The Winner's Curse in Housing Markets

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Abstract

Homebuyers who participate in bidding wars are susceptible to a winner's curse. We theoretically quantify the winner's curse in housing markets, showing that the presence and intensity of a bidding war exacerbates the winner's curse. We empirically test our theoretical hypotheses by examining the subsequent performance of bidding war transactions in four large US cities. We find that homeowners who purchase their property via a bidding war are more likely to default and earn lower annualized returns than those who did not purchase their property via a bidding war. We highlight the far-reaching implications of these findings by showing that the winner's curse undermines housing affordability.

Keywords: Winner's Curse, Housing Affordability, Bidding War, Auction

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The homebuying process is conventionally modeled as a sequential bargaining game (Yinger, 1981; Haurin et al., 2010; Carrillo, 2012; Han and Strange, 2014). A seller considers an offer as it arrives and decides to accept or reject the offer. However, if a seller is willing to consider multiple offers simultaneously, the homebuying process follows a first-price sealed-bid auction (Williams, 1995; Quan, 2002). Since a house consists of both private and common value elements, a prospective buyer who submits a bid based on only its signal can suffer the winner's curse (Oren and Williams, 1975; Thaler, 1988).

In this paper, we investigate the winner's curse in the housing market. First, we theoretically study the symmetric Bayesian Nash equilibria under rational and irrational bidders. We show that the winner's curse exists in an auction with more than two bidders and that the curse worsens as a bidding war intensifies.[1] The key prediction generated by our model is that a bidding war exacerbates the winner's curse, which in turn elevates house prices and undermines housing affordability.

Intuitively, homeowners who purchase their property via a bidding war are more likely to suffer from the winner's curse than those who did not purchase their property via a bidding war. We test our model's hypotheses by quantifying the winner's curse in the subsequent performance of bidding war transactions using housing transaction data from four large US cities. We estimate the winner's curse using three performance measures: default, unlevered returns, and levered returns. Consistent with our theory, we find that the winners of bidding war transactions are more likely to default and earn lower annualized returns. The effects of the winner's curse are significant in the housing market. Homeowners who purchase their property via a bidding war are 4.8 percentage

[1] According to the National Association of Realtors (NAR), the average number of offers received on most recent sales from 2016 to 2020 is fewer than 3. After the pandemic, the average number reaches as high as 5 as shown in Figure 1. We define a bidding war as an auction with more than two bidders.

points (pp) more likely to default, earn 1.2 pp lower unlevered annualized returns, and earn 7.5 pp lower levered annualized returns than homeowners who did not purchase their property via a bidding war.

Our results also have implications regarding housing affordability via two channels: (i) elevated selling price (*ex-ante*) and (ii) negative financial consequences (*ex-post*). Since we expect the bidding war winners to overpay, the winner's curse effectively excludes the homebuyers who could afford the purchase under a rational equilibrium. Given the bidding war winners are more likely to suffer from default and lower returns, the winner's curse undermines their ability to afford an equivalent class of homes in future.

To the best of our knowledge, this article offers the first theoretical and empirical models that quantify the winner's curse in a housing market. Although the extant literature examines the impact of auction mechanism in real estate (Ong, 2006; Wong et al., 2014; Shi and Kabir, 2018; Huang et al., 2023), our paper is the first to measure the winner's curse as subsequent performance of bidding war transactions in an auction environment. The results of our study generate a number of policy implications. First, if bidding wars frequently occur in a region, elevated housing prices can induce price bubbles and worsen housing affordability. Second, the winner's curse is not only *ex-ante* present in the selling home price but also *ex-post* binding in the form of adverse financial outcomes; the curse haunts the winner even after the initial housing transaction is complete. Third, identifying whether a local market is increasingly susceptible to bidding wars can signal to policymakers to preemptively address housing affordability.

Our paper is related to existing research quantifying the effects of the winner's curse (Kagel and Levin, 1986; Lind and Plott, 1991; Charness and Levin, 2009). This paper is distinct from previous studies investigating the winner's curse where a typical measurement of the winner's curse resorts to simulating auction revenues under various reservation prices and a calibration to test distinct equilibrium outcomes. We develop a novel technique in computing the effect of the winner's curse by leveraging the fact that the auctioned good (home) undergoes repeated sales. This salient and unique feature of the housing market allows us to effectively decompose the winner's curse into *ex-ante* over-payment and *ex-post* negative financial consequences. Empirically, this decomposition enables us to use the former element in identify bidding war transactions and use the latter to quantify the curse's impact in the form of future credit risk and investment return.

Our paper also relates to a large literature identifying a bidding war in auctions (Han and Strange, 2014; Koster and Rouwendal, 2023; Liu and Smith, 2023). It is a challenge to unambiguously determine whether a transaction undergoes a sequential bargaining or an auction. In our theoretical set-up, we define a bidding war as an auction where there are more than two bidders. The bidding war definition is based on the stylized fact that the average number of offers received is below 3 between 2016 and 2020 (Figure 1). However, the number of bidders in a transaction is unobservable. For this reason, we use the sale and list prices as a proxy for a bidding war; we define a bidding war as a transaction where the sales price is greater than the list price (Bucchianeri and Minson, 2013; Han and Strange, 2014).[2] A disadvantage of this approach is that a property can be sold for reasons other than a bidding war. To mitigate this issue, we control for physical property characteristics and location attributes to credibly identify auction transactions.

Finally, our research is related to recent work by Buchak et al. (2022) concern-

[2]In a subsequent version of our paper, we plan to use a lexicon of auction terms to cross-check whether this empirical definition is robust.

ing measurement of housing affordability. Housing affordability[3] is typically a static measure examining whether a typical median-income household can afford to pay a mortgage without payment disruptions of other consumption in a given area and period (e.g., a median-income household in Boston can afford a median-priced Boston home given mortgage rates in 2024). Instead of taking a snapshot of local housing affordability, we propose that a more accurate estimate of housing affordability should be a dynamic measure where it tracks from purchase to sale household's ability to pay its mortgage without defaulting. In the context of the winner's curse, we normalize our coefficient estimates by the sample mean to provide this dynamic measure. Based on our housing affordability measure in the context of the winner's curse, we find that Houston and Detroit are the least affordable cities.

This paper is organized as follows. Section 1 introduces the theoretical model and predictions. In Section 2, we describe our empirical strategy and present key results. Section 3 concludes. Remaining sections are Tables, Figures, and Appendices.

1 Theory

1.1 Set up

We build on the previous literature by considering a model with a common-value auction structure in a static game of incomplete information (Milgrom and Weber, 1982; Fudenberg and Tirole, 1991; Tadelis, 2013; Harrington, 2015; Hortaçsu et al., 2018). The auctioned good is a house with n bidders in a first-

[3]The U.S. Department of Housing and Urban Development (HUD) suggests that keeping housing costs below 30 percent of income ensures households to have sufficient funds to cover non-discretionary costs. The National Association of Realtors (NAR) measures affordability by studying whether a family with the median income has sufficient income to qualify for a mortgage on a nationally median-price home.

price sealed bid auction. Each bidder i obtains a noisy signal (θ_i) about the value of the house; the signal is each bidder's type that is drawn independently and identically from the interval $\theta_i \in [\underline{\theta}_i, \bar{\theta}_i]$ based on the cumulative distribution function $F_i(\cdot)$ where $\underline{\theta}_i \geq 0$. Every bidder has the distributional information of other bidders' CDF to form belief about their types θ_{-i}.

$$v = \frac{1}{n}\sum_{i=1}^{n}\theta_i \tag{1}$$

$$b_i = \alpha\theta_i \tag{2}$$

The property's value (v) is the sum of the average of the bidders' signals[4] and bidder i downgrades its own signal by a factory of $\alpha > 0$.[5]

1.2 Rational Equilibrium

1.2.1 Expected Payoff

For tractability, we assume nature draws bidders' types from the uniform distribution $[0, 1]$. First, we investigate a rational bidder i's expected payoff. Suppose the rational bidder correctly computes the expected payoff conditional on (i) its own type θ_i and (ii) its bid being the highest. The latter piece of information establishes rationality, because it assumes that bidder i correctly forecasts winning the bid is equivalent to having the highest signal in the auction. Then, its expected payoff is:

$$P(b_i > b_{-i})\mathbb{E}\left(v - b_i|\theta_i, b_i > b_{-i}\right) \tag{3}$$

[4]If the noisy signals are drawn from the uniform distribution, then the house's value follows the Bates distribution.

[5]For example, see Milgrom and Weber (1982) and Hortaçsu et al. (2018) for bid shading and value downgrading behaviors in auctions.

1.2.2 Rational Bidder's Problem

Each bidder solves the following optimization problem:

$$\max_{b_i} \quad \left(\frac{b_i}{\alpha}\right)^{n-1}\left[\frac{\theta_i}{n}+\left(\frac{n-1}{n}\right)\frac{b_i}{2\alpha}-b_i\right] \tag{4}$$
$$\text{s.t.} \quad b_i \geq 0$$

1.2.3 Equilibrium

Assuming an interior solution, the first-order condition with respect to b_i yields the optimal bidding strategy:

$$b_i^* = \left(\frac{n-1}{n}\right)\left[\frac{2\alpha\theta_i}{2\alpha n - n + 1}\right]\theta_i \tag{5}$$

By rearranging the optimal bid for the mark-down rule, we derive Lemma 1:

Lemma 1 Suppose nature draws n bidders' types from uniform distribution $[0, 1]$. Assume each bidder knows its type and also correctly understands that winning the bid implies its bid must be the highest one. Then, in a symmetric Bayesian Nash Equilibrium, the optimal bidding is $b_i^* = \frac{(n+2)(n-1)}{2n^2}\theta_i$.

1.2.4 Expected Price of Home under Rationality

The expected revenue of the auction is equal to the expected selling price of the home, which is the expected highest bid submitted. Since the highest bidder admits the highest valuation of the home, it follows under the rational equilibrium:

$$\mathbb{E}[P_R^*] = \frac{(n+2)(n-1)}{2n^2}\mathbb{E}(\theta_i|\theta_i > \theta_{-i}) = \frac{(n+2)(n-1)}{2n^2}\mathbb{E}\left[\theta_{(1)}\right] \tag{6}$$

Since the expectation of the highest valuation is the expected value of the maximum among n independently and identically draws from the uniform distribution on a unit interval, it is the expected value of the first-order statistic ($\mathbb{E}\left[\theta_{(1)}\right]$). We derive the expected selling price of the home and derive Lemma 2.

Lemma 2 Suppose nature draws n bidders' types from uniform distribution $[0, 1]$. Assume each bidder knows its type and also correctly understands that winning the bid implies its bid must be the highest one. Then, the expected selling price of the home is $\mathbb{E}[P_R^*] = \frac{(n+2)(n-1)}{2n^2}\left(\frac{n}{n+1}\right)$.

1.3 Irrational Equilibrium

1.3.1 Expected Payoff

Under a rational equilibrium, a rational bidder i would utilize two pieces of information: (i) its own signal (θ_i) and (ii) winning the bid implies its bid is the highest one ($\theta_i > \theta_{-i}$). We investigate an irrational equilibrium in which the bidder i only takes its own signal into account when computing the expected payoff. We also assume that it irrationally infers other bidders' types to be θ_i, which implies $\mathbb{E}(\theta_{-i}|\theta_i) = \theta_i$.[6]

$$P(b_i > b_{-i})\mathbb{E}\left(v - b_i|\theta_i\right) = \left(\frac{b_i}{\alpha}\right)^{n-1}\left(\frac{1}{n}\sum_{i=1}^{n}\theta_i - b_i\right) \tag{7}$$

1.3.2 Rational Bidder's Problem

Irrational bidder i solves the following problem:

$$\max_{b_i} \quad \left(\frac{b_i}{\alpha}\right)^{n-1}\left(\sum_{i=1}^{n}\theta_i - b_i\right) \tag{8}$$
$$\text{s.t.} \quad b_i \geq 0$$

[6]This is a reasonable first approximation of a common error that an irrational homebuyer would make; based on its own type, it supposes other prospective homebuyers value the house as valuable as it values.

1.3.3 Equilibrium

The irrational bidder i submits with the following amount:

$$\tilde{b}_i = \left(\frac{n-1}{n}\right)\theta_i \tag{9}$$

1.3.4 Expected Price of Home under Irrationality

The expected price of home under the irrational equilibrium is:

$$\mathbb{E}[P_I^*] = \left(\frac{n-1}{n}\right)\mathbb{E}\left[\theta_{(1)}\right] = \left(\frac{n-1}{n}\right)\left(\frac{n}{n+1}\right) = \frac{n-1}{n+1} \tag{10}$$

Under the irrationaly equilibrium, we derive the following lemma.

Lemma 3 Suppose nature draws n bidders' types from uniform distribution $[0, 1]$. Assume each bidder knows its type. However, a bidder is irrational and does not know winning the bid implies its bid must be the highest one. Also, suppose a bidder irrationally infers other bidders' types to be its own type. Under the irrational equilibrium, the optimal bidding strategy and expected selling price of the home are respectively $\tilde{b}_i = \left(\frac{n-1}{n}\right)\theta_i$ and $\mathbb{E}[P_I^*] = \frac{n-1}{n+1}$.

1.4 Winner's Curse

The winner's curse is defined as the difference between rational and irrational optimal bidding amount. We show that the curse is non-positive.

$$WC_i = b_i^* - \tilde{b}_i \leq 0 \tag{11}$$

Based on the optimal bidding amount under rational and irrational equilibria:

$$WC_i = b_i^* - \tilde{b}_i = \left[\frac{(n-1)(2-n)}{2n^2}\right]\theta_i \leq 0 \quad \text{for } n \geq 2 \tag{12}$$

Since homeowners who purchase their property under the irrational equilibrium suffer from the winner's curse, we hypothesize that they are more likely face negative financial consequences such as default and lower returns. We expect these negative financial consequences to exacerbate as a bidding war intensifies. We derive Proposition 2.

Proposition 1 Suppose nature draws n bidders' types from uniform distribution $[0, 1]$. Assume each bidder knows its type. In the rational equilibrium, a bidder understands that the winning bid is the highest. In the irrational equilibrium, a bidder does not know the winning bid is the highest and infers other bidders' types to be its own type. Define the winner's curse to be the difference between the optimal bidding strategy of the rational and irrational equilibria. Define a bidding war to be an auction with three or more bidders. The winner's curse exists in a bidding war, and the curse exacerbates as a bidding war intensifies.

1.5 Housing Affordability

1.5.1 Rational v. Irrational Equilibria

The expected selling price of home under irrational equilibrium begins to diverge significantly as a bidding war intensifies. As the number of bidders increase, not only does the winning bidder pays more than its own signal but also the expected home's price is significantly more expensive than the selling price under the rational equilibrium. We hypothesize that bidding wars critically and adversely impact the housing affordability by amplifying the selling price.

Proposition 2 Suppose nature draws n bidders' types from uniform distribution $[0, 1]$. Assume each bidder knows its type. In the rational equilibrium, a bidder understands that the winning bid is the highest. In the irrational equilibrium, a bidder does not know the winning bid is the highest and infers other bidders' types to be its own type. Define housing affordability to be the difference between the expected selling price of the homes in the rational and irrational equilibria. Define a bidding war to be an auction with three or more bidders. An intensifying bidding war erodes housing affordability.

2 Empirical Strategy

2.1 Data and Measurement

We examine the subsequent performance of bidding war transactions using single-family detached housing transaction data from January 2000 through June 2023. We use multiple listing service (MLS) data from four large MSAs that we obtain from CoreLogic. We selected the MSAs based on the size of their population (Top 50 in the US), historical data availability (coverage starting in 2000), and to provide geographic diversification in terms of variation in location-specific attributes such as price, supply constraints, and the underlying housing stock. The four MSAs include Boston, Massachusetts (BOS); Detroit, Michigan (DET); Houston, Texas (HOU); and Seattle, Washington (SEA). We plan on using the comprehensive nationwide CoreLogic MLS data in the next version of this paper.

The MLS data includes physical house attributes (square feet living area, number of bathrooms, etc.), location attributes (street address, zip code, etc.), and transaction information such as list price, sales price, and sale date. Following Bucchianeri and Minson (2013) and Han and Strange (2014), we define a bidding war as any transaction where the sales price exceeds the list price. Panel A of Table 1 reports the average list and sale price separated by transaction type (bidding war versus non-bidding war) for every listing that sold in the combined four-city transaction sample. We apply several filters to remove outliers and mis-keyed information.[7] After applying the filters, the sample includes over 3.0 million transactions across the four MSAs.

Panel B of Table 1 reports the average list and sale price separated by transaction type for the filtered non-distressed transaction sample. We refrain from interpreting differences in raw sale prices in the summary statistics table because houses purchased via bidding wars may differ in quality compared to houses not purchased via bidding wars. In the empirical analysis below, we focus on subsequent default and housing returns which hold the property constant.

Figure 6 plots the percent of bidding war transactions over time for the filtered four-city transaction sample. From 2000 through 2019, the share of bidding wars constituted roughly 10 to 30% of all transactions. Then in 2020, there was a sharp increase in the share of bidding wars. In 2021, bidding wars accounted for more than 50% of all transactions.

2.1.1 Measuring Subsequent Performance

We examine the subsequent performance of bidding war transactions using three district measures: default, unlevered returns, and levered returns. All three measures require that we identify consecutive transactions (i.e., repeat sales) for each property. This section describes how we construct the three measures of subsequent performance.

Our first measure of subsequent performance examines whether a buyer

[7] The internet appendix provides a detailed description of each filter and tracks the number of observations the filter removes.

subsequently defaults on their loan resulting in a distressed transaction. We construct the subsequent default measure by examining whether the transaction following the buyer's purchase is a distressed transaction. The subsequent default variable equals 1 for transactions where the subsequent transaction is either a short sale or real estate owned (REO) transaction and 0 otherwise. We construct the subsequent default variable and then remove distressed transactions from the subsequent default transaction sample.

Panel C of Table 1 displays the summary statistics for transactions in which we can credibly identify whether a buyer subsequently defaulted on their loan. We limit the subsequent default sample in Panel C to include transactions from 2000 through 2017, which provides a five-plus year post-purchase default measurement window for transactions at the tail end of the sample. We assume all purchases prior to 2008 without a subsequent transaction did not default. This conservative assumption biases the mean default rate in Panel C upwards. Our empirical findings do not change when we use a less conservative assumption or limit the sample to only include the repeat sales in Panel D of Table 1.

Our second measure of subsequent performance examines unlevered realized returns earned in the period from purchase to sale. Our approach is similar to Goldsmith-Pinkham and Shue (2023), who examine housing returns by gender. We identify the unlevered annualized return for property i in sale year s as $r_{is} = (\frac{P_{is}}{P_{ib}})^{\frac{1}{(s-b)}} - 1$, where P_{ib} is the purchase price for the property in year b and P_{is} is the subsequent sale price in year s. When calculating the holding period for each transaction, we allow years b and s to be nonintegers.

Our third measure of subsequent performance addresses the fact that most homeowners in the United States use leverage (i.e., take out a mortgage) to purchase a house. We find many of the fields (i.e., mortgage type, term, interest rate, and downpayment) necessary to calculate the levered return are not reliably populated in the data. Following Goldsmith-Pinkham and Shue (2023), we address this data issue by computing the hypothetical levered returns based on the most common mortgage type in the data: a 30-year fixed rate loan with an initial loan-to-value (LTV) ratio of 80%.

We estimate the downpayment D_{ib} and mortgage amount M_{ib} for each transaction based on the purchase price and the aforementioned 80% LTV assumption. Using the 30-year fixed-rate mortgage interest rate from Freddie Mac in the month and year of the purchase ρ_{ib}, we calculate the amount of the principal paid down (i.e., amortized) at every monthly duration horizon. Assuming no refinancing, we use the amortization schedule to identify the remaining mortgage balance (i.e., outstanding principal) when the house is sold as M_{is}. We then estimate the homeowner's equity reversion (i.e., cash remaining from the sale after paying off their mortgage) at the time of sale as $Equity_{is} = max\{P_{is} - M_{is}, 0\}$. Next, we estimate the present value of the homeowner's equity investment as the sum of the downpayment plus the discounted value of the principal paydown payment as $Equity_{ib} = D_{ib} + \sum_{\tau=b}^{s} W_{i\tau}/(1+\rho_{ib})^{\tau-b}$. Finally, we estimate the levered annualized return as $r_{is}^{lev} = (\frac{Equity_{is}}{Equity_{ib}})^{\frac{1}{(s-b)}} - 1$.

2.2 Methodology

Our empirical analysis takes two forms. Both approaches use a simple linear regression framework to examine the subsequent performance of mortgages associated with bidding war transactions. The first is an analysis of the probability that the homeowner subsequently defaults, resulting in a distressed transaction:

$$Pr(Distress_{is}) = BiddingWar_{ib}\beta_1 + X_{ib}\beta_X + \epsilon_{ib} \tag{13}$$

where $Distress_{is}$ is an indicator identifying if the subsequent transaction is either a short sale or REO, $BiddingWar_{ib}$ is an indicator variable for a bidding war transaction at time b, and X_{ib} is a vector of control variables. The control variables in Equation 13 include housing characteristics, time, and location controls. We allow the housing characteristics to have non-linear effects on price and create indicator variables for 100-square-foot-wide bins of living space ($SQFT_{500-599,nt}, SQFT_{600-699,nt}, ...$), 10-year-wide bins of house age ($AGE_{0-9,nt}, AGE_{10-19,nt}, ...$), number of bedrooms, number of bathrooms, and number of acres in lot size. The time and location controls include zip code-by-year-by-quarter fixed effects at the time of purchase.

Our second set of analyses focuses on unlevered and levered annualized returns for bidding war transactions relative to non-bidding war transactions:

$$r_{is} = BiddingWar_{ib}\beta_1 + Hold_{ib}\beta_2 + X'_{ib}\beta_X + \epsilon_{ib} \quad (14)$$

where $BiddingWar_{ib}$ is an indicator variable for a bidding war transaction at time b, r_{is} is the annualized return, $Hold_{ib}$ is the holding period length in years, and X'_{ib} is a vector of control variables. The control variables in Equation 14 include zip-year-quarter fixed effects for the initial purchase transaction and zip-year-quarter fixed effects for the sale transaction. Including the fixed effects allows us to estimate the average difference in returns by transaction type in the same zip code and time period of purchase and sale.

2.3 Results

2.3.1 Default

The results for Equation 13 are presented in the first two columns of Table 2. Column 1 uses the subsequent default sample of transactions in Panel C of

Table 1 that assumes any current homeowner who purchased prior to 2008 did not default on their mortgage. The coefficient estimate for bidding war transactions is positive and statistically significant, indicating homeowners who purchase their property in a bidding war are 4.8 percentage points (pp) more likely to default on their mortgages than homeowners who did not purchase their property in a bidding war. This coefficient is economically significant as the probability of default in the sample is 11.6pp.

Figure 7 plots the corresponding city-level bidding war coefficient estimates from Equation 13 using the subsequent default sample. The coefficient estimate for bidding war transactions is positive and statistically significant for all four cities. Moreover, the bidding war coefficient is economically significant in all four cities: 1pp in Boston where the probability of default in the sample is 6.8pp; 6.2pp in Detroit where the probability of default in the sample is 18pp; 7.2pp in Houston where the probability of default in the sample is 10.4pp; and 3.6pp in Seattle where the probability of default in the sample is 10.6pp.

The results in Column 1 may be biased as we assume any homeowner who did not sell their property did not default. Column 2 limits the sample to all transactions with a subsequent transaction in the sample (i.e., the returns sample in Panel D of Table 1). The coefficient estimate for bidding war transactions is positive and statistically significant, indicating homeowners who purchase their property in a bidding war are 5.7pp more likely to default on their mortgages than homeowners who did not purchase their property in a bidding war. This coefficient is economically significant as the probability of default in the sample is 17.0pp.

2.3.2 Returns

The results for Equation 14 are presented in columns 3 to 6 of Table 2. Column 3 examines homeowners' unlevered returns by transaction type using the repeat sales returns sample in Panel D of Table 1. The coefficient estimate for bidding war transactions is negative and statistically significant, indicating homeowners who purchase their property in a bidding war experience 1.2pp smaller annualized returns than homeowners who did not purchase their property in a bidding war. This coefficient is economically significant as the average annualized unlevered return in the sample is 5.1pp.

Figure 8 plots the corresponding city-level bidding war coefficient estimates from Equation 14 examining homeowners' unlevered returns by transaction type. The coefficient estimate for bidding war transactions is negative and statistically significant in all four cities, indicating homeowners who purchase their property in a bidding war experience smaller annualized returns than homeowners who did not purchase their property in a bidding war. Moreover, the bidding war coefficient is economically significant in all four cities: -1.1pp in Boston where the average annualized unlevered return in the sample is 6.2pp; -2.1pp in Detroit where the average annualized unlevered return in the sample is 2.6pp; -1.3pp in Houston where the average annualized unlevered return in the sample is 4.9pp; and -0.8pp in Seattle where the average annualized unlevered return in the sample is 6.6pp.

The results in Columns 1 and 2 of Table 2 indicate that homeowners' who purchase their house via a bidding war are more likely to default. Column 4 filters the repeat sales sample in column 3 to only include repeat sales transactions with a subsequent non-distressed transaction. Even after dropping distressed transactions, we continue to find the coefficient estimate for bidding war transactions is negative and statistically significant, indicating homeowners who purchase their property in a bidding war experience 0.6pp smaller annualized returns than homeowners who did not purchase their property in a bidding war. This coefficient is economically significant as the annualized unlevered return for this non-distressed returns subsample is 7.4pp.

Column 5 of Table 2 examines homeowners' levered returns by transaction type using the repeat sales returns sample in Panel D of Table 1. The coefficient estimate for bidding war transactions is negative and statistically significant, indicating homeowners who purchase their property in a bidding war experience 7.5pp smaller annualized returns than homeowners who did not purchase their property in a bidding war. This coefficient is economically significant as the annualized levered return in the sample is 16.6pp.

Figure 9 plots the corresponding city-level bidding war coefficient estimates from Equation 14 examining homeowners' levered returns by transaction type. Once again, the coefficient estimate for bidding war transactions is negative and statistically significant in all four cities, indicating homeowners who purchase their property in a bidding war experience smaller annualized returns than homeowners who did not purchase their property in a bidding war. Moreover, the bidding war coefficient is economically significant in all four cities: -7.8pp in Boston where the average annualized unlevered return in the sample is 25.5pp; -10.7pp in Detroit where the average annualized unlevered return in the sample is 4.6pp; -8.1pp in Houston where the average annualized unlevered return in the sample is 17.7pp; and -5.5pp in Seattle where the average annualized unlevered return in the sample is 19.6pp.

Column 6 filters the returns sample in Column 5 to only include repeat sales transactions with a subsequent non-distressed transaction. Even after removing distressed transactions, we continue to find that the coefficient estimate for bidding war transactions is negative and statistically significant, indicating homeowners who purchase their property in a bidding war experience 3.5pp smaller annualized returns than homeowners who did not purchase their property in a bidding war. This coefficient is economically significant as the annualized levered return in the sample is 30.3pp.

2.4 The Winner's Curse & Housing Affordability

Housing affordability conventionally focuses on three factors: (i) ability to qualify for a mortgage loan, (ii) ability to pay for non-discretionary purchases after incurring housing costs, and (iii) ability to embody first-time or low-income homebuyers. Since income levels, demographics, and house prices vary over time and location, housing affordability based on these measures is typically calculated in a specific time period (e.g., In 2024, a median-income household in Boston can afford a median-priced home given a mortgage rate of 6%).

We propose a novel and dynamic measure of housing affordability in the context of the winner's curse. Since our empirical strategy allows us to track the subsequent performance of bidding war transactions, we are able to compare our estimates to the sample mean and measure to what extent the bidding war winners suffer from deterioration of housing affordability relative to their sample peers. Our measure of housing affordability focuses on the group of homebuyers who are willing to bid above the asking price and win the bid.[8]

We focus primarily on two performance metrics: default (credit risk) and levered return (equity return). Intuitively, if the coefficient estimate-to-sample mean ratio is high (e.g., above 50%), the bidding war winners subsequently become significantly credit risky and experience notably negative levered returns

[8]The bidding war winner candidates may not necessarily be wealthy households (e.g., have sufficient means to over-bid). Charles et al. (2009) find Blacks and Hispanics allocate significant portion of their discretionary bundles such as jewelry, car, and housing expenditures. Certain ethnic groups (e.g., Asian) have strong desire for land ownership.

compared to the sample. After the bidding war winners sell their property, we suppose that they once again become homebuyers. We argue that their negative financial consequences will undermine their ability to afford homes in the next cycle of house hunting. We quantify the extent to which the winner's curse impacts the housing affordability of the potential bidding war winners by comparing our estimates to the sample's first moment.

Table 3 documents our main findings. Homeowners in Houston who purchase their property in a bidding war are 7.2 percentage points more likely to default on their mortgages than non-bidding war homebuyers when the sample mean of the default probability is 10.4pp. The coefficient estimate-mean ratio is approximately 70%, which implies the subsequent credit risk of the bidding war winners becomes significantly high (relative to the sample's first moment) when the subsequent sale event occurs.

We compute the second measure of housing affordability by examining the coefficient estimate-mean ratio for levered returns. Detroit's ratio is approximately 232% (-10.7 pp to 4.6 pp), which implies the subsequent investment return of the bidding war winners' homes is significantly reduced relative to the sample mean. Houston's ratio is approximately 50%, which is a sizeable reduction compared to the sample average. Based on the two measures we compute, Houston is the least affordable city for those who are willing to fight to win the bid. Detroit is the least affordable city when looking at the levered return affordability ratio.

3 Conclusion

This article makes two contributions. First, we decompose the winner's curse into two parts: *ex-ante* overpayment and *ex-post* credit and investment risks.

In our theoretical model, we show that the winner's curse exists and worsens as a bidding war intensifies. The expected selling price of the home increases significantly more with respect to the number of bidders under the irrational equilibrium compared to the price under the irrational equilibrium. We argue that this *ex-ante* component of the winner's curse undermines housing affordability.

Since the number of bidders in a transaction is unobservable, we empirically quantify the winner's curse by using the *ex-post* credit risk and investment performance (default, unlevered and levered returns) of bidding war transactions in Boston, Detroit, Houston, and Seattle. We provide unambiguous measure of the winner's curse in four cities and find homeowners who purchase their property via a bidding war are more likely to default and earn lower annualized unlevered and levered returns.

Second, by examining the subsequent performance of bidding war transaction, we expand and enhance the definition of housing affordability. We leverage the fact that houses are sold in a repeated manner and argue affordability should be a dynamic measure. In the context of the winner's curse, we provide a novel measure of comparing the negative financial consequences of bidding war winners to their sample peers. Among the four cities, we find that Houston is the last affordable city based on the coefficient estimate-sample mean ratio for default and levered returns. Looking at the estimate-mean ratio for levered returns only, Detroit is the least affordable city for the bidding war winners.

References

Bucchianeri, Grace W, and Julia A Minson. 2013. "A homeowner's dilemma: Anchoring in residential real estate transactions." *Journal of Economic Behavior & Organization* 89 76–92.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru. 2022. "Why is Intermediating Houses so Difficult? Evidence from iBuyers." *NBER Working Paper No. w28252* 1–94.

Carrillo, Paul. 2012. "AN EMPIRICAL STATIONARY EQUILIBRIUM SEARCH MODEL OF THE HOUSING MARKET." *International Economic Review* 53 (1): 203–234.

Charles, Kerwin Kofi, Erik Hurst, and Nikolai Roussanov. 2009. "Conspicuous Consumption and Race." *The Quarterly Journal of Economics* 124 (2): 425–467.

Charness, Gary, and Dan Levin. 2009. "The Origin of the Winner's Curse: A Laboratory Study." *American Economic Journal: Microeconomics* 1 (1): 207–36.

Fudenberg, Drew, and Jean Tirole. 1991. *Game Theory*. The MIT Press.

Goldsmith-Pinkham, Paul, and Kelly Shue. 2023. "The gender gap in housing returns." *The Journal of Finance* 78 (2): 1097–1145.

Han, Lu, and William C Strange. 2014. "Bidding wars for houses." *Real Estate Economics* 42 (1): 1–32.

Harrington, Joseph. 2015. *Games, Strategies, and Decision Making*. Worth Publishers.

Haurin, Donald R., Jessica L. Haurin, Taylor Nadauld, and Anthony Sanders. 2010. "List Prices, Sale Prices and Marketing Time: An Application to U.S. Housing Markets." *Real Estate Economics* 38 (4): 659–685.

Hortaçsu, Ali, Jakub Kastl, and Allen Zhang. 2018. "Bid Shading and Bidder Surplus in the US Treasury Auction System." *American Economic Review* 108 (1): 147–69.

Huang, Ying, J. Reid Cummings, Ronald W. Spahr, and Mark A. Sunderman. 2023. "Public Auction versus Private Negotiation in Residential Property Sales." *Journal of Housing Research* 32 (1): 21–40.

Kagel, John H., and Dan Levin. 1986. "The Winner's Curse and Public Information in Common Value Auctions." *The American Economic Review* 76 (5): 894–920.

Koster, Hans R.A., and Jan Rouwendal. 2023. "HOUSING MARKET DISCOUNT RATES: EVIDENCE FROM BARGAINING AND BIDDING WARS." *International Economic Review* n/a (n/a): .

Lind, Barry, and Charles R. Plott. 1991. "The Winner's Curse: Experiments with Buyers and with Sellers." *The American Economic Review* 81 (1): 335–346.

Liu, Crocker H., and Patrick S. Smith. 2023. "School quality as a catalyst for bidding wars and new housing development." *Real Estate Economics* 51 (4): 785–818.

Milgrom, Paul R., and Robert J. Weber. 1982. "A Theory of Auctions and Competitive Bidding." *Econometrica* 50 (5): 1089–1122.

Ong, Seow. 2006. "Price Discovery in Real Estate Auctions: The Story of Unsuccessful Attempts." *Journal of Real Estate Research* 28 (1): 39–60.

Oren, M. E., and A. C. Williams. 1975. "On Competitive Bidding." *Operations Research* 23 (6): 1072–1079.

Quan, Daniel C. 2002. "Market Mechanism Choice and Real Estate Disposition: Search Versus Auction." *Real Estate Economics* 30 (3): 365–384.

Shi, Song, and M. Humayun Kabir. 2018. "Catch Animal Spirits in Auction: Evidence from New Zealand Property Market." *Real Estate Economics* 46 (1): 59–84.

Tadelis, Steven. 2013. *Game Theory: An Introduction*. Princeton University Press.

Thaler, Richard H. 1988. "Anomalies: The Winner's Curse." *Journal of Economic Perspectives* 2 (1): 191–202.

Williams, Joseph T. 1995. "Pricing Real Assets with Costly Search." *The Review of Financial Studies* 8 (1): 55–90.

Wong, Woei Chyuan Wong, Janice Lee, Md Nasir Daud, Pooi Leng Ng, and Wai Seen Chan. 2014. "Strategic Development of Property Auctions Market in Malaysia." *Journal of Real Estate Literature* 22 (2): 261–278.

Yinger, John. 1981. "A Search Model of Real Estate Broker Behavior." *The American Economic Review* 71 (4): 591–605.

Tables and Figures

Table 1: Summary statistics

	Bidding War	Non-bidding War	Total
	(1)	(2)	(3)
Panel A: Unfiltered sample			
Log(List Price)	12.4970	12.4462	12.4585
Log(Purchase Price)	12.5474	12.3730	12.4151
Sample Size	1,066,669	3,347,165	4,413,834
Panel B: Filtered sample			
Log(List Price)	12.5983	12.4793	12.5097
Log(Purchase Price)	12.6451	12.4190	12.4766
Sample Size	775,098	2,264,007	3,039,105
Panel C: Subsequent default sample			
Log(List Price)	12.2640	12.3566	12.3392
Log(Purchase Price)	12.3003	12.2982	12.2986
Subsequent Default	0.1560	0.1067	0.1160
Sample Size	259,487	1,124,453	1,383,940
Panel D: Returns sample			
Log(List Price)	12.3034	12.3751	12.3611
Log(Purchase Price)	12.3393	12.3169	12.3213
Log(Subsequent Sale Price)	12.4869	12.5011	12.4983
Subsequent Default	0.2195	0.1573	0.1695
Annualized Unlevered Return	0.0473	0.0514	0.0506
Annualized Levered Return	0.1311	0.1738	0.1655
Holding Period (Years)	6.6726	7.1558	7.0616
Sample Size	184,102	760,314	944,416

Note: Table 1 reports summary statistics for the samples used in the analysis, split by transaction type (bidding war versus non-bidding war) and also pooled. Panels A and B represent the full unfiltered and filtered sample of arms-length transactions before we filter on repeat sales. Panel C represents transactions where we can credibly identify whether a buyer subsequently defaulted on their loan. Panel D represents repeat-sales transactions with a minimum holding length of six months.

Table 2: Subsequent performance of bidding war transactions

	Subsequent Default		Unlevered Returns		Levered Returns	
	(1)	(2)	(3)	(4)	(5)	(6)
Bidding war	0.048^{***}	0.057^{***}	-0.012^{***}	-0.006^{***}	-0.075^{***}	-0.035^{***}
	(0.002)	(0.002)	(0.001)	(0.001)	(0.007)	(0.007)
Holding period			-0.002	-0.006^{**}	-0.035^{*}	-0.060^{**}
			(0.002)	(0.003)	(0.020)	(0.024)
Observations	1,383,940	944,416	944,416	784,378	944,416	784,378
Adjusted R^2	0.078	0.184	0.231	0.226	0.146	0.171
House Characteristics	✓	✓				
Zip-BuyQY FE	✓	✓	✓	✓	✓	✓
Zip-SaleQY FE			✓	✓	✓	✓

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: Table 2 examines the subsequent performance of bidding war transactions using the combined four-city sample. Columns 1 and 2 display coefficient estimates from Equation 13 examining the probability that a bidding war transaction subsequently defaults relative to non-bidding war transactions. Column 1 uses the subsequent default transaction sample in Panel C of Table 1. Column 2 uses the returns transaction sample in Panel D of Table 1. Columns 3 and 4 display coefficient estimates from Equation 14 examining the unlevered returns of bidding war transactions relative to non-bidding war transactions. Columns 5 and 6 display coefficient estimates from Equation 14 examining the levered returns of bidding war transactions relative to non-bidding war transactions. Columns 4 and 6 restrict the returns sample to only include transactions that did not subsequently default. Standard errors are clustered by zip code.

Table 3: The Winner's Curse & Housing Affordability

Boston	Default Probability	Unlevered Return	Levered Return
Estimate	1	-1.1	-7.8
Sample Mean	6.8	6.2	25.5
Est/Mean	14.71%	-17.74%	-30.59%

Detroit	Default Probability	Unlevered Return	Levered Return
Estimate	6.2	-2.1	-10.7
Sample Mean	18	2.6	4.6
Est/Mean	34.44%	-80.77%	-232.61%

Houston	Default Probability	Unlevered Return	Levered Return
Estimate	7.2	-1.3	-8.1
Sample Mean	10.4	4.9	17.7
Est/Mean	69.23%	-26.53%	-45.76%

Seattle	Default Probability	Unlevered Return	Levered Return
Estimate	3.6	-0.8	-5.5
Sample Mean	10.6	6.6	19.6
Est/Mean	33.96%	-12.12%	-28.06%

Note: Table 3 provides a measure of housing affordability in the context of the winner's curse. For each city, it juxtaposes the coefficient estimates, sample mean, and their ratios for default, unlevered return, and levered return. If the estimate-mean ratio is greater than 50% for default probability, the subsequent credit risk is sufficiently high to deteriorate housing affordability in the given city. If the levered return estimate-mean ratio is greater than 50%, the subsequent investment return is sufficiently adverse to undermine housing affordability.

Figure 1: Average number of offers received on most recent sales ©2023 National Association of Realtors. All rights reserved.

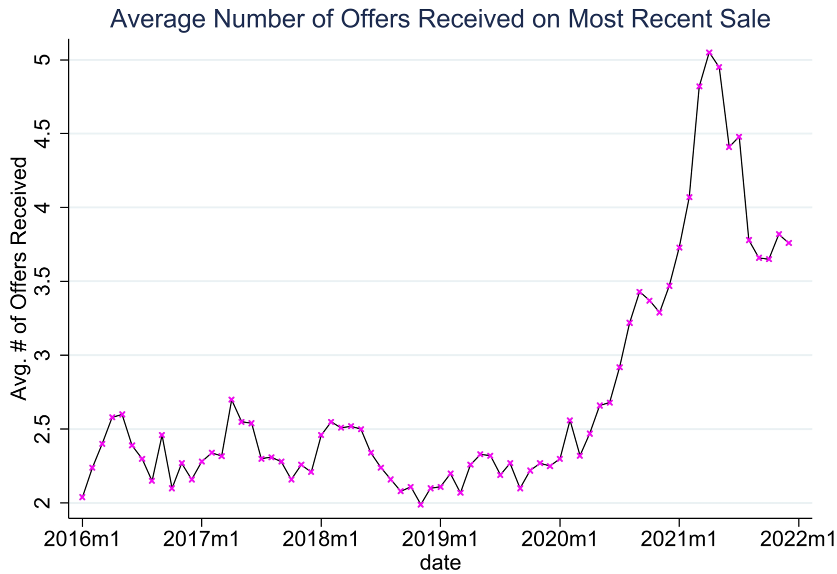
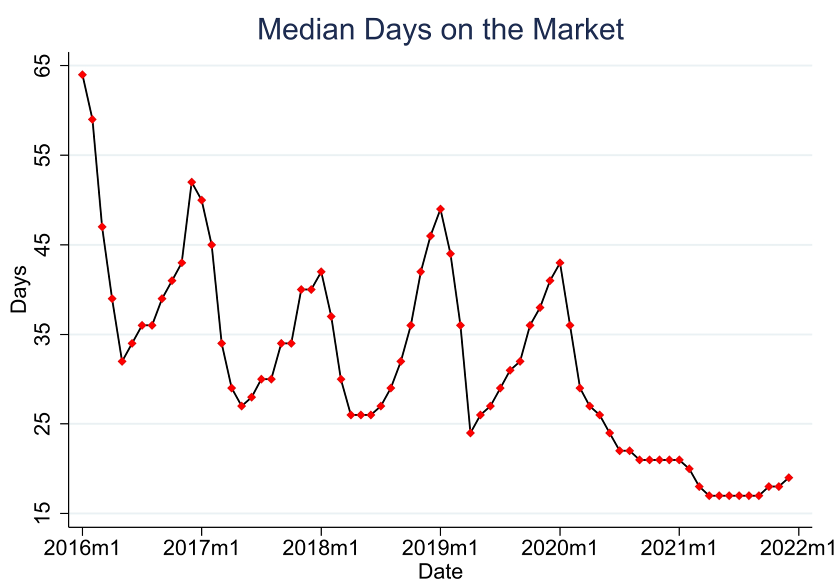


Figure 2: Median days on the market ©2023 National Association of Realtors. All rights reserved.



Note: According to the National Association of Realtors (NAR) confidence index survey, the average number of offers received on most recent sale 5.46 in April 2022 and the median days on the market reached the historical low of 14 days in July 2022.

Figure 3: The expected home selling price under rational equilibrium

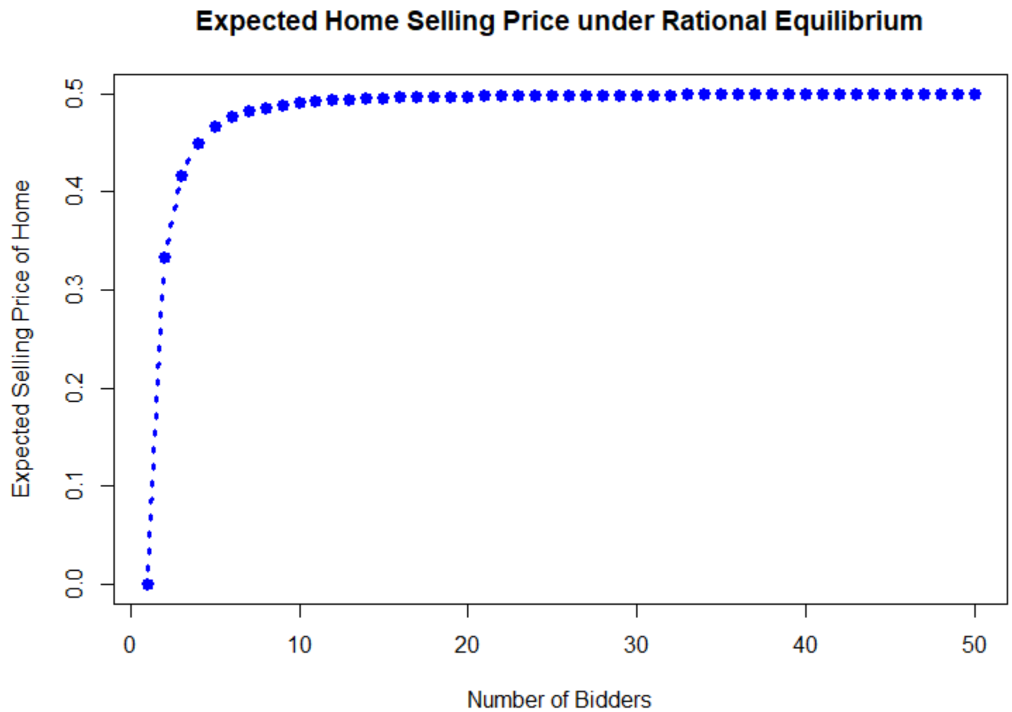


Figure 4: The expected home selling price under irrational equilibrium

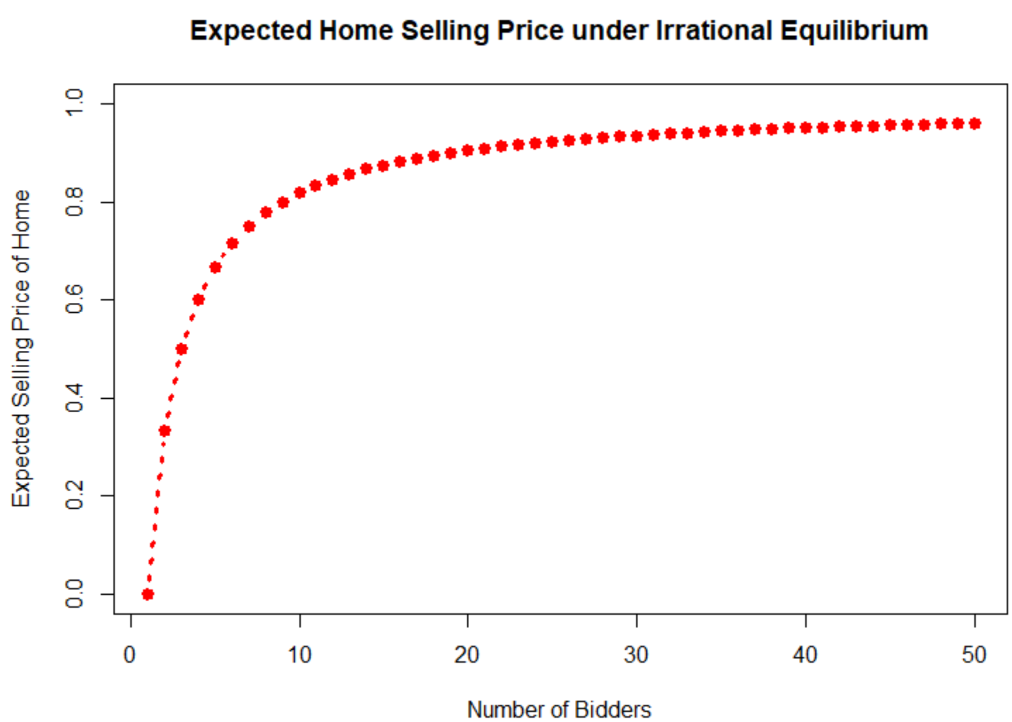
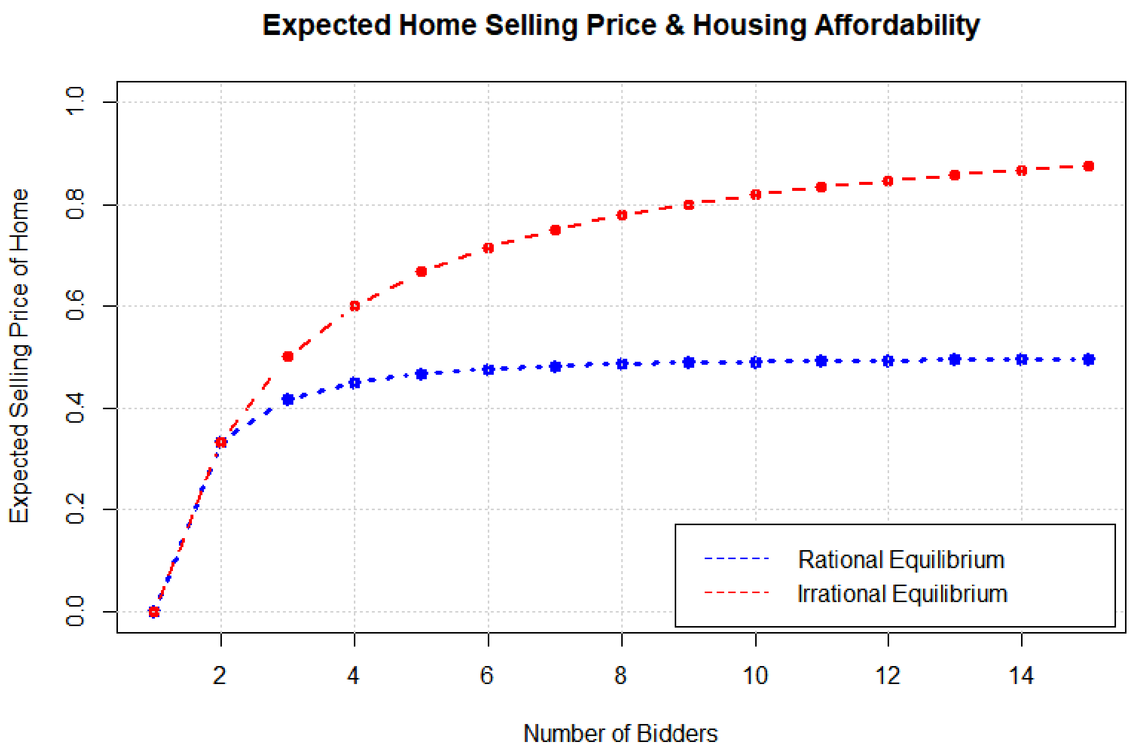
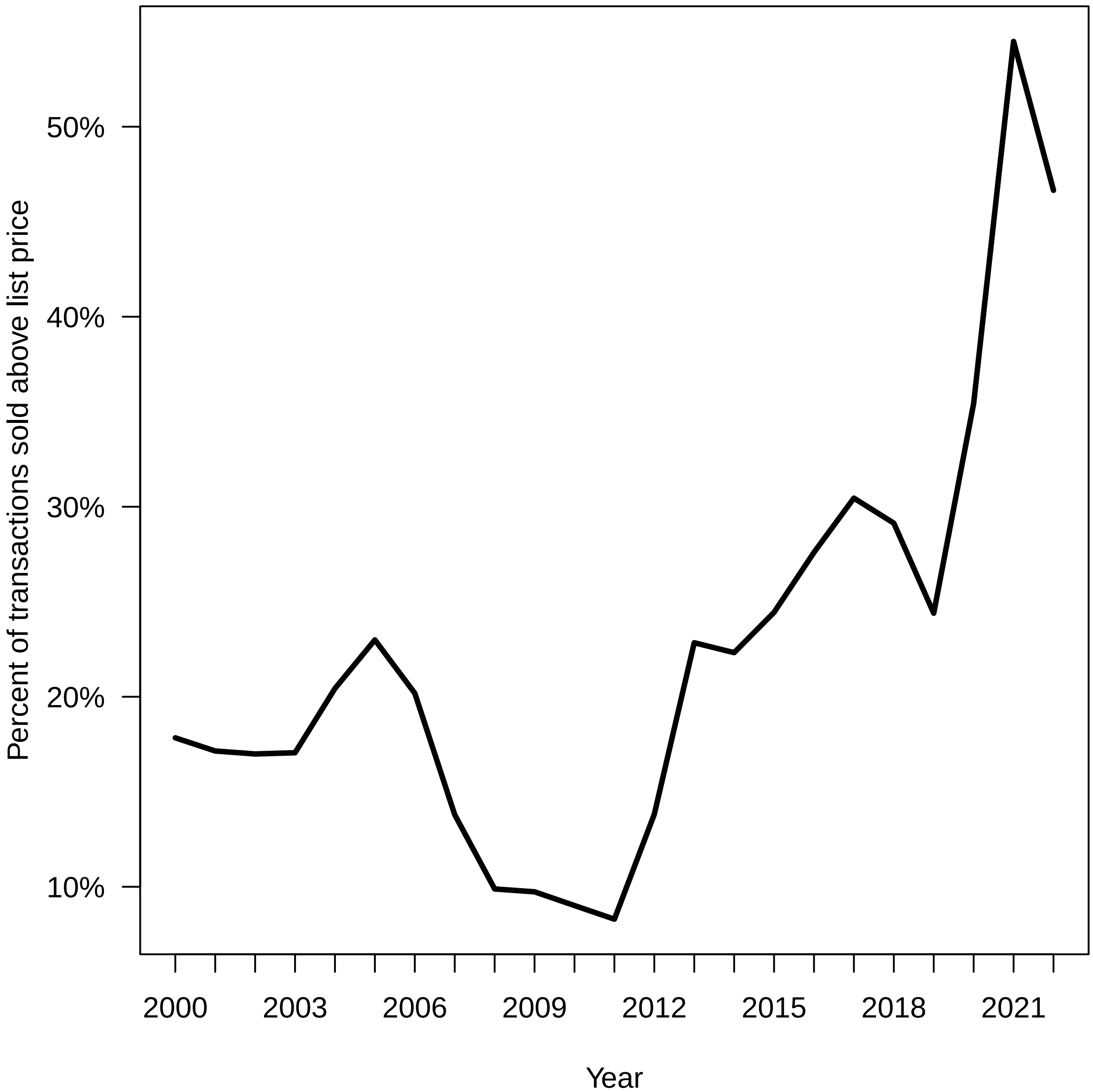


Figure 5: The expected housing affordability as auction intensifies



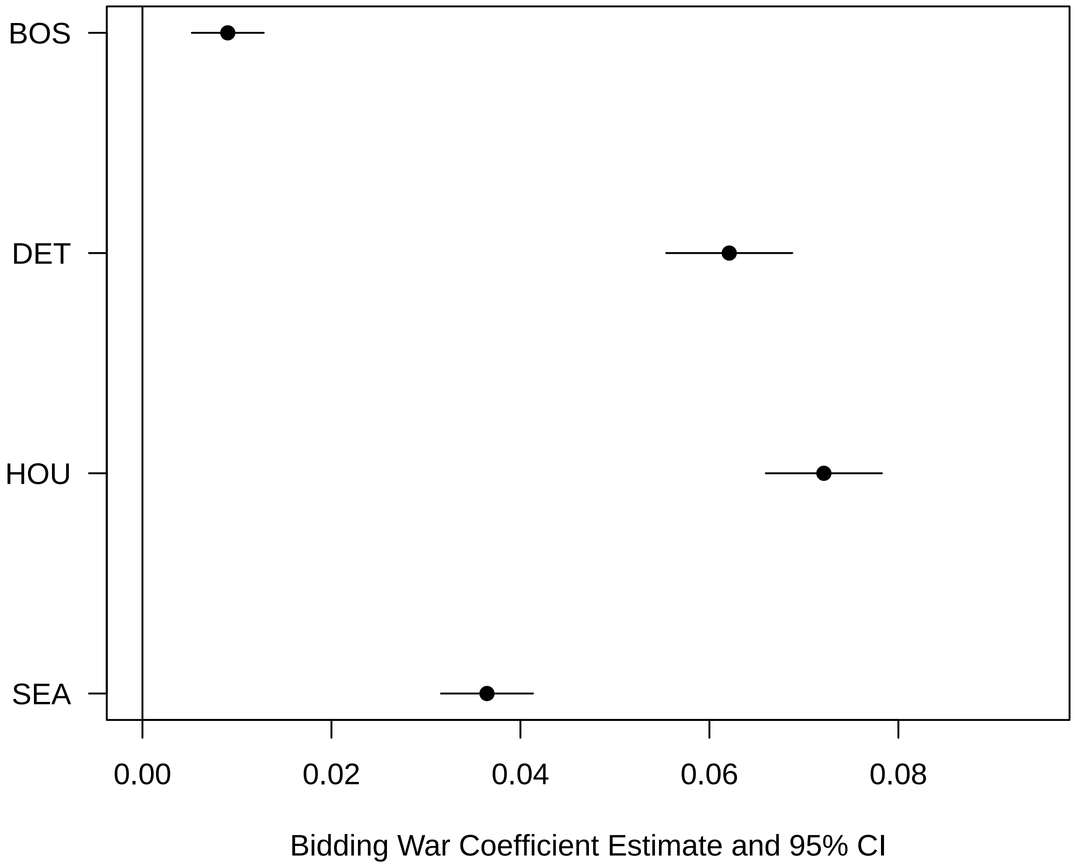
Note: Figure 5 plots the expected selling home prices under the rational (blue) and irrational (red) equilibria. The difference between the expected prices with respect to the number of bidders establish the ex-ante over-payment measure of the winner's curse.

Figure 6: Percent of bidding war transactions



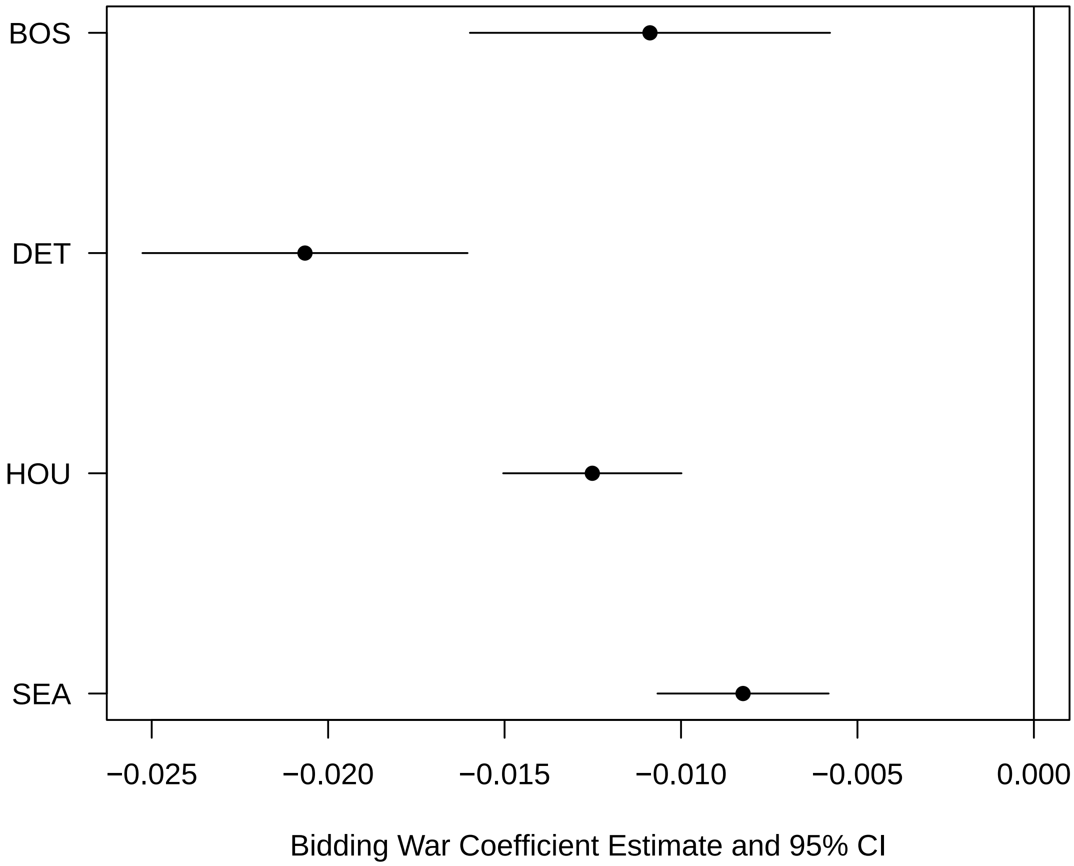
Note: Figure 6 plots the percent of transactions that sold via a bidding war over time for the filtered four-city transaction sample.

Figure 7: Subsequent default by city



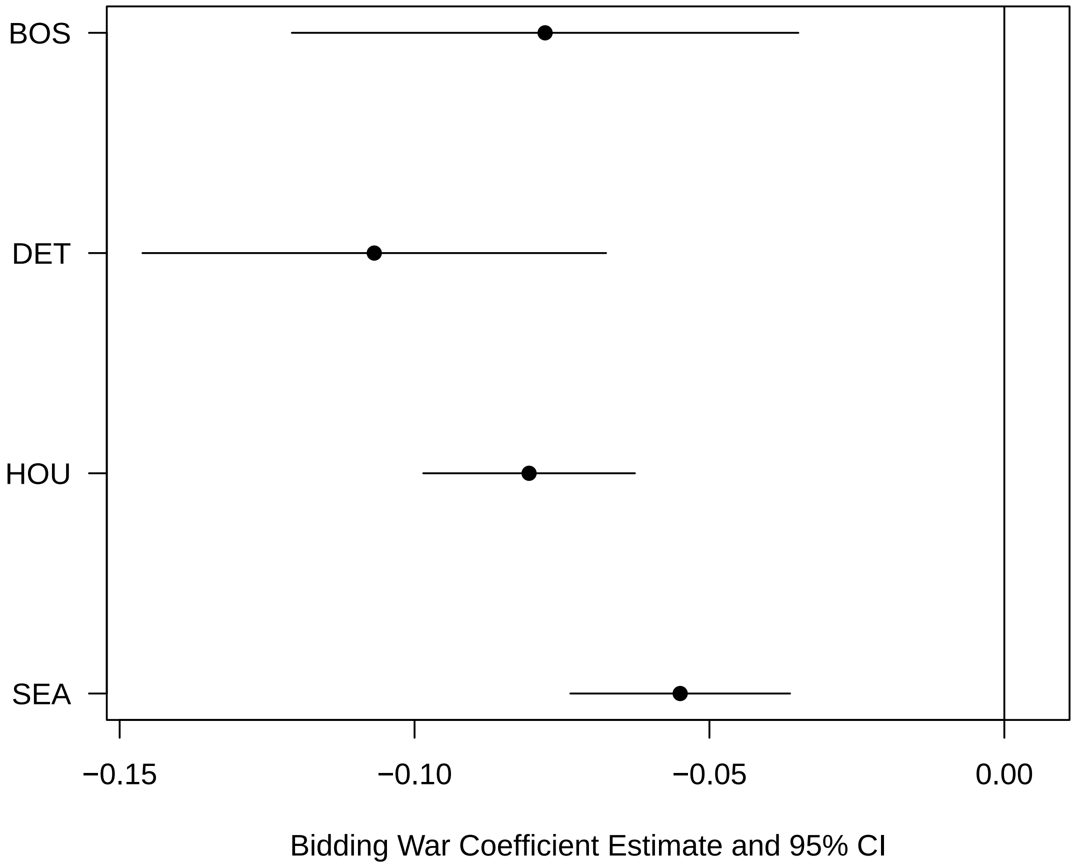
Note: Figure 7 plots the city-level bidding war coefficient estimates and 95% confidence intervals from Equation 13 using the subsequent default transaction sample in Panel C of Table 1.

Figure 8: Unlevered return by city



Note: Figure 8 plots the city-level bidding war coefficient estimates and 95% confidence intervals from Equation 14 using the returns transaction sample in Panel D of Table 1 and annualized unlevered returns as the dependent variable.

Figure 9: Levered return by city



Note: Figure 9 plots the city-level bidding war coefficient estimates and 95% confidence intervals from Equation 14 using the returns transaction sample in Panel D of Table 1 and annualized levered returns as the dependent variable.

Appendices

Contents

A Data Overview

A.1 Data Availability Statement

The multiple listing service (MLS) data used to examine the subsequent performance of bidding war transactions in housing markets was obtained from CoreLogic. Our agreement with the data provider does not allow us to post or otherwise distribute the data. Researchers interested in replicating our results can purchase MLS data from CoreLogic. Additional information about the data is available on the CoreLogic website.

A.2 Data Filters

Prior to running the empirical analysis, we apply several filters to the single-family detached residential transaction data. We list the filters below and provide a detailed overview of the number of transactions that are dropped by MSA in Table A1. Records are dropped that do not meet the following criteria:

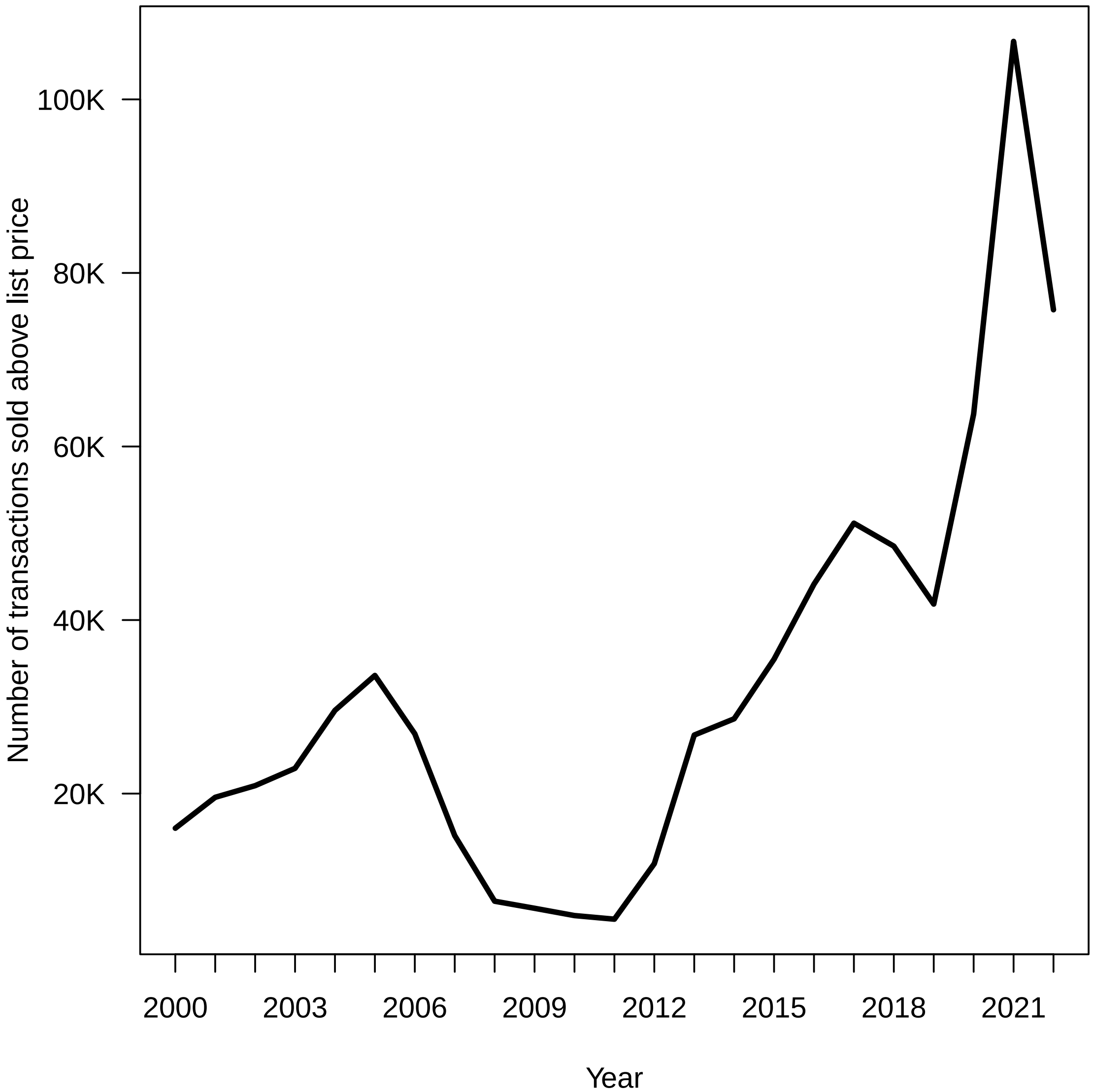
1. filter 1: listing successfully sold
2. filter 2: 2000 $\leq$ list year $\leq$ 2023
3. filter 3: \$20,000 $\leq$ sale price $\leq$ \$2,000,000
4. filter 4: \$20,000 $\leq$ list price $\leq$ \$2,000,000
5. filter 5: 0 $\leq$ days-on-market $\leq$ 730
6. filter 6: 1 $\leq$ bathrooms $\leq$ 6
7. filter 7: 1 $\leq$ bedrooms $\leq$ 6
8. filter 8: square feet of living area missing
9. filter 9: 500 $\leq$ square feet of living area $\leq$ 4,000
10. filter 10: lot size missing
11. filter 11: lot size $\leq$ 5 acres
12. filter 12: 1 $\leq$ age
13. filter 13: 1900 $\leq$ year built
14. filter 14: latitude or longitude missing
15. filter 15: census tract not in county
16. filter 16: not duplicate listing
17. filter 17: number of sales in zip code each year $\geq$ 50
18. filter 18: distressed transaction
19. filter 19: no subsequent transaction
20. filter 20: sale year $\leq$ 2017
21. filter 21: property has single transaction each quarter

Table A1: Filtered transaction data by MSA

	MSA			
Filter	BOS	DET	HOU	SEA
no filter	1,319,784	3,012,190	2,421,564	1,585,331
filter 1	901,840	1,470,278	1,606,585	1,102,954
filter 2	735,294	1,261,168	1,481,763	1,099,606
filter 3	722,890	1,160,057	1,470,300	1,072,271
filter 4	720,520	1,155,509	1,467,889	1,069,916
filter 5	719,984	1,149,275	1,462,717	1,068,244
filter 6	711,421	1,144,982	1,457,241	1,059,821
filter 7	708,647	1,144,027	1,456,358	1,057,858
filter 8	704,773	1,143,844	1,446,402	1,057,798
filter 9	668,557	1,129,542	1,360,778	1,008,691
filter 10	668,340	1,072,002	1,205,657	1,008,304
filter 11	660,453	1,051,621	1,202,211	995,485
filter 12	639,092	1,016,680	1,131,028	901,961
filter 13	592,883	1,012,130	1,130,284	900,297
filter 14	589,157	980,344	1,128,286	899,822
filter 15	589,153	980,343	1,128,258	899,822
filter 16	578,542	901,324	1,127,696	892,581
filter 17	572,931	900,877	1,127,403	892,276
filter 18	531,980	722,858	982,201	802,066
filter 19	256,053	350,946	452,474	422,306
filter 20	244,484	325,902	417,200	398,625
filter 21	244,299	324,424	416,876	398,341

Notes: Table A1 tabulates the number of records that are dropped for each filter across the four MSAs examined in this study. The final row for each column identifies the number of transactions that are included in the MSA-level analysis.

Figure A1: Bidding war transaction count



B City-level Analysis

B.1 City-level Summary Statistics

Table B1: City-level Subsequent Default Sample Summary Statistics

	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Panel A: Boston						
Bidding War	244,299	0.14	0.34	0	0	0
Purchase Year	244,299	2,006.05	4.59	2,003	2,005	2,008
Log(List Price)	244,299	12.83	0.44	12.54	12.81	13.09
Log(Purchase Price)	244,299	12.78	0.44	12.50	12.76	13.04
Subsequent Default	244,299	0.07	0.25	0	0	0
Square Feet Living Area	244,299	1,821.09	683.11	1,320	1,687	2,200
Square Feet Lot Size	244,299	24,022.43	27,955.68	7,405.00	13,203.00	30,056.00
Number of bedrooms	244,299	3.28	0.76	3	3	4
Number of bathrooms	244,299	2.10	0.85	1	2	3
Age (Years)	244,299	48.88	29.03	26	48	69
Panel B: Detroit						
Bidding War	324,424	0.15	0.36	0	0	0
Purchase Year	324,424	2,005.86	4.86	2,002	2,004	2,007
Log(List Price)	324,424	12.03	0.59	11.69	12.04	12.41
Log(Purchase Price)	324,424	11.97	0.60	11.66	12.00	12.36
Subsequent Default	324,424	0.18	0.38	0	0	0
Square Feet Living Area	324,424	1,601.75	659.34	1,100	1,412	1,960
Square Feet Lot Size	324,424	9,202.23	24,597.06	0.00	0.00	7,840.80
Number of bedrooms	324,424	3.19	0.63	3	3	4
Number of bathrooms	324,424	2.11	0.94	1	2	3
Age (Years)	324,424	42.08	23.21	24	46	57
Panel C: Houston						
Bidding War	416,876	0.14	0.35	0	0	0
Purchase Year	416,876	2,006.91	4.93	2,003	2,006	2,011
Log(List Price)	416,876	12.02	0.54	11.65	11.98	12.37
Log(Purchase Price)	416,876	11.98	0.54	11.61	11.93	12.31
Subsequent Default	416,876	0.10	0.31	0	0	0
Square Feet Living Area	416,876	2,153.86	708.60	1,612	2,064	2,615
Square Feet Lot Size	416,876	10,827.93	16,436.85	6,500.00	7,770.00	9,743.00
Number of bedrooms	416,876	3.41	0.67	3	3	4
Number of bathrooms	416,876	2.54	0.84	2	2	3
Age (Years)	416,876	23.65	18.34	9	21	34

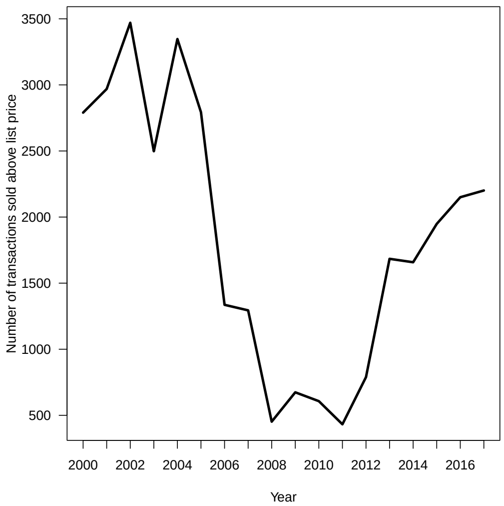
Table B1: City-level Subsequent Default Sample Summary Statistics (cont.)

	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Panel D: Seattle						
Bidding War	398,341	0.30	0.46	0	0	1
Purchase Year	398,341	2,006.07	4.67	2,003	2,005	2,007
Log(List Price)	398,341	12.62	0.49	12.30	12.61	12.94
Log(Purchase Price)	398,341	12.61	0.49	12.28	12.58	12.91
Subsequent Default	398,341	0.11	0.31	0	0	0
Square Feet Living Area	398,341	1,925.29	692.32	1,400	1,830	2,368
Square Feet Lot Size	398,341	13,799.91	25,710.69	5,227	7,841	11,326
Number of bedrooms	398,341	3.30	0.78	3	3	4
Number of bathrooms	398,341	2.39	0.83	2	2	3
Age (Years)	398,341	33.37	27.97	10	26	51
Panel E: Combined Four City Sample						
Bidding War	1,383,940	0.19	0.39	0	0	0
Purchase Year	1,383,940	2,006.27	4.80	2,003	2,005	2,009
Log(List Price)	1,383,940	12.34	0.63	11.92	12.35	12.77
Log(Purchase Price)	1,383,940	12.30	0.63	11.88	12.32	12.73
Subsequent Default	1,383,940	0.12	0.32	0	0	0
Square Feet Living Area	1,383,940	1,899.90	717.66	1,344	1,783	2,356
Square Feet Lot Size	1,383,940	13,631.41	24,030.56	4,770.00	7,605.00	11,761.20
Number of bedrooms	1,383,940	3.31	0.72	3	3	4
Number of bathrooms	1,383,940	2.32	0.88	2	2	3
Age (Years)	1,383,940	35.22	26.21	12	31	52

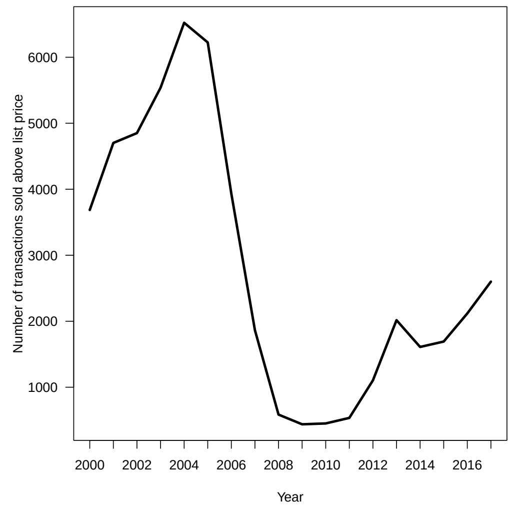
B.2 City-level Figures

Figure B1: Bidding war transaction count by city

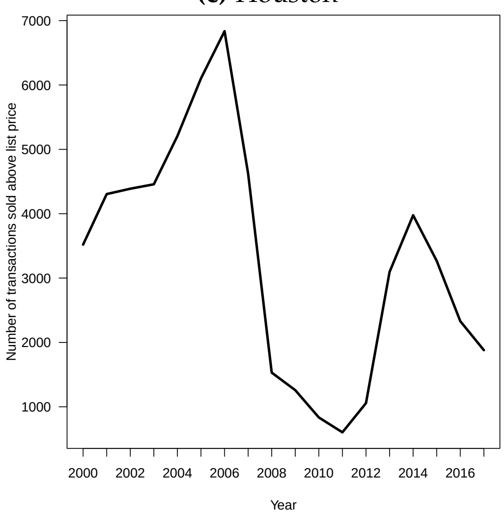
(a) Boston



(b) Detroit



(c) Houston



(d) Seattle

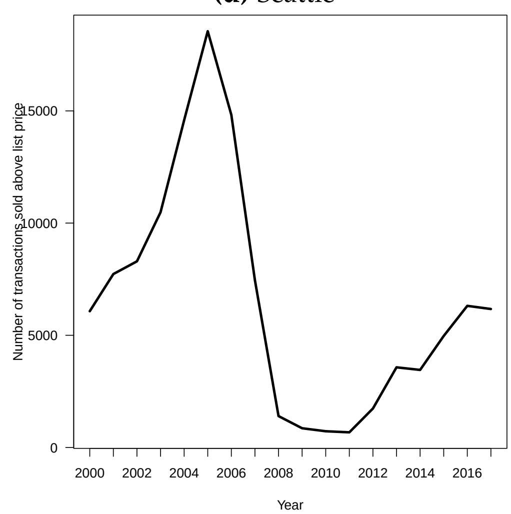


Figure B2: Percent of bidding war transactions by city