Outshine to Outbid:

Weather-Induced Sentiments on Housing Market

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Abstract

This paper examines how sentiments affect homebuyers' decision in housing transactions, especially in auction sales. Utilizing housing transaction data in Sydney from 2000 to 2014, we find that the transaction price is significantly higher for auction sale, consistent with winner's curse. Further, employing four sentiment proxies including three weather-based sentiment proxies and a survey-based sentiment index, we show that positive sentiment boosts this auction premium more when the auction day has high sentiment. Sentiment boosts auction premium particularly more when housing market is in boom, or the purpose of the property is for investment. Our result is robust to using national sport events as sentiment shocks, selection bias and unobserved variable bias. Overall, our evidence suggests that sentiments affect homebuyers' housing market decisions.

Key words: *behavioral economics, auction, sentiment, weather, housing price*

JEL Classification Code: *D03, D14, R21*

1. Introduction

Over the most recent years, the roller-coaster ride of the housing market has garnered considerable attention from the financial and popular press. Given the significant interest in the growth in Australia's housing market, this paper investigates the role consumer exuberance plays in driving residential house prices in Sydney, particularly in auction sale.

Unlike in the U.S., where auctions are frequently used to dispose of distressed properties, auctions are used quite commonly in Australia for selling properties. About 14% of all residential properties in Sydney are sold in auctions from 2000 to 2014, and the rest are sold in private negotiation. Auctions are an especially popular method of selling properties when general demand for properties is high, or the particular property and location is unique and in high demand[1].

Given its popularity, we test whether auction sale contributes to the soaring Australian housing price in the recent years. Using a detailed transaction-level property market dataset covering the Sydney Metropolitan Area from 2000 to 2014, we provide the first large-scale empirical evidence on how houses are priced in auction sales. Our findings are consistent with the "winner's curse", which posits that the winners in an auction overpay due to incomplete information and emotional sentiment.

Theoretically, if perfect information was available to everyone and all participants were completely rational in their decisions and skilled at valuation, no overpayments would occur, and private negotiation and auction sale would yield the same transaction price. However, due to the time urgency and competitive tension in auction sale, bidding wars may occur, and auction fever may develop (Heyman et al 2004; Ku et al 2005, 2006). Buyers could have a more difficult time determining the home's overall value, hence they are more likely to be irrational and push the price beyond its intrinsic value. Consequently, the winning bidder ends up with the largest overestimation of a home's value (Capen et al 1971; Kagel and Levin 1986; Thaler 1988; Cox et al 2001).

To further examine the reason for overpayment and winner's curse, we study the extent to which the overvaluation in housing auction sale is driven by sentiment. As these bidding decisions almost always involve substantial amount of subjective judgment, especially in bidding wars or when emotional attachment has developed towards the auctioned item, bidding prices could be affected by the bidders' psychological factors and sentiments, such as fluctuations in mood and emotional state.

[1] Source: https://www.sa.gov.au/topics/planning-and-property/buying-a-home-or-property/buying-property/auctions

The housing market is an attractive setting to study the notion of winner's curse and the effect of sentiment on auction premium, as this market affords us the opportunity to study the role of both private value and intrinsic value. First, a house is a durable consumption good that can have private value if the buyer lives in it. For instance, a buyer may have private preference about certain feature of a house, such as adjacency to his or her parents' place, so a house can have independent or private value which may not be closely correlated with the private value of other bidders.

Meanwhile, a house is also an investment good, when the buyer decides to resell it due to life events such as changing job to a different city, or to convert it into a rental property. In these cases, other people's preferences of the house significantly affect this buyer's valuation, so a house can have common value across all bidders. When potential buyers place their bidding prices, their valuation is formulated by adding up these two components. Buyers' subjective judgment on private value of the house largely determines their final bidding price.

Considering the amount of subjective valuation involved in housing purchase decision and its susceptibility to sentiment, it is of great importance to understand the role of sentiment in influencing homebuyers' decisions in housing auctions. There is an abundant literature on the influence of sentiment in investment decisions at personal or corporate level. Sentiment may increase or hinder an agent's productivity and alter the assessment of investment projects. For example, Graham et al (2015) provide survey evidence that up to one-half of managers rely on their 'gut feel' in investment decisions. Shiller (2015) attributes the recent financial crisis to positive sentiment in the financial sector which skewed managerial expectations and overextended financial firms. Cortés et al (2016) show that sunshine-induced sentiment affects loan officers' credit approval decisions. However, empirical evidence is scant on how sentiment affects housing auction transactions.

A method commonly used in the literature to test the existence of the winner's curse is a direct comparison between auctions and other marketplaces (Massad and Tucker 2000; Mehta and Lee 1999; Oh 2002). Oh (2002) reports that 60% of consumer-to-consumer online bidders paid more than the minimal prices observed from 12 online fixed-price vendors. To fill this gap in literature, we compare and contrast auction sale and private negotiation sale in the housing market on several important dimensions, including transaction price and property characteristics, to test the existence of winner's curse.

We then investigate whether sentiments add on to the tension in auction, and drive up the transaction price. On the auction day of a standard housing auction sale process, fast-talking auctioneers solicit offers at the auction from the potential buyers/bidders. The competitive tension and valuation pressure at this kind of auction is extremely high, as the bidding amount can easily jump to a few million dollars. Buyers are likely affected by mood and sentiment in their subjective judgment which may lead to suboptimal prices.

We utilize four main measures for sentiment, including a survey-based sentiment index and three weather-based sentiment proxies. For the survey-based sentiment, we use the monthly Consumer Sentiment Index for the state of New South Wales from Melbourne Institute[2]. The other three weather-based proxies are daily solar level, rain and temperature, which is a source of exogenous variation in sentiment uncorrelated with intrinsic valuation. We use the exact weather statistics for the transaction day when the sale takes place. The use of weather induced sentiment is motivated by prior studies on psychology (Schwarz and Clore, 1983; Wann et al 1994), economics and finance (Loewenstein et al 2001; Bassi et al 2013; Hirshleifer and Shumway, 2003; Goetzmann et al, 2015).

We begin by showing that property transaction prices in auction sale are significantly higher than private negotiation sale, in general. The average transaction price in auction sale is AUD 870,830, which is 46% significantly higher compared with AUD 595,600 in private negotiation sale. The auction premium becomes 7.1% or AUD 45,500 given the average transaction price in Sydney is AUD 640,900. These results take into account a comprehensive list of property-level features, location and time fixed effect, as shown in our multivariate analysis results. Thus, our estimates reflect changes in bidding prices relative to the baseline average observed over the same month, for the same type of property and in the same neighborhood. To the extent that the prices in private negotiation sale serve as a benchmark for the intrinsic value, this large auction premium is in strong support of the notion of winner's curse in auction sale.

Next, we show how sentiments drive up the transaction price in auction sale. We find that all four proxies of sentiments are significant in explaining housing transaction prices in auctions. Positive sentiment leads to higher transaction prices, and negative sentiment has the opposite effect. Melbourne Institute Sentiment Index, solar, and temperature are proxies associated with positive sentiment, and rain is considered a negative sentiment proxy. Using the housing auction sale sample, we find that the transaction prices are lower on rainy days, and it is higher on days associated with higher solar level, higher temperature and higher sentiment index. Using the combined sample with

[2] The Consumer Sentiment Index from Westpac-Melbourne Institute Survey of Consumer Sentiment is an average of five component indexes which reflect consumers' evaluations of their household financial situation over the past year and the coming year, anticipated economic conditions over the coming year and the next five years, and buying conditions for major household items. Consumers are also surveyed about their views on buying conditions for cars and dwellings, the wisest place for savings, and economic news recall. This report is produced monthly.

both auction and private negotiation sale, we find that auction sales are more likely to be affected by sentiments, as measured in all four proxies, compared with private negotiation sale.

The effect of sentiments on transaction price could vary when the real estate market is in different boom and bust cycles. Based on the housing price index for Sydney area during our sample period, we identify the booming market as periods between January 2000 and February 2004, between January 2009 to April 2010, and between June 2013 and December 2014. We find that sentiment has a stronger effect on auction sale premium when the housing market is in boom period, and this boosting effect is statistically significant when using all four proxies of sentiments.

To ensure the robustness of our result, we have the following robustness checks. First, we acknowledge the possibility that the choice of auction sale might be endogenous, as sellers may self-select into auction sale when the property market is in boom, or that particular property is in high demand. We employ a two-stage least square approach with two instrument variables to address this concern. The two IVs are the previous week's auction premium and whether the auction day falls on a Saturday. Auction sale method is more likely to be chosen when lagged period auction premium is high, and lagged period auction premium is not correlated with the current period auction premium. Another IV is the Saturday dummy. As majority of the auctions are conducted on Saturday, Saturday dummy is highly correlated with auction but not correlated with transaction price. The 2SLS results confirm our baseline finding, which shows consistent finding that auction premium is higher on high sentiment days.

Second, one may be concerned that our result could suffer from unobserved variable bias due to some unobserved investor characteristics, suburb-level characteristics or latent variables at the property level which might affect housing market decisions. To control for this unobserved variable bias, we employ the propensity score matching (PSM) approach. For each observation in the auction sale sample, we create a matched observation from the private sale sample based the estimated propensity scores, which are estimated using logit regressions with the auction dummy as the dependent variable and housing characteristics and all other controls as independent variables for each region, each property type and each year. We repeat the main regressions using the PSM sample, and we find qualitatively similar result.

Third, we employ alternative proxies for sentiment. The major sentiment events we look at in this paper are listed in Appendix 2, including the Melbourne Cup and a list of public holidays in Sydney. Researches in psychology show that these types of events are associated with rapid and economically large changes in human mood, and that these changes are plausibly orthogonal to economic fundamentals. Presumably, people are typically in a pleasant mood on holidays or when holidays are coming (Bollen et al 2011; Sharpe 2014). We define the sentiment event window as from one week prior to one week after these sentiment events. Our key results largely hold using these event windows as alternative sentiment proxy. We find that national sports events are indeed associated with higher auction sentiment; however, the effect of holiday is not so obvious on auction sentiment. We argue that people may be still on leave immediately before or after holiday. Demand or interests for housing is lower for days immediately around the holidays.

Last, we also use sudden change in weather to further examine the effect of sentiment. Sudden change in weather is in general unpleasant, and we argue that this might lead to negative impact on housing market transaction prices and especially auction premium. We find that sudden changes in rain and temperature indeed have a negative influence on auction premium.

Overall, our study makes several important contributions. First, our results confirm the winner's curse problem in the housing auction market. We compare the auction sale with private negotiation sale and find the transaction prices in auction are significantly higher. In particular, we document this result in a unique setting where both private and common valuations of the property are important determinants of the bidding price. As housing is both a consumption good and investment good, it has both private enjoyment value and common investment value for a homebuyer. In a housing auction, the winning bidder is oftentimes overly optimistic about his or her private value and bids the highest.

Second, our findings suggest that the sentiments of homebuyers have a significant causal effect on their housing investment decisions. On a high sentiment day we show buyers end up paying even more in auction sales compared with a low sentiment day, ceteris paribus. We argue that the mechanism underlying the effect of mood on housing auction decisions is likely linked to changes in subjective judgment. Sentiments tend to boost the level of overestimation for house value at housing auction sale.

Third, we are able to test the effect of sentiments using the exact weather condition of the transaction day within the same city. Housing auctions are held mostly in the open space, and all the bidders are gathered at one location and share the same weather condition, making weather an important influence. This is an improvement over the existing studies on how weather affect stock market investment, which use weather in major stock market locations as a proxy for investor mood. In stock investment, weather conditions vary significantly across investor locations, while investors' trading decisions are unobservable across locations, and stock prices are recorded only at the aggregate level at the stock exchange, which makes it hard to interpret the evidence (Loughran and Schultz, 2004; Goetzmann and Zhu, 2005). In our study, the final bidding price are usually concluded and recorded at the same place as the location of the house where all the bidders gather. The sentiment proxy and economic outcomes are observable for the same set of agents at the same location, which makes the interpretation more discernable.

The paper proceeds as follows. Section 2 discusses the background of the housing market and related literature. Section 3 describes the data sample. Section 4 discusses the detailed methodology. Section 5 presents the empirical results. Section 6 provides further robustness check of the key results. And Section 7 concludes.

2. Background and Literature

2.1 Background on Housing Auction Market

Sales of property within Australia are conducted mainly through real estate agents by the private negotiation method. Another method of buying property is by public auction. Unlike in the U.S., where auctions are frequently used to dispose of distressed properties, home sellers in Australia are more likely to choose auction sale when there's greater prospect of higher prices and positive news for the property market and, such as a recent decrease of interest rate by the central bank.

A typical housing auction has the following process. At least 30 minutes before the auction, the seller's property agent is required by law to display documentation regarding the property. As the auctioneer begins he/she will make an announcement detailing the information: the state laws applying to auctions in general.

There are national and state rules governing the practice of housing auctions. In particular, below are some basic rules that apply in all house auctions in Australia.

1) Auctions are unconditional and do not have a cooling-off period;
2) Dummy bids – non-genuine attempts to raise the bidding – are illegal;
3) When bidding reaches a vendor's reserve price, the property is on the market;
4) The highest bidder has the first right to negotiate if a property fails to reach its reserve price;
5) A deposit is paid and contracts signed immediately after an auction sale;
6) Vendor bids must be announced to buyers.

For house auction rules in Sydney, there are some specific rules including buyers must pre-register to bid at property auctions, and only one vendor bid can be made per property auction3.

After the rules are announced and understood, the auctioneer will then ask for an opening bid, setting an amount by which all bids must rise, such as in $5,000 increments. Alternative amounts can be bid – such as $1,000 – however it is up to the auctioneer's discretion if the amount is accepted.

A reserve price must be set by the seller in writing before auction day. This is the lowest amount the seller would sell the property for. It isn't made known to bidders and the seller can decide to lower this amount if the price isn't met at auction.

At an auction the bidders ultimately decide how much they are willing to pay for the property. All bidders will be given an opportunity to place a bid. Once the reserve price has been reached the property is considered to be 'on the market'. The auction is considered complete when the highest bid has been reached, and the house will be sold to the highest bidder.

If the reserve price isn't reached the auctioneer will privately ask the seller if they wish to sell at a lower price. If the maximum bid is below the seller's lowest price, the home is "passed in" and remains unsold. When the final bid is reached and the seller is happy with the price, the auctioneer will announce "going once, twice, three times…" and if no more bids are offered he will then call, "SOLD". An immediate deposit – usually 10% of the purchase price – is required after the auction. The balance is paid on settlement, normally set by the seller at 30, 60 or 90 days.

Due to certain features of the auction sale method, sentiments are more likely to play a role in affecting the transaction price. First, property buyers normally have two weeks' cooling off period after the sign the sales and purchase agreement in private negotiation sale method. Compared with private sale, auctions do not have a cooling-off period, which leaves no opportunity for the buyer to change mind and cancel the deal after having made a purchase if the buyer later regrets his or her bid has been too high. As a result, the decision on that auction day is an even more important one compared with in private sale.

Second, an auction can happen very fast, which forces buyers to make quick decisions. However, the buyers' bidding prices will have immediate legal implications once the hammer is down. As the proverb goes, "haste makes waste". When the buyer is eager to seal the deal, he or she may end up submitting an irrationally high bid, hence the term "winner's curse" (Kagel and Levin 1986;

[3] Source: https://www.domain.com.au/news/the-rules-of-house-auctions-around-australia-20160413-go4hoe/

Heyman et al 2004; Ku et al 2005, 2006). The tension and anxiety associated with bidding on a big ticket item like a house is extremely high. This implies that buyers are more likely to be affected by sentiment in auction sale, and the winner's curse problem gets exacerbated in this situation.

2.2 Related Literature on Winner's Curse in Auction

The typical example of the winner's curse is provided by the jar of coins experiment by Bazerman and Samuelson (1983), who auctioned off a jar containing an unknown number of coins to their students. Though the students tended to bid a little below their estimates of the number of pennies in the jar in order to obtain a profit, the winner was still the student who had the most optimistic estimate, thus overpaid by the most.

The essence of the winner's curse in an auction is that the highest (and winning) bidder in an auction paid too much. Submitting the highest bid tends to mean that others' value estimates were relatively low, and a bidder who does not realize this may bid too high and end up paying more than the prize is worth.

There is considerable evidence that bidders fall prey to the winner's curse, both in field situations and in controlled laboratory experiments (Kagel, 1995). Roll (1986) shows overconfident managers fall prey to the winner's curse and overbid when acquiring other corporations. Surveys of behavioral finance (Thaler, 1988; Barberis and Thaler, 2003; Baker, Ruback, and Wurgler, 2007) conclude that the winner's curse holds in the corporate takeover market. The likelihood and magnitude of the winner's curse is affected by two factors: 1) the degree of divergence of opinion concerning the auctioned item, and 2) the degree of competition among potential buyers (Capen et al, 1971; Bazerman and Samuelson, 1983).

In empirical studies, one difficulty in definitively determining the presence of the winner's curse is the lack of a benchmark market value for auctioned assets such as an untapped oil field (Capen, et al, 1971; Hendricks and Porter, 1988) or a highway construction contract (Thiel, 1988). The unique setting of our study enables us to provide a benchmark market value for auctioned assets as there are two main transaction methods in the Australian housing market: auction sale method and private negotiation.

Two testable implications are drawn from the above literature: first, the ultimate buyer in a housing auction on average should pay more than the value of the house; second, the magnitude of the winner's curse or overpayment should increase when the divergence or uncertainty on the value of the house increase. Using the market value from the private negotiation sale as a benchmark valuation of the asset and comparing the auction sale versus private negotiation sale, we are able to draw strong inference on the existence of winner's curse. We also test the second implication based on buyer heterogeneity and varying housing market conditions in later sections.

2.3 Related Literature on Sentiment

The effect of weather on mood has been well established in a variety of prior social psychology and experimental economics research. Psychology literature suggests that individuals misattribute mood induced by weather as information when making assessments about objects that should be otherwise unrelated. Persinger and Levesque (1983) show that weather conditions explain about 40% of daily variation in mood. In experimental economics, Bassi, Colacito, and Fulghieri (2013) provide evidence that weather-induced positive mood increases agents' risk tolerance in a choice of lottery payoffs.

Finance and economics literature also documents consistent evidence with that of the psychology literature. Earlier work has shown a positive effect of sunshine (Saunders 1993; Hirshleifer and Shumway 2003, Cortés et al 2016,), temperature (Cao and Wei, 2005), and daylight (Kamstra, Kramer, and Levi, 2003) on stock returns. For example, using data from international stock exchanges, Hirshleifer and Shumway (2003) show that stock market returns are higher on days when the weather is sunny, which is presumably when market participants are in a good mood. Goetzmann et al (2014) show that weather-based indicators of mood impact perceptions of mispricing and trading decisions of institutional investors.

In this paper, we focus on the economic mechanism through which weather-induced sentiment affects housing transaction prices. In particular, we investigate how sentiment affects the bidding behavior of potential homebuyers and price formation process at housing auction market. Motivated by the relation between weather and sentiment or emotion as documented in multiple contexts in psychology literature, we utilize variation in local weather as a proxy for homebuyers' sentiment on the auction day.

The central contribution of this study is that we provide micro evidence on the effect of daily weather induced sentiment on housing purchase decisions and document that buyer optimism boosts the transaction price. To our knowledge, our study is the first to directly test for the weather induced sentiment effect in investors' behavior in the housing market, particularly in housing auction sales. One advantage of our setting is that housing auctions are usually conducted in the open space if weather permits. Participants in the auction are affected by the same weather condition and the final bidding price is concluded and recorded at the same location where all the bidders gather. The sentiment proxy and economic outcomes are observable for the same set of agents at the same location, which makes the interpretation more straightforward. Whereas for the stock market, participants trade at various different locations, and their trading decisions are unobservable to each other, although stock prices are recorded electronically at the aggregate level, which makes it harder to interpret the evidence (Loughran and Schultz, 2004; Goetzmann and Zhu, 2005).

3. Data

3.1 Housing Market Data

The principal dataset we use is the individual housing transaction data of the Sydney Metropolitan Area from 2000 to 2014 from Australian Property Monitors (APM)[4]. The dataset includes a comprehensive list of variables, including the transaction price, transaction date, property address, buyer and seller names, whether the transaction is an auction sale, whether the property is a new development, number of bedrooms and bathrooms, whether the property has parking, area size, and other housing characteristics (balcony, garage, ocean views, etc.).

3.2 Sentiment Proxies

We employ four sentiment proxies in this study, including a survey-based sentiment index and three weather-based sentiment measures. The survey-based sentiment proxy is the Melbourne Institute Consumer Attitudes, Sentiments and Expectations survey for the state of New South Wales where Sydney is located. The monthly index is constructed based on a survey of households[5] similar to the Sentiment Survey of Consumers at the University of Michigan. The survey comprises 1,200 household respondents and is sorted by age, gender and state so that it is representative of the Australian population. The three weather based measures are rainfall, solar exposure and temperature at the daily interval. The weather data is from the Bureau of Meteorology's station in Observatory Hill, Sydney[6]. Specifically, the daily rainfall amount in millimeters, the daily solar exposure amount in megajoules per square meter and the day's maximum temperature in degrees Celsius.

Figure 1 plots the Sydney housing price index, the survey-based sentiment index and the three weather-based sentiment measures including the monthly average rain, solar exposure and

[4]APM is one of Australia's leading national suppliers of online property price information to banks, financial markets, professional real estate agents and consumers. See www.apm.com.au for further details.

[5] For a more detailed explanation, see: https://theconversation.com/why-and-how-do-we-measure-what-consumers-feel-68804

[6] Its geographic coordinates are (-33.86, 151.21).

temperature in Sydney from 2000 to 2014. Sydney housing prices have steadily increased 2.5 times during the entire period although there was a slight fall in prices between 2003 and 2006. The sentiment index in blue has no clear trend for the entire sample period although we can see it was at the lowest after the global financial crisis in 2008. As expected, the three weather-based sentiment proxies including solar exposure, temperature and rainfall display clear seasonal changes annually.

[INSERT FIGURE 1 HERE]

3.3 Univariate Tests

Table 1 reports summary statistics for key variables used in our analysis. There are 852,734 individual housing sales in total in our sample. The average price sold is $640,900[7], and 16% of homes were sold at auction, as shown in Table 1 Panel A. The average home in our sample has 2.9 beds, 1.59 bathrooms. 75% of homes have parking and 58% are free standing houses. 4% of homes sold are new developments. On average homes sold when survey-based sentiment was at 105.65. This means more homes were sold when sentiment was optimistic as the sentiment index level is above 100.[8]

Table 1 Panel B reports univariate test statistics of property characteristics by auction and private sale. Homes sold in auctions tend to be of higher price, having more bedrooms and bathrooms, and are more likely to be free standing houses. For example, the transaction price for auction homes is on average $275,230 higher than home prices sold in private negotiation. Auction homes also have slightly more bedrooms and bathrooms and have less parking. 71% of homes sold at auction are houses compared with just 56% in private negotiation. There does not seem to be large differences in the survey-based sentiment level or weather-based sentiment proxies between auction and private sale, which implies sentiments are exogenous variables unrelated to the choice of sale methods. Auction sale is more likely to be chosen in property market boom relative to private sale. There is little difference in the number of local buyers buying between auction and private sales. We also find that most auction homes sell on Saturday (66%) compared with only 8% for private sale, as Saturday is a traditionally convenient day to hold auctions.

[INSERT TABLE 1 HERE]

Table 2 reports the correlation matrix for price, sentiment, weather and other relevant variables. We can see that the auction dummy is highly correlated to being sold on Saturday, with correlation

[7] Sales prices and area sizes at the 1st and 99th percentile are winsorized to remove outliers.
[8] A sentiment value above 100 is optimistic, at 100 is neutral and below 100 is pessimistic.

coefficient 0.56. It has positive and low correlation to the four sentiment measures, with correlation coefficients ranging from 0.01 to 0.02. This is in support of the notion that choice of auction sale is determined orthogonal to sentiment. Also Saturday has low correlation to price. In later section on robustness test, we could therefore instrument auction with Saturday to control for selection bias in auction sale.

[INSERT TABLE 2 HERE]

4. Empirical Methodology

Our basic methodology is to estimate a hedonic housing price model based on the following empirical specification and variable definitions:

$$\ln(P_{ist}) = \alpha_0 + \beta_1 Sentiment_t + \beta_2 Auction_i + \beta_3 Auction_i * Sentiment_t + property\ char_i + \mu_s + \gamma_t + \varepsilon_{it} \quad \text{--- (1)}$$

Where

$\boldsymbol{ln(P_{ist})}$ denotes natural logarithm of housing prices paid by home investor of sale *i* at suburb *s* at time *t*;

Auction is a dummy of 1 if the home is sold at auction, 0 otherwise.

Sentiment denotes one of our four sentiment proxies:

1) *SurveySenti*, the lagged Monthly level of Melbourne Institute Sentiment index for the state of New South Wales where Sydney is located;

2) *Rain*, daily rainfall amount in millimeters;

3) *Solar*, daily solar exposure in megajoules per square meter;

4) *Temp*, the highest daily temperature in degrees Celsius.

$\boldsymbol{property\ char}$ is various property characteristics such as number of bedrooms, number of bathrooms, parking, property type and area size[9];

$\boldsymbol{\mu_s}$ is the suburb location specific fixed effects;

$\boldsymbol{\gamma_t}$ is year and quarter fixed effects;

$\boldsymbol{\varepsilon_{it}}$ is the error term.

A positive coefficient on the auction dummy β_2 would suggest buyers overpay in auction sales, which would confirm the presence of winner's curse in housing auctions. β_2 could be interpreted as the auction premium. The coefficient of most interests is β_3, the interaction of auction and the

[9]Appendix 1 shows the full list of housing characteristics that we use in the regression specification.

sentiment measure. A positive β_3 means that especially higher prices are paid in housing auctions when sentiments are high, i.e., sentiment could boost auction premium more.

5. Multivariate Result

5.1 Baseline Multivariate Regression Result

Table 3 Panel A reports the estimation result for the baseline hedonic regressions. In model 1 and 2 we find a positive and statistically significant coefficient for SurveySenti, suggesting that housing prices are higher when recent sentiment is high. We also find the coefficient for Auction*SurveySenti is positive and statistically significant, suggesting that transaction prices in auctions are increased further by high sentiment.

[INSERT TABLE 3 HERE]

The result using the three weather-based sentiment measures are presented in model 3 to 8, and are consistent with the result using the survey-based sentiment measure. We use higher level of solar and temperature, and lower level of rainfall to denote high sentiment. The interaction terms of weather-based sentiment and auction dummy are positive and significant for solar and temperature, and negative and significant for rainfall, which support our hypothesis that high sentiment leads to higher auction premium. For example, the coefficient on the Auction*Rain interaction term is -0.174 (scaled up by 1000), statistically significant at the 5% level. This suggests that for every 1mm of rain on the day of an auction, the sales price falls by -0.017%. As 10 mm of rain is considered heavy rain and using the mean auction house price of $870,820, a home sold at auction during heavy rain has -0.17% or -$1,515 lower price than a home sold at auction on a clear day.

A similar calculation may be made for solar and temperature where higher measures mean higher prices during auctions with sunnier or warmer weather. For solar exposure, auction homes sold on a very sunny day (22 MJ/m^2, the 75th percentile of our sample) sell at higher prices than homes sold on overcast days (10.5 MJ/m^2, 25th percentile of sample) by 0.97% or $8,482.[10] A 6 degrees Celsius increase in temperature (equivalent to going from the 25th to 75th percentile in temperatures in our sample) results in 0.39% or $3,373 higher prices. These baseline results therefore suggest that high sentiment times (e.g. when the weather is good) also increases the selling price at auctions.

[10] (22-10.5)*0.847/1000*870,820=8,482.

5.2 Interaction Effect of Housing Market Boom

In the previous section, we show that the auction premium is higher when sentiment is higher. In this section, we examine whether the sentiment-induced auction premium would differ in different market boom and bust cycles. The rationale is that during a housing market boom, there could be more potential buyers who are interested in investing in this market. The demand is higher in general and we would expect housing auctions would be attended by more interested parties, although we do not have statistics on the number of participants at each auction. We estimate the following regression model to test the interaction effect of market boom with sentiment:

$$\ln(P_{ist}) = \alpha_0 + \beta_1 Sentiment_t + +\beta_2 Boom_t * Sentiment_t + \beta_3 Boom_t + property\ char_i + \mu_s + \gamma_t + \varepsilon_{it} \quad \text{--- (2)}$$

where *Boom* is a dummy of 1 if a home sold between Jan 2000 and Feb 2004 or between Jan 2009 and Apr 2010 or between Jun 2013 and Dec 2014, 0 otherwise. These periods correspond to times when Sydney housing prices were overall increasing as seen in Figure 1. Table 4 reports results for our boom period interaction regression. As expected, the coefficients on *Boom* are positive and significant in all the specifications, and the coefficients on the interaction term of Boom and Sentiment Indicators are positive and significant, confirming our conjecture that sentiment pushes prices even higher in booming markets. The coefficients on the interaction terms *Boom*Sentiment* are mostly statistically significant and carry expected sign, which largely supports our hypothesis that sentiment boosts the auction premium even more in housing market boom.

[INSERT TABLE 4 HERE]

5.3 Interaction Effect with Investor Dummy

We also test whether investors are more prone to sentiment in housing auctions. Compared to owner-occupiers who purchase the real estate to stay in, investors have already secured their primary residents and have extra funds to invest in properties. Naturally investors tend to have more financial resources, and they bid more aggressively. We hypothesize that property investors could be more prone to sentiment in auction sales. To test this idea, we divide the sample into two parts: rental investment properties and owner-occupied homes, and examine the differential sensitivity to sentiments for investors and owner-occupiers.

To identify real estate transactions that are likely to have an investment motive, we construct a investor dummy for each observation, which takes the value of 1 if there is a rental listing on this particular property within 180 days after that sale date, and 0 otherwise. We then run the following regression to examine the interaction effect of investor dummy with sentiment.

$$\ln(P_{ist}) = \alpha_0 + \beta_1 Sentiment_t + +\beta_2 Invest_{i,t} * Sentiment_t + \beta_3 Invest_{i,t} + property\ char_i + \mu_s + \gamma_t + \varepsilon_{it} \quad \text{--- (4)}$$

The results in Table 5 suggest that investors are not significantly affected by survey based sentiment, rain or solar, but prone to temperature in that auction day. We find that investor buyers pay significantly higher housing prices compared with owner-occupiers when the auction day has higher temperature, as shown in the positive and significant coefficients on *Temp*Investor*. The coefficient on the Temp*Investor dummy is 0.75, which means that an investor pays 0.075% more than a non-investor per 1 degree increase in degrees Celsius of temperature for an auctioned home. Given one standard deviation of temperature is 4 degrees, a one standard deviation increase in temperature results in 0.3% higher prices paid by investors at auctions.

[INSERT TABLE 5 HERE]

6 Robustness Tests

6.1 Controlling for Endogeneity of Auction (Selection Bias)

As sellers may self-select into auction sale when the property market is in boom, or that particular property is in high demand, there may be concerns for endogeneity of our results. To address potential selection bias, we employ a two-stage least squares approach. In the first stage, we run the following Probit model:

$$\Pr(Auction = 1|X) = F(\beta_1 Auc\_Prem_t + \beta_2 Saturday_t + \beta_3 Boom_t + \beta_4 Topturn_{st} + \mu_s + \gamma_t + \varepsilon_{ist}) \quad \text{--- (5)}$$

Where *Auc_Prem* is the lagged week rolling 12-week average auction premium estimated from the coefficient on the auction dummy on a weekly hedonic regression of *log(price)* on auction dummy and control variables. *Saturday* is a dummy of 1 if the home is sold on Saturday, 0 otherwise. We argue that *Auc_Prem* and *Saturday* are correlated to *Auction* but uncorrelated to the sales price based on their correlation coefficients. We find evidence in Table 2 that there is a 56% correlation of Saturday and auction and only a 11% correlation of Saturday to price. The past 12 week's auction premium is expected to be more correlated with the choice of auction but not as much related with the transaction price.

We present the two-stage least square estimation results in Table 6. Table 6 Panel A reports the first stage Probit results and we find *Auc_Prem* to be positive and statistically significant, supporting the hypothesis that sellers are more likely to choose auction sale method when the suburb has experienced high auction premiums in the previous week. Saturday dummy is also found to be strongly related with auction sale.

Table 6 Panel B reports our second stage results where estimates of $Auction$, $\widehat{Auction}$, are taken from the first stage. Our results confirm our baseline findings in Table 3. We find coefficient for $\widehat{Auction}$*SurveySenti* and $\widehat{Auction}$*Solar* is positive and statistically significant. However, we do not find significance for *Rain* or *Temp*.

[INSERT TABLE 6 HERE]

6.2 Matched Sample Analysis

For each observation in the auction sale sample, we create a matched observation from the private sale sample based on the estimated propensity scores from propensity score matching. We first estimate the propensity scores using logit regressions with the auction dummy as the dependent variable and housing characteristics and all other controls as independent variables. Once we have matched each auction sale with a private sale, we run the baseline equation as in equation 3.

Table 7 shows that the interaction term of auction and sentiment using the four sentiment proxies including the survey-based sentiment measure, solar, and temperature are all positive and significant, and negative and significant. These findings are consistent with our baseline result in Table 3, which confirm that our results are robust even when using propensity score matching.

[INSERT TABLE 8 HERE]

6.3 Event Based Sentiment Measures

To further check the robustness of our result, we employ event-based sentiment proxies, including the national sport event the Melbourne Cup and public holidays. Psychology research shows that these types of events are associated with rapid and economically large changes in human mood, and that these changes are plausibly orthogonal to economic fundamentals. It is documented that people are typically in a pleasant mood on holidays or when holidays are coming (Bollen et al. 2011; Sharpe 2014).

We define the sentiment event window as from one week prior to one week after the events. The sentiment dates that we use are public holidays and Melbourne Cup in Sydney which are listed in detail in Appendix 2. We rerun the baseline regression replacing our four sentiment measures with event period based sentiment dummies. Table 9 reports our results. Melbourne Cup interacted with auction is positive and statistically significant which suggests sentiment from Melbourne Cup has a positive effect.

Contrary to our expectation, we find that *auction*holiday* is negative and statistically significant, suggesting that auctions around holidays tend to have lower prices. The reason could be that people may take longer holiday leaves around holidays. Or they may be on holiday leave immediately before or after a specific holiday. Consequentially, demand or interests for housing could be lower for days around holidays. Further, as housing transactions require the assistance of real estate agents, conveyance lawyers, and auctioneers, etc, the absence of any of these parties due to holiday leave would lead to fewer participants in the housing market.

[INSERT TABLE 8 HERE]

6.4 Sudden Change in Weather

Sudden change in weather may have a stronger effect than using the level of weather variables as sentiment proxies. We define sudden change in weather as an indicator variable that equals one when the transaction day's weather measure is 100% higher than the previous day's measure. We test the effect of sudden change in weather in Table 10 by replacing the three weather proxies with the sudden change dummies. We find that sudden changes in rain and temperature have a negative effect on auction premiums, although the effect of solar is insignificant.

[INSERT TABLE 9 HERE]

7. Conclusion

Several studies on financial markets document that weather-based mood proxies explain variations in investment outcome such as aggregate trading volume and stock prices. We employ a unique setting in the Australian housing market to test the effect of sentiment on housing auction behavior. Both auction sale and private negotiation methods are popular methods for housing transactions in Australia, which offers us a benchmark to determine the magnitude of overpayment, and test for the presence of winner's curse. Further, housing is both an investment good and consumption good, which make both the private value and common value important considerations in the bidding decision.

We first find the transaction price in auction sale is significantly higher than that of the private negotiation sale, ceteris paribus, which confirms the presence of winner's curse in housing auction. We then test whether sentiment affects the transaction price in housing auctions. Employing four main sentiment proxies, we also show that sentiments exacerbate this overpayment in housing auctions. Our findings are robust to using national sport events as sentiment shocks, selection bias and unobserved variable bias. To our knowledge, our study is the first to examine the direct impact of weather induced sentiments on auction prices in the housing market. Collectively, these findings complement existing studies that document the effect of weather-induced sentiment on financial market decisions.

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Appendix 1: Variable Definitions

Variable	Variable Frequency	Description
SurveySenti	Time series	Lagged monthly level of Melbourne Institute Sentiment index for the state of New South Wales (where Sydney is located)
Rain	Time series	Rainfall amount in millimeters for the transaction day
Solar	Time series	Solar exposure in megajoules per square meter for the transaction day
Temp	Time series	Highest daily temperature in degrees Celsius for the transaction day
Rain_suddenchange	Time series	An indicator variable that equals one when the transaction day's rainfall level is 100% higher than the previous day's measure
Solar_suddenchange	Time series	An indicator variable that equals one when the transaction day's level of solar exposure is 100% higher than the previous day's measure
Temp_suddenchange	Time series	Dummy which equals 1 if the transaction day's temperature is 100% higher than the previous day's measure
Melbcup	Time series	Dummy which equals 1 if one week before or after is Melbourne Cup day.
Boom	Time series	Dummy which equals 1 if home sold between Jan 2000 and Feb 2004 or between Jan 2009 and Apr 2010 or between Jun 2013 and Dec 2014, 0 otherwise.
Price (AUD$'000s)	Property level	Sales price of home in thousands of Australian dollars
Saturday	Property level	Dummy which equals 1 if home sold on Saturday, 0 otherwise.
Beds	Property level	Number of bedrooms
Baths	Property level	Number of bathrooms
Auction dummy	Property level	Dummy which equals 1 if the home was sold at auction, 0 otherwise
New	Property level	Dummy which equals if the home was a new development, 0 otherwise
Investor dummy	Property level	Dummy which equals 1 for a sale if there is a rental listing within 180 days after that sale date, 0 otherwise.
Parking	Property level	Dummy which equals 1 if home has one or more parking spots, 0 otherwise
Street type dummies	Property level	Dummy which equals 1 if a certain street type (e.g. avenue, highway, lane, street, road, etc.), 0 otherwise
Housing type dummies	Property level	Dummy which equals 1 if a certain housing type (e.g. apartment/condominium, house, semi, studio, townhouse, villa, etc.), 0 otherwise
Area size	Property level	Land area size of home (square metres)
LocalBuyer	Property level	Dummy which equals 1 if owner has Anglo Saxon surname, 0 otherwise
HasAirConditioning	Property level	Dummy which equals 1 if home has air conditioning, 0 otherwise
HasAlarm	Property level	Dummy which equals 1 if home has alarm system, 0 otherwise
HasBalcony	Property level	Dummy which equals 1 if home has balcony, 0 otherwise
HasBarbeque	Property level	Dummy which equals 1 if home has barbeque, 0 otherwise
HasBeenRenovated	Property level	Dummy which equals 1 if home has been renovated, 0 otherwise
HasBilliardRoom	Property level	Dummy which equals 1 if home has billiard room, 0 otherwise
HasCourtyard	Property level	Dummy which equals 1 if home has courtyard, 0 otherwise
HasEnsuite	Property level	Dummy which equals 1 if home has ensuite, 0 otherwise
HasFamilyRoom	Property level	Dummy which equals 1 if home has family room, 0 otherwise
HasFireplace	Property level	Dummy which equals 1 if home has fire place, 0 otherwise
HasGarage	Property level	Dummy which equals 1 if home has garage, 0 otherwise
HasHeating	Property level	Dummy which equals 1 if home has heating, 0 otherwise
HasInternalLaundry	Property level	Dummy which equals 1 if home has internal laundry, 0 otherwise
HasLockUpGarage	Property level	Dummy which equals 1 if home has lock up garage, 0 otherwise
HasPolishedTimberFloor	Property level	Dummy which equals 1 if home has polished timber floors, 0 otherwise
HasPool	Property level	Dummy which equals 1 if home has swimming pool, 0 otherwise
HasRumpusRoom	Property level	Dummy which equals 1 if home has rumpus room, 0 otherwise
HasSauna	Property level	Dummy which equals 1 if home has sauna, 0 otherwise
HasSeparateDining	Property level	Dummy which equals 1 if home has separate dining room, 0 otherwise
HasSpa	Property level	Dummy which equals 1 if home has spa, 0 otherwise
HasStudy	Property level	Dummy which equals 1 if home has study room, 0 otherwise
HasSunroom	Property level	Dummy which equals 1 if home has sunroom, 0 otherwise

HasTennisCourt	Property level	Dummy which equals 1 if home has tennis court, 0 otherwise
HasWalkInWardrobe	Property level	Dummy which equals 1 if home has walk in wardrobe, 0 otherwise
View dummies	Property level	Dummy which equals 1 if home has a certain view (e.g. bush, city, district, harbour, ocean, park, river, etc.), 0 otherwise

Appendix 2: Dates of Sentiment Events

Event	**Type**	**Date/Date End**
Melbourne Cup	Melbourne Cup	First Tuesday of November every year
New Year's Day	Public Holiday	January 1 of every year
Good Friday	Public Holiday	Friday in March or April of every year
Anzac Day	Public Holiday	April 25 of every year
Queen's Birthday	Public Holiday	Second Monday of June every year
Labor Day	Public Holiday	First Monday of October of ever year
Christmas	Public Holiday	December 25 of every year

Figure 1: Sydney Housing Prices, Sentiment and Weather

The graph shows the Sydney Dwellings Price Index from RP Data, Melbourne Institute New South Wales Sentiment Index and also the monthly average rain, solar exposure and temperature in Sydney from 2000 to 2014. Weather data is obtained from the Bureau of Meteorology. There is a break in the solar exposure data as the weather data was not recorded for some days. The left horizontal axis is for the two indices while the right horizontal axis is for the weather measures.

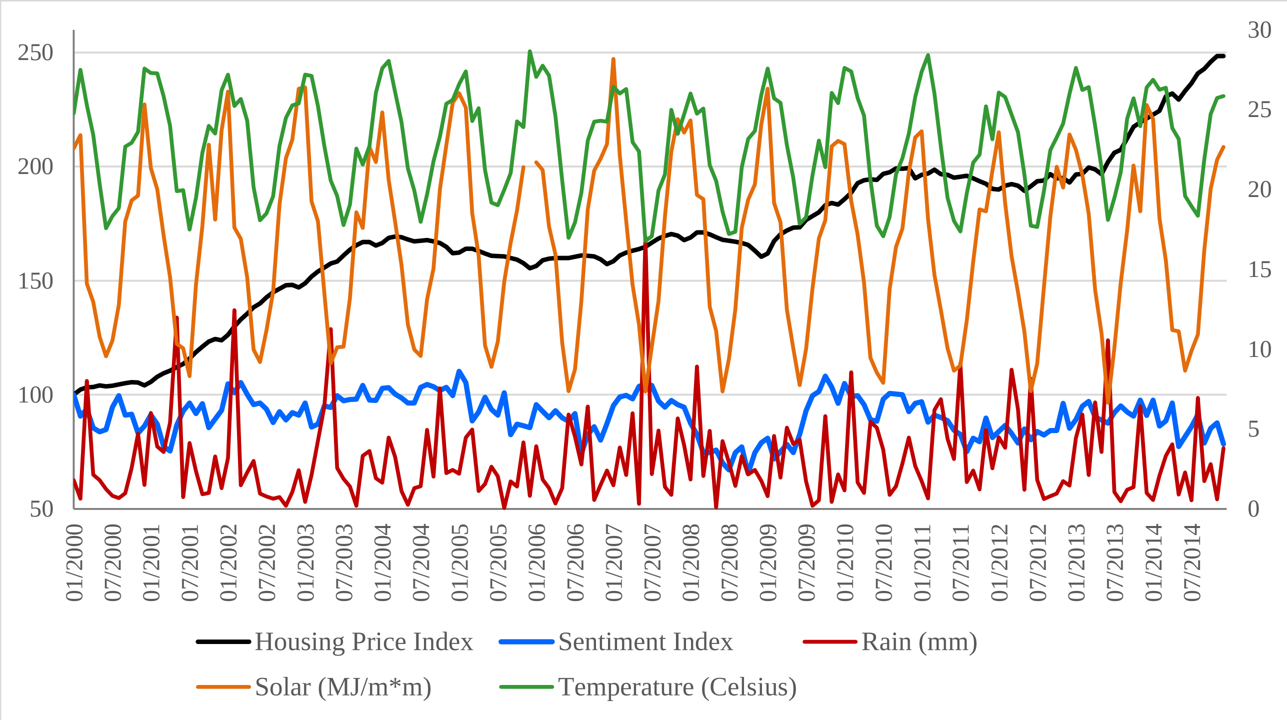

Table 1: Descriptive Statistics

The table reports mean summary statistics for home sales in the Sydney metropolitan area from 2000 to 2014. *Auction* is a dummy variable equal to one for a housing sale sold at auction. *Price* is the sales price in thousands of Australian dollars. *SurveySenti* is the lagged month Melbourne Institute Sentiment index level. *Rain* is the amount of rain in millimeters for the transaction day. *Solar* is the amount of solar exposure for the transaction day. *Temp* is the temperature in degrees Celsius for the transaction day. Definitions of other variables are in Appendix 1. Panel A reports summary statistics for the overall sample. Panel B reports summary statistics by whether the sale is by auction or private sale. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Panel A: Summary Statistics for the Entire Sample

Variable	Mean	Median	Std	P25	P75
Price	640.90	505.00	470.07	360.00	750.00
Auction	0.16	0.00	0.37	0.00	0.00
Beds	2.90	3.00	1.05	2.00	4.00
Baths	1.59	1.00	0.72	1.00	2.00
Parking	0.75	1.00	0.44	0.00	1.00
House	0.58	1.00	0.49	0.00	1.00
New	0.04	0.00	0.20	0.00	0.00
SurveySenti	105.65	106.40	10.28	98.80	113.70
Rain	3.07	0.00	9.40	0.00	1.00
Solar	16.16	14.90	7.73	10.50	22.00
Temp	22.83	22.70	4.29	19.60	25.70
Boom	0.48	0.00	0.50	0.00	1.00
Investor	0.10	0.00	0.29	0.00	0.00
LocalBuyer	0.16	0.00	0.37	0.00	0.00
Saturday	0.18	0.00	0.38	0.00	0.00

Panel B: Univariate Test Statistics for Auction and Private Sale

	Auction			**Private Sale**			**Diff**			
Variable	Mean	Median	Std	Mean	Median	Std	Mean	*t*-stat	Median	Z-stat
Price	870.82	727.00	547.68	595.58	473.00	439.23	275.24***	(205.44)	254.00***	243.75
Beds	2.99	3.00	1.05	2.88	3.00	1.05	0.11***	(35.12)	0.00***	31.69
Baths	1.64	1.00	0.77	1.59	1.00	0.71	0.05***	(25.72)	0.00***	18.65
Parking	0.76	1.00	0.48	0.76	1.00	0.43	-0.11***	(-86.15)	0.00***	-85.78
House	0.71	1.00	0.46	0.56	1.00	0.50	0.15***	(104.60)	0.00***	103.93
New	0.01	0.00	0.07	0.05	0.00	0.22	-0.04***	(-75.35)	0.00***	-75.10
SurveySenti	106.03	106.70	10.10	105.57	106.20	10.31	0.46***	(15.46)	0.50***	17.48
Rain	3.26	0.00	9.75	3.03	0.00	9.33	0.23***	(8.28)	0.00***	-2.70
Solar	16.28	15.10	7.62	16.14	14.90	7.74	0.14***	(6.32)	0.2.00***	7.89
Temp	22.72	22.70	4.17	22.85	22.70	4.32	-0.12***	(-9.81)	0.00***	-7.79
Boom	0.52	1.00	0.50	0.47	0.00	0.50	0.05***	(33.64)	1.00***	33.62
Investor	0.13	0.00	0.33	0.09	0.00	0.29	0.04***	(42.44)	0.00	0.00
LocalBuyer	0.16	0.00	0.37	0.16	0.00	0.37	0.00***	(3.60)	0.00***	3.60
Saturday	0.66	1.00	0.47	0.08	0.00	0.28	0.58***	(622.76)	1.00***	243.75

Table 2: Correlation Matrix of Housing and Weather Variables

The table reports the correlation matrix of variables in housing sales dataset for the Sydney metropolitan area from 2000 to 2014. *Price* is the sales price in thousands of Australian dollars. Auction premium estimated from the coefficient of the auction dummy on a hedonic regression of log(price) on auction dummy and control variables estimated weekly. *SurveySenti* is the lagged month Melbourne Institute Sentiment index level. *Rain* is the amount of rain in millimeters for the transaction day. *Solar* is the amount of solar exposure for the transaction day. *Temp* is the temperature in degrees Celsius for the transaction day. *Boom* is a dummy which equals 1 if the transaction occurs between Jan 2000 and Feb 2004 or between Jan 2009 and Apr 2010 or between Jun 2013 and Dec 2014, and 0 otherwise. *House* is a dummy variable equal to one for a freestanding house and zero otherwise. Saturday is a dummy of 1 if home sold on Saturday, 0 otherwise. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

	Auction	Price	SurveySenti	Rain	Solar	Temp	Boom	Investor	House	Saturday
Auction	1.00									
Price	0.22***	1.00								
SurveySenti	0.02***	-0.01***	1.00							
Rain	0.01***	-0.00*	-0.00***	1.00						
Solar	0.01***	-0.00	0.07***	-0.23***	1.00					
Temp	-0.02***	0.01***	0.05***	-0.16***	0.60***	1.00				
Boom	0.04***	-0.02***	0.09***	-0.03***	0.02***	0.06***	1.00			
Investor	0.05 ***	0.02 ***	-0.02 ***	-0.00	-0.02 ***	-0.00 ***	-0.04 ***	1.00		
House	0.11***	0.29***	0.01***	0.00	0.01***	0.01***	-0.00***	-0.02 ***	1.00	
Saturday	0.56***	0.11***	-0.01***	0.01***	0.02***	-0.01***	0.02***	0.04 ***	0.12***	1.00

Table 3: Sentiments in Housing Auctions (Baseline Hedonic Regression)

This table reports coefficient estimates for the following hedonic model across the full sample of individual housing prices:

$$\ln(P_{ist}) = \alpha_0 + \beta_1 Sentiment_t + \beta_2 Auction_i + \beta_3 Auction_i * Sentiment_t + property\ char_i + \mu_s + \gamma_t + \varepsilon_{it}$$

Where $ln(P_{ist})$ denotes natural logarithm of housing prices paid of sale i in suburb s at time t; $Sentiment_i$ denotes one of the four sentiment measures for a home sold at time t; $property\ char$ are various property characteristics such as number of bedrooms, number of bathrooms, parking, property type and area size; μ_s is the suburb location specific fixed effects; γ_t is year fixed effects. The four sentiment measures are *SurveySenti, Rain, Solar* and *Temp*. *SurveySenti* is the lagged month Melbourne Institute Sentiment index level. *Rain* is the amount of rain in millimeters for the transaction day. *Solar* is the amount of solar exposure for the transaction day. *Temp* is the temperature in degrees Celsius for the transaction day. Coefficient estimates of sentiment measures and their interactions are multiplied by 1000 for display purposes. Other variables are described in Appendix 1. The sample is home sales in the Sydney metropolitan area from 2000 to 2014. Standard errors in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively. Panel A uese the full sample, while Panel B and C use the auction and private treaty sample respectively.

Panel A: Sentiment Regressions using the Entire Sample

Variables	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)	(5) log(price)
Auction	0.072***	-0.007	0.071***	0.056***	0.056***
	(0.003)	(0.01)	(0.003)	(0.003)	(0.006)
SurveySenti		0.718***			
		(0.001)			
Auction*SurveySenti		0.734***			
		(0.003)			
Rain			-0.123***		
			(0.001)		
Auction*Rain			-0.174**		
			(0.003)		
Solar				0.028	
				(0.001)	
Auction*Solar				0.847***	
				(0.003)	
Temp					0.185**
					(0.003)
Auction*Temp					0.635***
					(0.006)
New	0.128***	0.131***	0.131***	0.131***	0.131***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Beds	0.129***	0.126***	0.126***	0.126***	0.126***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Baths	0.136***	0.131***	0.131***	0.131***	0.131***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Parking	0.041***	0.042***	0.042***	0.043***	0.042***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	3.153***	2.26***	3.472***	2.992***	3.534***
	(0.473)	(0.536)	(0.531)	(0.538)	(0.532)
Other Housing Char.	Yes	Yes	Yes	Yes	Yes
Suburb F.E.	Yes	Yes	Yes	Yes	Yes
Monthly Time Trend	Yes	Yes	Yes	Yes	Yes
Year and Quarter F.E.	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Suburb	Suburb	Suburb	Suburb	Suburb
Adjusted R-square	0.836	0.842	0.842	0.842	0.842
Observations	852,734	852,734	852,734	836,523	852,734

Panel B: Sentiment Regressions using the Auction Sale Sample

Variables	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)
SurveySenti	1.047***			
	(0.003)			
Rain		-0.326***		
		(0.002)		
Solar			0.827***	
			(0.004)	
Temp				0.656***
				(0.006)
Other Housing Char.	Yes	Yes	Yes	Yes
Suburb F.E.	Yes	Yes	Yes	Yes
Monthly Time Trend	Yes	Yes	Yes	Yes
Year and Quarter F.E.	Yes	Yes	Yes	Yes
Cluster S.E.	Suburb	Suburb	Suburb	Suburb
Adjusted R-square	0.797	0.797	0.797	0.797
Observations	140,420	140,420	137,523	140,420

Panel C: Sentiment Regressions using the Private Treaty Sale Sample

Variables	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)
SurveySenti	0.071			
	(0.002)			
Rain		-0.059*		
		(0.001)		
Solar			-0.087*	
			(0.001)	
Temp				0.11
				(0.003)
Other Housing Char.	Yes	Yes	Yes	Yes
Suburb F.E.	Yes	Yes	Yes	Yes
Monthly Time Trend	Yes	Yes	Yes	Yes
Year and Quarter F.E.	Yes	Yes	Yes	Yes
Cluster S.E.	Suburb	Suburb	Suburb	Suburb
Adjusted R-square	0.842	0.842	0.843	0.842
Observations	712,314	712,314	699,000	712,314

Table 4: Sentiments in Housing Auctions with Boom Period Interaction

This table reports coefficient estimates for the following hedonic model across the full sample of individual housing prices:

$$\ln(P_{ist}) = \alpha_0 + \beta_1 Sentiment_t + +\beta_2 Boom_t * Sentiment_t + \beta_3 Boom_t$$
$$+ property\ char_i + \mu_s + \gamma_t + \varepsilon_{it}$$

Where $ln(P_{ist})$ denotes natural logarithm of housing prices paid of sale i in suburb s at time t; *Sentiment*$_i$ denotes one of the four sentiment measures for a home sold at time t; $property\ char$ are various property characteristics such as number of bedrooms, number of bathrooms, parking, property type and area size; μ_s is the suburb location specific fixed effects; γ_t is year fixed effects. *Boom* is a dummy which equals 1 if the home sale occurred between Jan 2000 and February 2004 and between Jan 2009 to Apr 2010 and between Jun 2013 and Dec 2014. For the four sentiment measures, *SurveySenti* is the previous month's Melbourne Institute Sentiment index level. *Rain* is the amount of rain in millimeters for the transaction day. *Solar* is the amount of solar exposure for the transaction day. *Temp* is the temperature in degrees Celsius for the transaction day. Coefficient estimates of sentiment measures and their interactions are multiplied by 1000 for display purposes. Other variables are described in Appendix 1. Standard errors in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Variables	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)
SurveySenti	2.717***			
	(0.003)			
Boom*SurveySenti	0.125			
	(0.006)			
Rain		-0.299***		
		(0.003)		
Boom*Rain		-0.624***		
		(0.005)		
Solar			0.415***	
			(0.005)	
Boom*Solar			0.752***	
			(0.006)	
Temp				0.671***
				(0.008)
Boom*Temp				-0.70**
				(0.01)
Boom	3.227	20.431***	5.935	34.895***
	(0.688)	(0.093)	(0.128)	(0.261)
New	0.036**	0.034**	0.035**	0.034**
	(0.014)	(0.014)	(0.014)	(0.014)
Beds	0.127***	0.127***	0.127***	0.127***
	(0.004)	(0.004)	(0.004)	(0.004)
Baths	0.132***	0.132***	0.132***	0.132***
	(0.004)	(0.004)	(0.004)	(0.004)
Parking	0.026***	0.023***	0.024***	0.023***
	(0.007)	(0.007)	(0.007)	(0.007)
Constant	6.994***	7.392***	7.381***	7.372***
	(0.078)	(0.076)	(0.076)	(0.076)
Other Housing Char.	Yes	Yes	Yes	Yes
Suburb F.E.	Yes	Yes	Yes	Yes
Monthly Time Trend	Yes	Yes	Yes	Yes
Year and Quarter F.E.	No	No	No	No
Cluster S.E.	Suburb	Suburb	Suburb	Suburb
Adjusted R-square	0.784	0.781	0.782	0.781
Observations	140,420	140,420	137,523	140,420

Table 5: Sentiments in Housing Auctions with Investor Interaction

This table reports coefficient estimates for the following hedonic model across the full sample of individual housing prices:

$$\ln(P_{ist}) = \alpha_0 + \beta_1 Sentiment_t + +\beta_2 Invest_{i,t} * Sentiment_t + \beta_3 Invest_{i,t} + property\ char_i + \mu_s + \gamma_t + \varepsilon_{it}$$

Where $ln(P_{ist})$ denotes natural logarithm of housing prices paid of sale *i* in suburb *s* at time *t*; *Sentiment*$_i$ denotes one of the four sentiment measures for a home sold at time *t*; $property\ char$ are various property characteristics such as number of bedrooms, number of bathrooms, parking, property type and area size; μ_s is the suburb location specific fixed effects; γ_t is year fixed effects. The four sentiment measures are *SurveySenti*, *Rain*, *Solar* and *Temp*. *SurveySenti* is the previous month's Melbourne Institute Sentiment index level. *Rain* is the amount of rain in millimeters for the transaction day. *Solar* is the amount of solar exposure for the transaction day. *Temp* is the temperature in degrees Celsius for the transaction day. Coefficient estimates of sentiment measures and their interactions are multiplied by 1000 for display purposes. Other variables are described in Appendix 1. Standard errors in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Variables	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)
SurveySenti	1.047***			
	(0.104)			
Invest*SurveySenti	-0.039			
	(0.195)			
Rain		-0.339***		
		(0.078)		
Invest *Rain		0.146		
		(0.190)		
Solar			0.820***	
			(0.119)	
Invest *Solar			0.421	
			(0.443)	
Temp				0.617***
				(0.220)
Invest *Temp				0.750***
				(0.241)
Invest	0.008	0.003	-0.006	-0.008*
	(0.021)	(0.003)	(0.010)	(0.004)
New	0.036**	0.035**	0.036***	0.036***
	(0.014)	(0.014)	(0.014)	(0.014)
Beds	0.130***	0.130***	0.131***	0.131***
	(0.004)	(0.004)	(0.004)	(0.004)
Baths	0.137***	0.137***	0.136***	0.136***
	(0.004)	(0.004)	(0.004)	(0.004)
Parking	0.050***	0.050***	0.051***	0.051***
	(0.007)	(0.007)	(0.007)	(0.007)
Constant	-0.228	0.837	0.866	0.419
	(1.226)	(1.209)	(1.219)	(1.216)
Other Housing Char.	Yes	Yes	Yes	Yes
Suburb F.E.	Yes	Yes	Yes	Yes
Monthly Time Trend	Yes	Yes	Yes	Yes
Year and Quarter F.E.	Yes	Yes	Yes	Yes
Cluster S.E.	Suburb	Suburb	Suburb	Suburb
Adjusted R-square	0.787	0.787	0.788	0.788
Observations	140,420	140,420	137,523	137,523

Table 6: Two Stage Least Squares to Address Endogeneity

We run a two stage least squares regressing where in the first stage we run a Probit regression with auction as a dependent variable as:

$\Pr(Auction = 1|X) = \beta_1 Saturday_t + \beta_2 Sentiment_t + \mu_s + \gamma_t + \varepsilon_{ist}$

We then take the predicted value of *auction* as a dependent variable into the second stage. The second stage regression is:

$\ln(P_{ist}) = \alpha_0 + \beta_1 Sentiment_t + \beta_2 \widehat{Auction}_i + \beta_3 \widehat{Auction}_i * Sentiment_t + property\ char_i + \mu_s + \gamma_t + \varepsilon_{it}$

where $\widehat{Auction}$ is the predicted value from the first stage regression. The instrument for auction that we use is *Saturday*. *Saturday* is a dummy variable to denote if the transaction occurs on a Saturday. For the four sentiment measures, *SurveySenti* is the previous month's Melbourne Institute Sentiment index level. *Rain* is the amount of rain in millimeters for the transaction day. *Solar* is the amount of solar exposure for the transaction day. *Temp* is the temperature in degrees Celsius for the transaction day. Coefficient estimates of sentiment measures and their interactions are multiplied by 1000 for display purposes. Other variables are described in Appendix 1. The sample is home sales in the Sydney metropolitan area from 2000 to 2014. Panel A reports the Probit regressions. Panel B reports the second stage regressions. Standard errors in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Panel A: First Stage Probit Regressions

	(1)	(2)	(3)	(4)	(5)
Variables	Auction	Auction	Auction	Auction	Auction
Saturday	1.921***	1.925***	1.924***	1.928***	1.924***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Surveysenti		-0.006***			
		(0.001)			
Rain			0.001***		
			(0)		
Solar				-0.002***	
				(0)	
Temp					-0.001
					(0.001)
New	-0.726***	-0.727***	-0.728***	-0.723***	-0.728***
	(0.019)	(0.019)	(0.019)	(0.02)	(0.019)
Beds	0.05***	0.05***	0.05***	0.05***	0.05***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Baths	-0.025***	-0.025***	-0.025***	-0.026***	-0.025***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Parking	-0.056***	-0.056***	-0.056***	-0.057***	-0.056***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Constant	-80.466***	-73.206***	-81.812***	-84.218***	-81.888***
	(3.845)	(3.937)	(3.861)	(3.905)	(3.861)
R-square	0.336	0.338	0.338	0.338	0.338
Observations	852,734	852,734	853,138	836,925	853,138

Panel B: Second Stage Regression

Variables	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)	(5) log(price)
$\widehat{Auction}$	0.121***	0.066***	0.12***	0.11***	0.116***
	(0.004)	(0.016)	(0.004)	(0.005)	(0.008)
SurveySenti		0.042			
		(0.002)			
$\widehat{Auction}$*SurveySenti		0.503***			
		(0.005)			
Rain			-0.089***		
			(0.001)		
$\widehat{Auction}$ *Rain			-0.147		
			(0.004)		
Solar				-0.078	
				(0.001)	
Auction*Solar				0.489***	
				(0.005)	
Temp					0.195**
					(0.003)
$\widehat{Auction}$ *Temp					0.117
					(0.009)
New	0.135***	0.135***	0.134***	0.134***	0.134***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Beds	0.125***	0.125***	0.125***	0.125***	0.125***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Baths	0.131***	0.131***	0.131***	0.131***	0.131***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Parking	0.043***	0.043***	0.043***	0.043***	0.043***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	4.483***	3.894***	4.031***	3.738***	4.051***
	(0.531)	(0.54)	(0.535)	(0.539)	(0.538)
Other Housing Char.	Yes	Yes	Yes	Yes	Yes
Suburb F.E.	Yes	Yes	Yes	Yes	Yes
Monthly Time Trend	Yes	Yes	Yes	Yes	Yes
Year and Quarter F.E.	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Suburb	Suburb	Suburb	Suburb	Suburb
Observations	852,734	852,734	853,138	836,925	853,138
Adj R-squared	0.842	0.843	0.843	0.844	0.843

Table 7: Propensity Score Matching Result

This table reports coefficient estimates for the following hedonic model across a sample of auction housing sale with private sales paired using propensity score matching:

$$\ln(P_{ist}) = \alpha_0 + \beta_1 Sentiment_t + \beta_2 Auction_i + \beta_3 Auction_i * Sentiment_t + property\ char_i + \mu_s + \gamma_t + \varepsilon_{it}$$

Where $ln(P_{ist})$ denotes natural logarithm of housing prices paid of sale i in suburb s at time t; $Sentiment_i$ denotes one of the four sentiment measures for a home sold at time t; $property\ char$ are various property characteristics such as number of bedrooms, number of bathrooms, parking, property type and area size; μ_s is the suburb location specific fixed effects; γ_t is year fixed effects. For the four sentiment measures, *SurveySenti* is the previous month's Melbourne Institute Sentiment index level. *Rain* is the amount of rain in millimeters for the transaction day. *Solar* is the amount of solar exposure for the transaction day. *Temp* is the temperature in degrees Celsius for the transaction day. Coefficient estimates of sentiment measures and their interactions are multiplied by 1000 for display purposes. Other variables are described in Appendix 1. The sample is created by first estimating propensity scores using a logit regression with the auction dummy as the dependent variable and each sentiment measure and housing characteristics as independent variables. Each auction home is then paired with a non-auctin home sale based on propensity scores. Coefficient estimates of sentiment measures and their interactions are multiplied by 1000 for display purposes. Standard errors in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Variables	(1) log(price)	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)
SurveySenti		-0.245**			
		(0.120)			
Auction* SurveySenti		0.698***			
		(0.115)			
Rain			-0.150*		
			(0.078)		
Auction*Rain			-0.139		
			(0.104)		
Solar				-0.156	
				(0.103)	
Auction*Solar				0.629***	
				(0.130)	
Temp					0.140
					(0.204)
Auction*Temp					0.510**
					(0.246)
Auction	0.060***	-0.014	0.061***	0.050***	0.049***
	(0.003)	(0.012)	(0.003)	(0.004)	(0.007)
New	0.102***	0.102***	0.102***	0.102***	0.102***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Beds	0.122***	0.122***	0.122***	0.122***	0.122***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Baths	0.132***	0.132***	0.132***	0.132***	0.132***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Parking	0.052***	0.052***	0.052***	0.052***	0.052***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Constant	1.434	1.481*	1.407	1.582*	1.494*
	(0.886)	(0.887)	(0.886)	(0.892)	(0.886)
Other Housing Char.	Yes	Yes	Yes	Yes	Yes
Suburb F.E.	Yes	Yes	Yes	Yes	Yes
Year and Quarter F.E.	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Suburb	Suburb	Suburb	Suburb	Suburb
Observations	275,046	275,046	275,032	275,032	275,032
Adj R-squared	0.810	0.810	0.810	0.810	0.810

Table 8: Using Major Sentiment Events as Robustness Check

This table reports coefficient estimates for the following hedonic model across the full sample of individual housing prices:

$$\ln(P_{ist}) = \alpha_0 + \beta_1 Holidays\ (or\ Melbcup) + \beta_2 Auction_i + \beta_3 Auction_i * Holidays\ (or\ Melbcup) + property\ char_i + \mu_s + \gamma_t + \varepsilon_{it}$$

Where $ln(P_{ist})$ denotes natural logarithm of housing prices paid of sale i in suburb s at time t; $property\ char$ are various property characteristics such as number of bedrooms, number of bathrooms, parking, property type and area size; μ_s is the suburb location specific fixed effects; γ_t is year fixed effects. The sentiment dates are *Holidays* and *Melcup*. *Holidays* is a dummy which equals 1 if the sale is made one week before or one week after the public holiday date, 0 otherwise. *MelbCup* is a dummy which equals 1 if the sale is one week before and after the Melbourne Cup (first Tuesday in November). Other variables are described in Appendix 1. Sentiment dates are in Appendix 2. Standard errors in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Variables	(1) log(price)	(2) log(price)
Holidays	-0.002**	
	(0.001)	
Auction*Holidays	-0.013***	
	(0.003)	
Melcup		0.003
		(0.002)
Auction*Melcup		0.016***
		(0.004)
Auction	0.073***	0.071***
	(0.003)	(0.003)
New	0.132***	0.132***
	(0.007)	(0.007)
Beds	0.126***	0.126***
	(0.004)	(0.004)
Baths	0.131***	0.131***
	(0.004)	(0.004)
Parking	0.042***	0.042***
	(0.005)	(0.005)
Constant	11.894***	11.895***
	(0.074)	(0.074)
Other Housing Char.	Yes	Yes
Suburb F.E.	Yes	Yes
Year and Quarter F.E.	Yes	Yes
Cluster S.E.	Suburb	Suburb
Observations	853,143	853,143
Adj R-squared	0.841	0.841

Table 9: Sudden Change in Weather

This table reports coefficient estimates for the following hedonic model across the full sample of individual housing prices:

$$\ln(P_{ist}) = \alpha_0 + \beta_1 Weather_t + \beta_2 Auction_i + \beta_3 Weather\_SuddenChange_t + \beta_4 Auction_i * Weather\_SuddenChange_t + property\ char_i + \mu_s + \gamma_t + \varepsilon_{it}$$

Where $ln(P_{ist})$ denotes natural logarithm of housing prices paid of sale *i* in suburb *s* at time *t*; *Weather* denotes the three weather measures for a home sold at time *t*, including *Rain*, *Solar* and *Temp*. *Rain* is the amount of rain in millimeters. *Solar* is the amount of solar exposure. *Temp* is the temperature in degrees Celsius. *Weather_SuddenChange* is a dummy which equals 1 if the weather measure on the date of transaction is 100% higher than the previous day's measure. $property\ char$ is various property characteristics such as number of bedrooms, number of bathrooms, parking, property type and area size; μ_s is the suburb location specific fixed effects; γ_t is year fixed effects. Other variables are described in Appendix 1. Standard errors in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

VARIABLES	(1) log(price)	(2) log(price)	(3) log(price)
auction	0.074***	0.073***	0.074***
	(0.003)	(0.003)	(0.003)
rain_suddenchange	-0.003***		
	(0.001)		
rain_suddenchange*auction	-0.006***		
	(0.002)		
solar_suddenchange		-0.002*	
		(0.001)	
solar_suddenchange*auction		0.002	
		(0.003)	
temp_suddenchange			-0.003***
			(0.001)
temp_suddenchange*auction			-0.009***
			(0.002)
newdev	0.129***	0.129***	0.129***
	(0.008)	(0.008)	(0.008)
bed	0.129***	0.129***	0.129***
	(0.004)	(0.004)	(0.004)
bath	0.136***	0.136***	0.136***
	(0.004)	(0.004)	(0.004)
parkings	0.041***	0.041***	0.041***
	(0.005)	(0.005)	(0.005)
Constant	11.785***	11.782***	11.786***
	(0.065)	(0.064)	(0.065)
Observations	853,143	853,143	853,143
Other Housing Char.	Yes	Yes	Yes
Suburb F.E.	Yes	Yes	Yes
Year and Quarter F.E.	Yes	Yes	Yes
Cluster S.E.	Yes	Yes	Yes
R-squared	0.836	0.836	0.836
Adj R-squared	0.835	0.835	0.835

Internet Appendix 1: Deseasoned

Table IA1: Hedonic Regression using Deseasoned Sentiment Measures

Sentiment measures are de-seasoned by subtracting the average daily measures over the past three years for the same month. De-seasoning removes potential trends in the sentiment data. Coefficient estimates of sentiment measures and their interactions are multiplied by 1000 for display purposes.

Panel A: Sentiment Regressions using the Entire Sample

Variables	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)	(5) log(price)
SurveySenti	0.882***				0.896***
	(0.001)				(0.001)
Auction*SurveySenti	0.525***				0.5***
	(0.003)				(0.003)
Rain		-0.099***			0.039
		(0.001)			(0.001)
Auction*Rain		-0.113			-0.076
		(0.003)			(0.003)
Solar			0.101**		0.042
			(0.002)		(0.002)
Auction*Solar			0.959***		1.119***
			(0.005)		(0.006)
Temp				0.386***	0.33***
				(0.003)	(0.003)
Auction*Temp				0.279	-0.645**
				(0.008)	(0.01)
Auction	0.064***	0.071***	0.07***	0.07***	0.063***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
New	0.123***	0.131***	0.131***	0.131***	0.123***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Beds	0.126***	0.126***	0.126***	0.126***	0.126***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Baths	0.131***	0.131***	0.131***	0.131***	0.13***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Parking	0.059***	0.042***	0.042***	0.042***	0.06***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)
Constant	4.830***	3.447***	1.472***	3.471***	2.544***
	(0.506)	(0.531)	(0.552)	(0.531)	(0.528)
Other Housing Char.	Yes	Yes	Yes	Yes	Yes
Suburb F.E.	Yes	Yes	Yes	Yes	Yes
Monthly Time Trend	Yes	Yes	Yes	Yes	Yes
Year and Quarter F.E.	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Suburb	Suburb	Suburb	Suburb	Suburb
Adjusted R-square	0.838	0.842	0.843	0.842	0.839
Observations	709,421	852,734	823,451	852,734	683,029

Panel B: Auction Only Sample

Variables	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)	(5) log(price)
SurveySenti	1.289***				1.323***
	(0.003)				(0.003)
Rain		-0.273***			-0.134
		(0.002)			(0.003)
Solar			0.875***		0.819***
			(0.004)		(0.005)
Temp				0.808***	0.113
				(0.007)	(0.009)
New	0.033**	0.034**	0.037***	0.034**	0.036***
	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)
Beds	0.123***	0.126***	0.126***	0.126***	0.123***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Baths	0.128***	0.132***	0.131***	0.132***	0.127***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Parking	0.088***	0.047***	0.047***	0.047***	0.089***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)
Constant	1.758	0.61	-2.223	0.827	-1.884
	(1.302)	(1.322)	(1.356)	(1.328)	(1.302)
Other Housing Char.	Yes	Yes	Yes	Yes	Yes
Suburb F.E.	Yes	Yes	Yes	Yes	Yes
Monthly Time Trend	Yes	Yes	Yes	Yes	Yes
Year and Quarter F.E.	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Suburb	Suburb	Suburb	Suburb	Suburb
Adjusted R-square	0.8032	0.7965	0.7968	0.7965	0.8036
Observations	113,776	140,420	135,301	140,420	109,417

Panel C: Private Treaty Sample

Variables	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)	(5) log(price)
SurveySenti	0.896***				0.902***
	(0.001)				(0.001)
Rain		-0.087***			0.044
		(0.001)			(0.001)
Solar			0.098**		0.057
			(0.002)		(0.002)
Temp				0.325***	0.24**
				(0.003)	(0.003)
New	0.122***	0.129***	0.129***	0.129***	0.122***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Beds	0.126***	0.125***	0.125***	0.125***	0.126***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Baths	0.131***	0.13***	0.129***	0.13***	0.131***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Parking	0.053***	0.04***	0.04***	0.04***	0.053***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)
Constant	5.435***	3.975***	2.21***	3.978***	3.417***
	(0.55)	(0.59)	(0.6)	(0.591)	(0.565)
Other Housing Char.	Yes	Yes	Yes	Yes	Yes
Suburb F.E.	Yes	Yes	Yes	Yes	Yes
Monthly Time Trend	Yes	Yes	Yes	Yes	Yes
Year and Quarter F.E.	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Suburb	Suburb	Suburb	Suburb	Suburb
Adjusted R-square	0.8348	0.8403	0.8416	0.8403	0.8359
Observations	595,645	712,314	688,150	712,314	573,612

Table IA2: Hedonic Regression using 75th Percentile

Sentiment measures are a dummy of 1 if the measure is above the 75th highest percentile during the sample period, 0 otherwise. Coefficient estimates of sentiment measures and their interactions are multiplied by 1000 for display purposes.

Panel A: Sentiment Regressions using the Entire Sample

Variables	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)	(5) log(price)
SurveySenti75	3.677***				2.414**
	(0.03)				(0.03)
Auction*SurveySenti75	15.741***				14.583***
	(0.068)				(0.068)
Rain75		-2.759***			-2.659***
		(0.02)			(0.021)
Auction*Rain75		-7.07***			-1.824
		(0.053)			(0.056)
Solar75			0.812		-0.02
			(0.029)		(0.002)
Auction*Solar75			10.168***		0.759***
			(0.059)		(0.004)
Temp75				-0.091	-0.02
				(0.026)	(0.026)
Auction*Temp75				6.622***	-0.574
				(0.06)	(0.068)
Auction	0.067***	0.072***	0.068***	0.069***	0.055***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
New	0.131***	0.131***	0.131***	0.131***	0.131***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Beds	0.126***	0.126***	0.126***	0.126***	0.126***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Baths	0.131***	0.131***	0.131***	0.131***	0.131***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Parking	0.042***	0.042***	0.042***	0.042***	0.043***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	3.197***	3.462***	3.44***	3.528***	2.771***
	(0.534)	(0.531)	(0.526)	(0.532)	(0.541)
Other Housing Char.	Yes	Yes	Yes	Yes	Yes
Suburb F.E.	Yes	Yes	Yes	Yes	Yes
Monthly Time Trend	Yes	Yes	Yes	Yes	Yes
Year and Quarter F.E.	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Suburb	Suburb	Suburb	Suburb	Suburb
Adjusted R-square	0.8416	0.8416	0.8416	0.8416	0.8425
Observations	852,734	852,734	852,734	852,734	836,523

Panel B: Auction Only Sample

Variables	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)	(5) log(price)
SurveySenti75	9.001***				8.878***
	(0.065)				(0.065)
Rain75		-9.74***			-8.071***
		(0.05)			(0.05)
Solar75			10.779***		9.096***
			(0.06)		(0.062)
Temp75				4.052**	0.441
				(0.061)	(0.063)
New	0.034**	0.034**	0.034**	0.034**	0.035**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Beds	0.126***	0.126***	0.126***	0.126***	0.126***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Baths	0.132***	0.132***	0.132***	0.132***	0.132***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Parking	0.047***	0.047***	0.047***	0.047***	0.047***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Constant	0.268	0.661	0.775	0.889	0.064
	(1.338)	(1.327)	(1.325)	(1.333)	(1.339)
Other Housing Char.	Yes	Yes	Yes	Yes	Yes
Suburb F.E.	Yes	Yes	Yes	Yes	Yes
Monthly Time Trend	Yes	Yes	Yes	Yes	Yes
Year and Quarter F.E.	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Suburb	Suburb	Suburb	Suburb	Suburb
Adjusted R-square	0.7965	0.7965	0.7965	0.7964	0.7966
Observations	140,420	140,420	140,420	140,420	140,420

Panel C: Private Treaty Sample

Variables	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)	(5) log(price)
SurveySenti75	5.652***				5.617***
	(0.03)				(0.03)
Rain75		-2.742***			-2.656***
		(0.02)			(0.021)
Solar75			1.028		0.63
			(0.03)		(0.03)
Temp75				0.324	-0.227
				(0.026)	(0.026)
New	0.129***	0.129***	0.129***	0.129***	0.129***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Beds	0.125***	0.125***	0.125***	0.125***	0.125***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Baths	0.13***	0.13***	0.13***	0.13***	0.13***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Parking	0.04***	0.04***	0.04***	0.04***	0.04***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	3.713***	3.988***	3.945***	3.988***	3.69***
	(0.591)	(0.591)	(0.584)	(0.592)	(0.585)
Other Housing Char.	Yes	Yes	Yes	Yes	Yes
Suburb F.E.	Yes	Yes	Yes	Yes	Yes
Monthly Time Trend	Yes	Yes	Yes	Yes	Yes
Year and Quarter F.E.	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Suburb	Suburb	Suburb	Suburb	Suburb
Adjusted R-square	0.8403	0.8403	0.8403	0.8403	0.8403
Observations	712,314	712,314	712,314	712,314	712,314