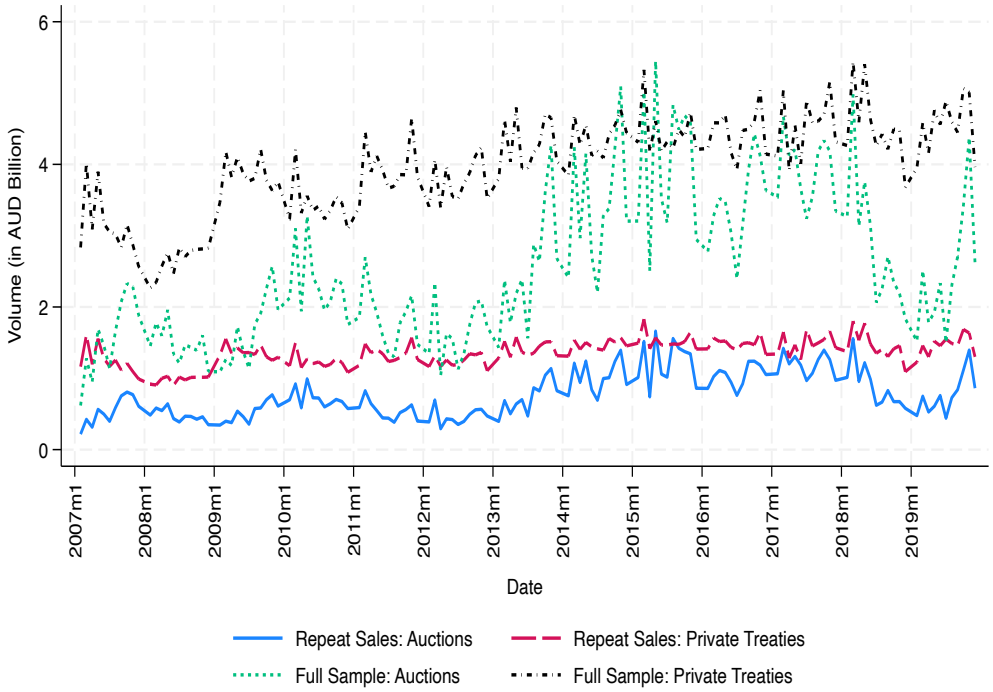
| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Dependent Variable: Below x50K | | | | |
| 𝟙.Listed For Auction | -0.2160*** | -0.1323*** | -0.0759*** | -0.0550*** | -0.0535*** |
| | (-3.6539) | (-4.5398) | (-3.1743) | (-2.6345) | (-5.6341) |
| 𝟙.Failed Auction | 0.0811 | 0.2139*** | 0.1278*** | 0.0871*** | 0.0731*** |
| | (0.8519) | (3.9455) | (2.9504) | (2.6813) | (4.0128) |
| $R^2$ | 0.6597 | 0.5126 | 0.4502 | 0.4290 | 0.3472 |
| N | 7,905 | 17,394 | 24,902 | 29,556 | 74,623 |
| Suburb×Property Type×Bedrooms×Bathrooms×Area Group×Year FE | Yes | Yes | Yes | Yes | Yes |
| Year×Month FE | Yes | Yes | Yes | Yes | Yes |
| Threshold around ×50K | ±1K | ±2K | ±3K | ±4K | ±5K |

Table 8: **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×Property Type×Bedrooms×Bathrooms×Area Group×Year, 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 | 60 | 0.3381** | (2.6074) | 8,081 | 0.5581 |
| 2 | 75 | 0.2770** | (1.9938) | 6,390 | 0.6319 |
| 3 | 20 | 0.2168** | (2.2194) | 8,671 | 0.5870 |
| 4 | 70 | 0.2006** | (2.0818) | 8,351 | 0.6091 |
| 5 | 95 | 0.1875 | (1.1857) | 5,832 | 0.6483 |
| 6 | 100 | 0.1784** | (2.3826) | 8,553 | 0.6452 |
| 7 | 10 | 0.1728* | (1.6630) | 8,526 | 0.5347 |
| 8 | 50 | 0.1571 | (1.3780) | 8,841 | 0.5963 |
| 9 | 35 | 0.1315 | (1.0493) | 6,824 | 0.6194 |
| 10 | 56 | 0.1240** | (1.9994) | 17,021 | 0.4700 |

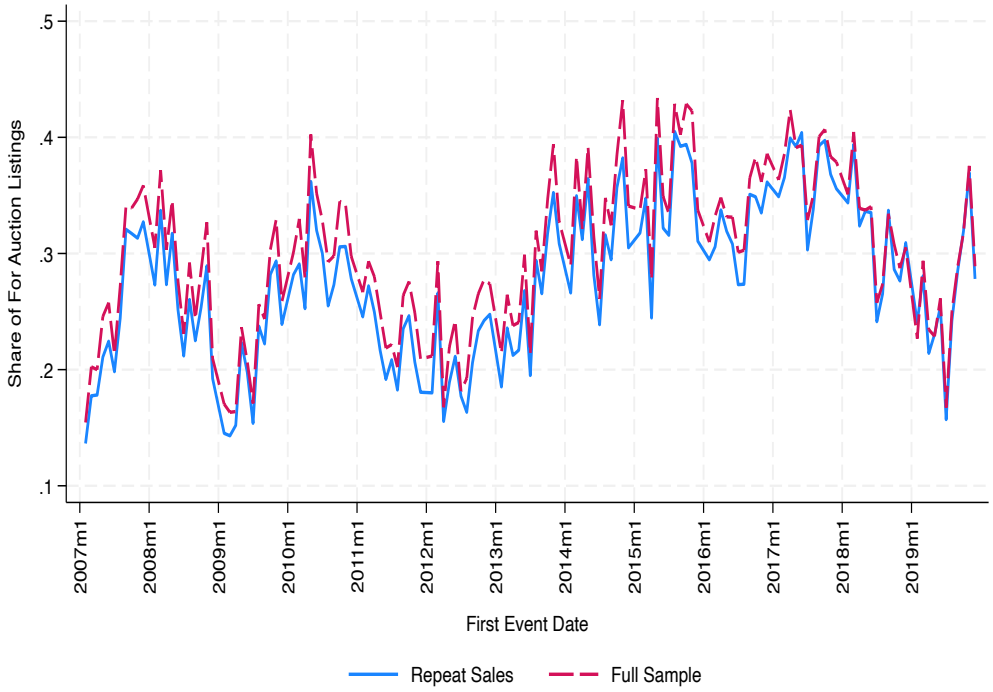



(a) Number of Listings

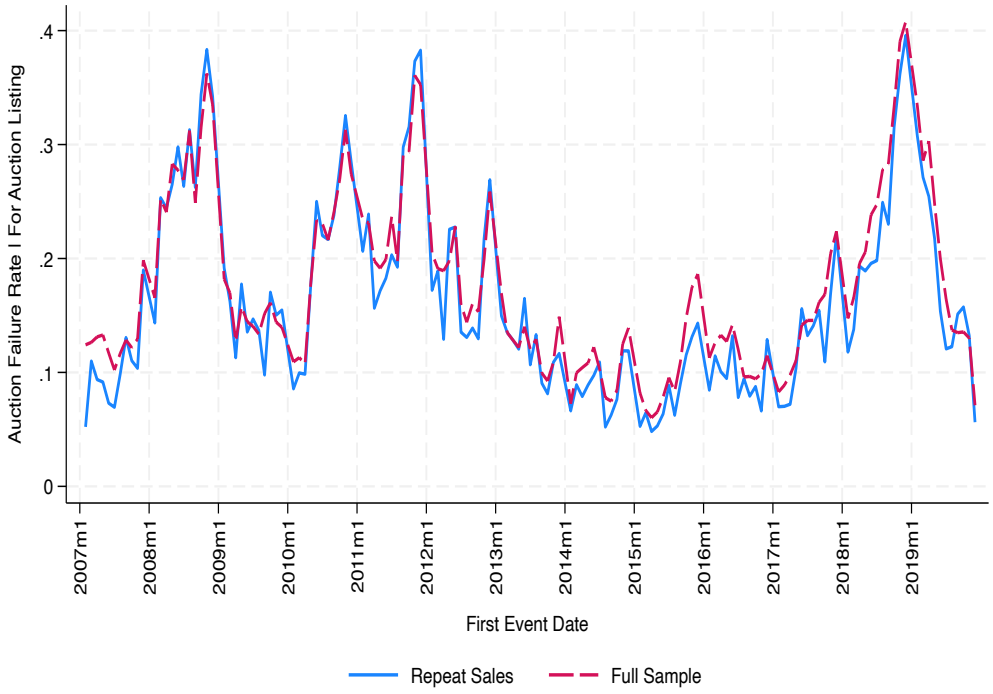



(b) Volume of Listings

Figure 1: This figure presents a time-series plot 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.

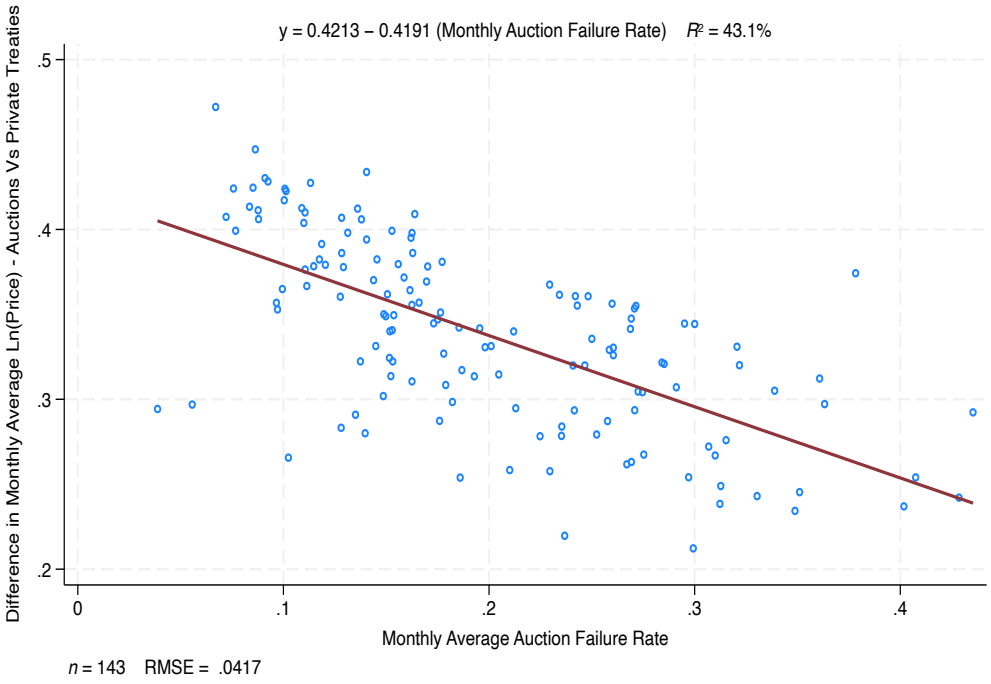



Figure 3: The figure presents a plot of the monthly average auction failure rate and the difference in the monthly average of the logarithm price of properties sold via auctions and that of properties sold via private treaty. This figure is based on the repeat sales sample, and the sample period is from 2007:M1 to 2019:M12.

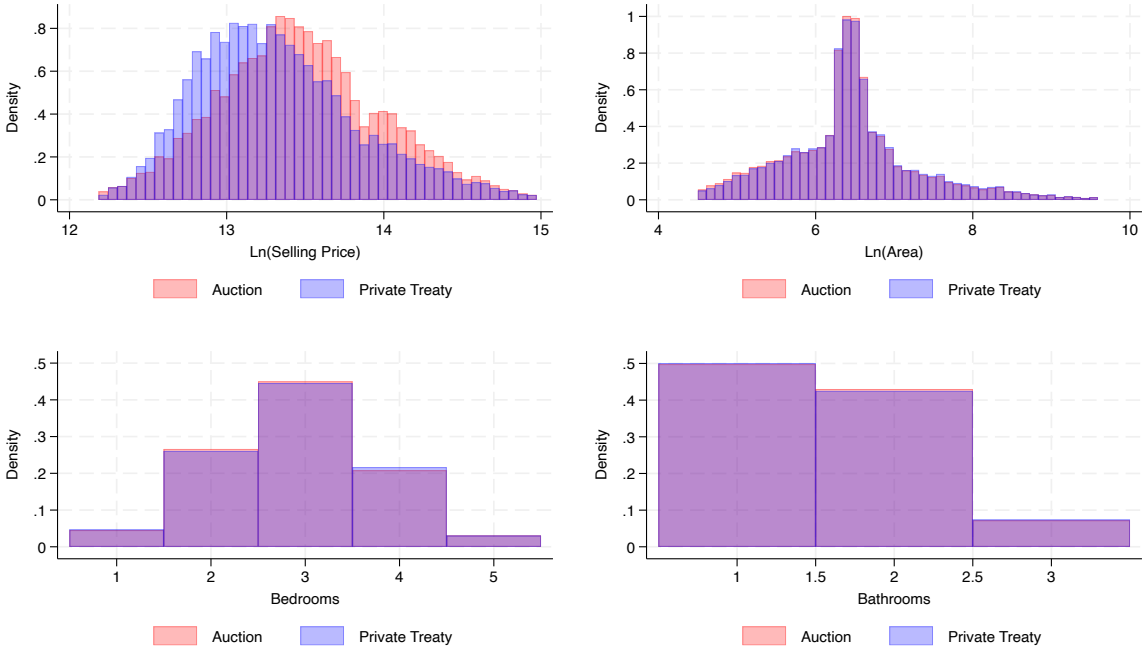



Figure 4: The figure presents a distributional plot of property characteristics separately for properties listed for auction and private treaty. This sample of properties is based on the identification sample underlying our baseline results, and the sample period is from 2007:M1 to 2019:M12.

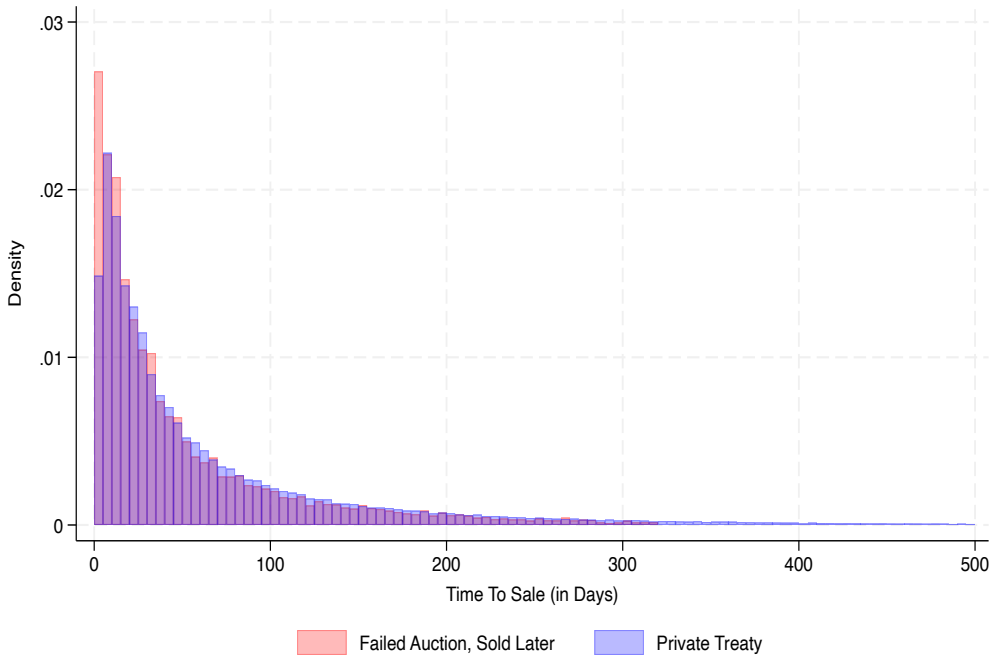
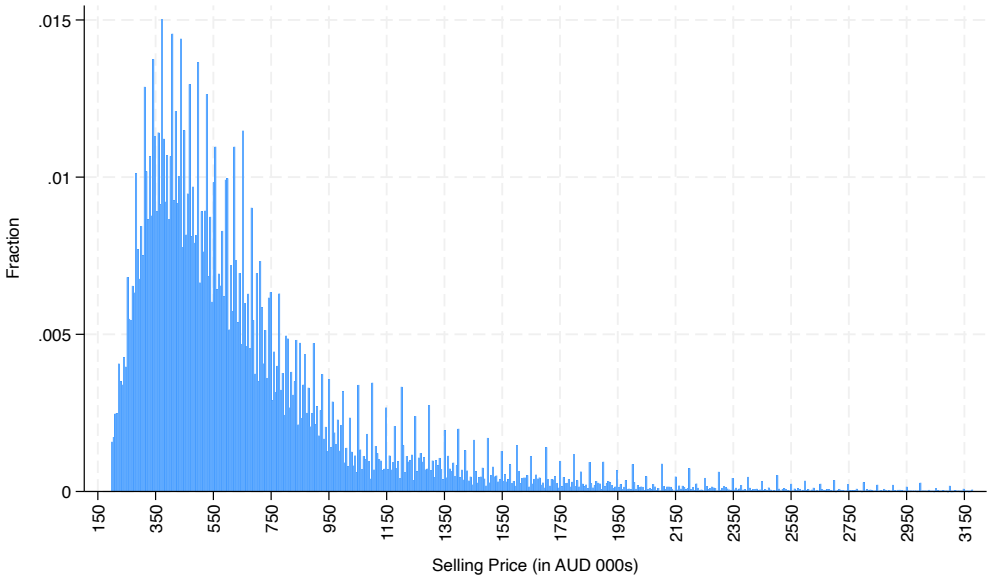



Figure 5: The figure presents a distributional plot of *Time to Sale* for two selling methods. '*Time to Sale*' equals the number of days between the sale and listing date for private equity sales and equals the number of days between the sale date and auction failure date for properties that fail the auction and are sold later. This figure is based on the repeat sales sample, and the sample period is from 2007:M1 to 2019:M12.




(a) Selling Price




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

Figure 6: 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

## How Perception Affects House Prices: Evidence from Failed Auctions

Table A.1: **Variance Decomposition of Listed For Auction Flag**
This table provides a variance decomposition of the Listed For Auction flag, a dichotomous variable that equals 1 if a property is listed for an auction. Regressions are estimated at the transaction level. In Panel A, the table reports the variance explained ($R^2$) by a specific fixed effect. In panel B, the table reports the incremental variance explained by adding a specific fixed effect. The sample period spans 13 years, starting in 2007:M1 and ending in 2019:M12.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Dependent variation: Listed For Auction (1 = Yes, 0 = No) | | | | |
| Panel A: Variance Explained | | | | | |
| Property FE | 0.6250 | | | | |
| Year×Month FE | | 0.0278 | | | |
| Suburb×Property Type×Area Group×Bedrooms×Bathrooms×Year FE | | | 0.4672 | | |
| Real Estate Agency FE | | | | 0.3422 | |
| Real Estate Agent FE | | | | | 0.4547 |
| Panel B: Incremental Variance Explained | | | | | |
| Variance Explained | 0.6250 | 0.6412 | 0.7864 | 0.8328 | 0.9285 |
| Incremental Variance Explained | | 0.0162 | 0.1452 | 0.0464 | 0.0957 |
| Property FE | Yes | Yes | Yes | Yes | Yes |
| Year×Month FE | No | Yes | Yes | Yes | Yes |
| Suburb×Property Type×Bedrooms×Bathrooms×Area Group×Year FE | No | No | Yes | Yes | Yes |
| Real Estate Agency FE | No | No | No | Yes | Yes |
| Real Estate Agent FE | No | No | No | No | Yes |

Table A.2: **Prices and Auction Outcomes - Robustness I**

This table presents the robustness of baseline results relating to the property prices and various auction outcomes. 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 column (1) ((2)), we exclude properties that change the selling method from private treaty (auction) to auction (private treaty). 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) |
|---|---|---|
| | Dependent Variable: Ln(Selling Price) | |
| 𝟙.Listed For Auction | 0.0016 | 0.0113*** |
| | (0.9921) | (8.5009) |
| 𝟙.Failed Auction | -0.0211*** | -0.0212*** |
| | (-11.6463) | (-11.2115) |
| $R^2$ | 0.9915 | 0.9913 |
| N | 444,178 | 455,160 |
| Property FE | Yes | Yes |
| Suburb×Property Type×Bedrooms×Bathrooms×Area Group×Year FE | Yes | Yes |
| Year×Month FE | Yes | Yes |
| Excluded Properties | Private Treaty→Auction | Auction→Private Treaty |

Table A.3: **Prices and Auction Outcomes - Robustness II**

This table presents the robustness of our baseline results limited to the set of properties listed *For Auction*. The key independent variable is *Failed Auction*. This dichotomous variable 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. 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) |
|---|---|---|---|---|---|
| | Dependent variable: Ln(Selling Price) \| Selling Method = Auction | | | | |
| 1.Failed Auction | -0.0076*** | -0.0045* | -0.0090*** | -0.0157*** | -0.0138*** |
| | (-3.0587) | (-1.7755) | (-3.3669) | (-5.1091) | (-3.6897) |
| N | 129,019 | 129,019 | 129,019 | 129,019 | 129,019 |
| $R^2$ | 0.9764 | 0.9790 | 0.9843 | 0.9890 | 0.9906 |
| Property FE | Yes | Yes | Yes | Yes | Yes |
| Suburb×Year FE | Yes | No | No | No | No |
| Suburb×Property Type×Year FE | No | Yes | No | No | No |
| Suburb×Property Type×Bedrooms×Year FE | No | No | Yes | No | No |
| Suburb×Property Type×Bedrooms×Bathrooms×Year FE | No | No | No | Yes | No |
| Suburb×Property Type×Bedrooms×Bathrooms×Area Group×Year FE | No | No | No | No | Yes |
| Year×Month FE | Yes | Yes | Yes | Yes | Yes |

Table A.4: **Prices and Auction Outcomes - Robustness III**

This table presents the robustness of baseline results relating to the property prices and various auction outcomes. 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 column (1)-(2), we exclude properties that fail an auction on a non-rainy day. In columns (3)-(4), we exclude properties that failed an auction on a non-rainy day, and properties with successful auction on a rainy day. 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) |
|---|---|---|---|---|
| | Dependent Variable: Ln(Selling Price) | | | |
| 1.Listed For Auction | 0.0155*** | 0.0074*** | 0.0163*** | 0.0083*** |
| | (6.9258) | (5.3046) | (7.0525) | (5.7234) |
| 1.Failed Auction | -0.0133*** | -0.0300*** | -0.0136*** | -0.0309*** |
| | (-3.1024) | (-7.8252) | (-3.1283) | (-7.7615) |
| $R^2$ | 0.9725 | 0.9913 | 0.9723 | 0.9912 |
| N | 458,710 | 458,710 | 449,716 | 449,716 |
| Property FE | Yes | Yes | Yes | Yes |
| Suburb×Property Type×Bedrooms×Bathrooms×Area Group×Year FE | No | Yes | No | Yes |
| Year×Month FE | Yes | Yes | Yes | Yes |



(a) A property listed *for auction*




(b) An auction in progress in front of the property.

Figure A.1: The figures present an example of a property listed for auction in panel (a). In Panel (b), the auction is in progress for the property shown in Panel (a). The potential bidders gathered in front of the house.