Bidding Wars for Houses

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Abstract

This paper analyzes the time series and cross-sectional patterns of bidding wars for houses. Bidding wars were once rare, a fairly constant 3-4% of transactions. This led to treating list price as a ceiling in empirical and theoretical research on housing. The bidding war share roughly tripled between 1995-2005, rising to more than 30% in some markets. The share fell during the subsequent bust, but it remains approximately twice as high as previously. The paper shows bidding war incidence to be greater during macroeconomic and housing booms. The paper also considers other potential contributing factors, including buyer irrationality, the use of the internet in home purchases, and land use regulation.

Introduction

This paper is concerned with housing market microstructure. Traditionally, housing transactions have been modeled as a process of search and negotiation (see Yinger, 1981 or more recently Haurin et al, 2010 or Carrillo, 2012a). In such a process, the seller puts a house on the market and advertises some of its features and a list price. The list price serves two roles: as an inducement for buyer search and as an initial offer from the seller. The list price induces search because it is assumed to be a ceiling in the sense that a seller must accept an offer equal to the list price. This search process tends to be slow, and the ultimate sales price is typically set by negotiation between one buyer and the seller. An alternative to this process is a formal auction (Quan, 2002). Auctions are used with some frequency in Australia. Unlike search and negotiation, auctions are resolved quickly, and the ultimate sales price is determined by the competitive bidding of multiple potential buyers.

There is another case with features of both processes, the so-called "bidding war." In a bidding war, multiple buyers compete for a house and push sales price above list price. In this situation, the seller lists her house as in the traditional search and negotiation process, but instead of dealing with buyers sequentially over a relatively long period, the seller receives offers from many buyers, typically soon after listing. In fact, real estate agents will sometimes counsel sellers to set a low price in the hope of attracting multiple bidders. Currently, economists – and, in fact, market participants – know very little about bidding wars.

This paper employs data from the National Association of Realtors (NAR) to analyze the time series and cross sectional patterns of bidding wars for housing. The paper generates a number of novel stylized facts. Bidding wars were once rare, a fairly constant 3-4% of housing sales.[1] The paper shows that bidding wars have become much more common during the recent housing boom, more than tripling as a share of housing sales between 1995-2005. The share of sales involving bidding wars has fallen, but it remains approximately twice as high as it was before the boom. Overall, the paper shows the incidence of bidding wars to be higher in circumstances associated with general macroeconomic and specific housing booms. However, bidding war frequency varies considerably by city, with the share in some cities rising to more than 30% during the boom and the share in other cities rising hardly at all. This variation, and

[1] We use the term "bidding war" to characterize ordinary house sales with multiple bidders where the sales price exceeds the list price. We consider distressed sales to be fundamentally different, and our empirical analysis will exclude them, except as noted. Our key empirical results do not change when foreclosures are included.

also the rarity of bidding wars during past booms, suggests that the recent growth of bidding wars is not simply a boom phenomenon. The paper also considers – at the MSA and individual housing transaction levels – other potential contributing factors, including buyer irrationality, the use of the internet in home purchases, and land use regulation.

We believe that these stylized facts fill an important gap in the housing economics literature. The rise of bidding wars that we document means that both empirical and theoretical research on housing market microstructure should account for the possibility of above-list sales. The rise of bidding wars also means that buyers and sellers of housing, at least in some markets, must consider the possibility of this sort of quasi-auction. In Toronto, where bidding wars are common, this is a source of anxiety and confusion, with buyers fearful that bidding wars are "overheated" and lead to an "emotionally charged value."[2] We believe that bidding wars are similarly fraught in other markets where they are common. This is, of course, understandable, since housing is typically the largest individual item in a household's portfolio. Housing is also a significant fraction of aggregate wealth, and housing market dynamics were an important driver of the recent "Great Recession," so the operation of the housing market is important beyond what it means to its participants. In sum, bidding wars are an increasingly important phenomenon in an obviously important market, so it seems to us that there is a clear case for learning more about them. The next section will begin by laying out the relevant theoretical and empirical literature that motivates the empirical analysis that is the core of the paper.

Literature

Academic research on housing has had a lot to say about the traditional search and negotiation disposition mechanism but almost nothing to say about bidding wars. The empirical literature has instead focused largely on the case where the list price is a ceiling and buyers arrive one-by-one.[3,4] There has been considerable attention paid to the relationship between list

[2] See the online discussion at http://www.hgtv.ca/articles/articledetails.aspx?ContentId=1901&cat=3&by=1

[3] It is worth pointing out that it is not usually a legal requirement that an offer equal to list price be accepted. Instead, it istypical for a listing agreement with a real estate agent contain the provision that the seller is obliged to pay the commission in the event of receiving an unrestricted offer equal to the list price. This presumably makes rejection rare for offers at the list price. It certainly does not preclude competition among buyers pushing the price above list price.

[4] An exception is the literature on auctions. Ashenfelter and Genesove (1992) compare the prices of identical condominiums sold under auctions and under private negotiations. Lusht (1996) compares the prices received under auctions and private negotiations in the Melbourne single-family house market. Mayer (1998) also considers auctions. Quan (2002) looks at prices under auctions and private negotiations with an emphasis on search costs.

price and time-on-market (i.e., Yavas and Yang (1995), Knight (2002), Anglin et al (2003), and many others). Some papers have considered how time-on-market relates to issues such as the heterogeneity of housing (Glower et al, 1998; Haurin, 1998; Haurin et al 2010). Others have considered how time-on-market influences the probability of a successful match with a buyer (Zuehlke, 1997) and the decision to revise the list price (Sass, 1988). Carrillo's (2012a, 2012b) recent models take a structural approach to this issue.

Merlo and Ortalo-Magne (2004) is an interesting paper in this tradition. They make use of data that are unusual in that they provide information on all offers that a house receives. They are, therefore, able to carry out both the conventional analysis of pricing and time-on-market and also a novel analysis of the back and forth between buyers and sellers. Their data, from the period 1995-1998, do include some above-list sales. The frequency of such sales is small, 30 out of 780 transactions in the sample, which at just under 4% is consistent with our findings for North American during the 1990s. Because their data have relatively few instances of bidding wars, Merlo and Ortalo-Magne are not able to provide the sort of stylized facts for bidding wars that they do for more traditional house sales. Our paper complements Merlo and Ortalo-Magne in this regard.

The theoretical housing literature has also primarily considered situations where the list price is a ceiling and buyers arrive one at a time. In this literature, Chen and Rosenthal (1996) consider the impact of list price on buyer search.[5] Buyers are more willing to incur the costs of visiting a particular house if the seller has committed to a low ceiling price. Arnold (1999) also specifies a model where the list price impacts the arrival rate of buyers, and thus time on market and the sales price. Yavas and Yang (1995) add brokerage to this sort of model. See Haurin et al (2010) for a recent model in this spirit. See Yinger (1981), Haurin (1988), and Wheaton (1990) for seminal early models of search and housing.

Albrecht et al (2012) – hereafter, AGV – is a recent model that does not treat the asking price as a ceiling and also allows for the receipt of multiple simultaneous offers. While the paper is not directly concerned with bidding wars, it reaches several conclusions that are relevant to our analysis. Initially, AGV present a model where sellers are identical in their reservation prices. In this model, list prices are payoff equivalent as long as they weakly exceed the sellers'

[5]All models with list prices involve "directed search." In contrast, the classic models of Diamond (1982) and Mortensen and Pissarides (1994) analyze search without direction. Novy-Marx's (2009) analysis of hot and cold markets is an important paper on search without direction in real estate markets.

reservation price. Any list price gives the sellers the same probability of making a sale (there is one period in the model), and it also gives the same price conditional on sale. This payoff equivalence is very important. It means that in equilibrium one might see some sellers setting a low list price while other sellers would set high list prices. Both strategies would have the same payoff. In this setting, AGV show that the expected sales price varies positively with the market tightness (the ratio of buyers to sellers), which is consistent with prior results showing that an increase in demand increases housing price. Since the list price is indeterminate, AGV have no comparative statics on list price. Since a bidding war occurs when sales price exceeds list price, the AGV analysis also has no comparative static predictions on the impact of housing demand on bidding wars.

AGV extend this analysis to a situation where sellers differ in their reservation prices. Those with low reservation prices are “motivated” in the conventional real estate usage since they are more willing to sell. In this case, a separating equilibrium exists where the list price signals the seller’s motivation.[6] Motivated sellers set lower list prices than less motivated sellers. Since buyers can infer reservation price from list price, this situation will feature motivated sellers having a higher probability of sale and receiving a lower price conditional on sale than will the less motivated sellers. However, even in this situation, a modified payoff equivalence result continues to hold. A motivated seller will continue to be indifferent between a low-list-negotiate-up and a high-list-negotiate-down strategy. So will a seller who is not motivated, but the motivated sellers will set lower asking prices to signal their type. This means that, as in the homogeneous case, the asking price is indeterminate for any type of seller, and there are no comparative statics about either asking price or about the occurrence of bidding wars in response to housing booms.

Thus, although it is common for bidding wars to be taken to be an indicator of a housing boom, this is not a prediction of the AGV model. Given the multiplicity of equilibria, whether bidding wars are procyclical or are related to other factors that might raise the sales price of housing is ultimately an empirical point, one that the rest of the paper will address.

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[6]As is common in signaling models, there exist both pooling and separating perfect Bayesian equilibria. In this case, AGV show that only the separating equilibrium satisfies a modified version of the Cho-Kreps(1987) Intuitive Criterion, which places restrictions on buyers’ out-of-equilibrium beliefs.

Data

NAR surveys

Our source of data on home transactions is fifteen separate surveys of individual homebuyers conducted by the Research Division of the National Association of Realtors (NAR). The surveys were biannual from 1987 to 2003 and annual between 2003 and 2010. The 1997 and 1999 surveys were unavailable. We employ the data both in transaction-level analysis and in MSA-level analysis. For the latter, we aggregated the 92,700 micro level survey responses up to the MSA level by year. The combined sample covers 334 unique metropolitan statistical areas (MSAs) and primary metropolitan statistical areas (PMSAs), which we will collectively refer to as MSAs.

Some of the transactions in our sample are reports of home purchase experiences, while other transactions are reports of home selling experiences. The specifics of the survey are as follows. Each year, the NAR collects transaction records from local title offices. Questionnaires are then sent to a random sample of homebuyers. In addition, surveyed homebuyers who had owned and sold a previous home were also asked to provide information on their home selling process.[7] Thus, the sellers who are surveyed are also included in the survey as buyers, with two separate transactions being covered in the data. The city of residence is directly reported by buyers for all years and for sellers beginning in 2007. Prior to 2007, sellers were asked if they had moved more than fifty miles. For the pre-2007 period, we only use responses for sales in which the respondent reported moving fifty miles or less. We infer the MSAs for these sellers from the location they report on the buyer survey, which is the location of their next home.

A more serious concern is the low response rates of the NAR surveys, which never exceed 19 percent. Despite the low response rates, there are several reasons that these data are attractive for our purposes. First, the NAR surveys are the largest longitudinal dataset that reports both list price and sales price for home transactions. They are also the only available data that document both buyers' and sellers' search experience over time and across MSAs. The longitudinal and cross-sectional aspects of the data are essential to the historical and cross-sectional analysis that we carry out here. Second, although one might be concerned that the average bidding experience among respondents might differ from that of the universe of

[7]Since the year of sale is reported only if the sale was within two or three years of the purchase date, our sample includes only sellers who bought another house within two or three years after selling. In some surveys the threshold is two years. In others, it is three years.

households, it is unclear what the direction of bias would be. One possibility is that respondents might be more patient than non-respondents. If patient households are less likely to give in to competitive pressures and participate in bidding wars, then our estimates would provide a lower bound for actual bidding wars. It is not clear to us that this bias would be quantitatively important. In the end, although we cannot rule out concerns about representativeness, our judgment is that the NAR data do not suffer from obvious sample selection bias. Third, as shown in Genesove and Han (2012), the distribution of responses from the NAR surveys is similar to that from other surveys with much higher response rates but relatively limited information.

For each transaction, the NAR reports the list price and sales price. We consider a transaction to involve a bidding war if the sales price exceeds the list price.[8] We do not observe the number of bidders in the NAR data. In fact, there is no national dataset of which we are aware that contains such information. Fortunately, the observation of a sales price greater than list price requires that there be multiple bidders, either active or potential. Of course, this means that there will be situations with multiple bidders who all bid below list price and where we thus do not observe the multiple bidding event. In this sense, we underestimate bidding wars. Having said this, the term “bidding war” has two elements. The “war” part of the expression seems to us to connote extreme bidding. Thus, the instances of bidding that we observe are plausibly interpreted as being the instances of extreme bidding and so of bidding wars.

For each transaction, the NAR surveys also report housing attributes, buyer/seller characteristics and their home searching/selling experience. This information is particularly useful for identifying factors that could be related to bidding wars. In addition, the panel structure of the data allows us to control for time-invariant MSA specific unobservables that might influence households’ expectations and actual decisions.[9]

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[8] The survey asks about “original list price.” For sellers, this should elicit a response of the initial list price. While a buyer knows the current list price, a buyer may not know whether there have been list price reductions. This may explain some of the differences between our buyer and seller samples. The survey also asks about the sales price in the house's agreement of sale. This is the traditional house price at the heart of the entire housing economics literature. It is worth noting, however, that in some markets (e.g., Washington, DC), it appears to be common for sellers to pay a part of the buyer’s closing costs as “seller subsidies. We do not observe this, and neither to we observe the related phenomenon of “seller financing.”

[9] Unfortunately, the NAR surveys do not ask about the exact date of sale, which prevents us from considering quarterly or monthly changes.

The NAR surveys thus generate three subsamples, one for buyers, one for sellers, and an aggregate sample that includes both buyers and sellers.[10] Table 1 presents descriptive statistics. On average, bidding wars account for about 10% of the overall transactions. Compared with sellers, buyers are generally younger and have lower incomes. In both samples, a majority of households are white, married, and English as the primary language. Suburban areas are the most represented in our sample (about 57% in both samples). Urban locations, small towns, rural areas, and resort areas, account for 19.88%, 13.94%, 8.59%, and 1.11% of the buyer sample; and 19.22%, 12.70%, 9.48%, and 1.15% of the seller sample, respectively. About 22% of buyers report that they found the home that they purchased through internet. About 81% of buyers and 85% of sellers report use of real estate agents.

Other data

In addition to the NAR surveys, we obtain MSA−level population and income from the Bureau of Economic Analysis. Yearly repeat sales housing price indices are obtained from the OFHEO, which tracks average single−family house price changes in repeat sales or refinancing.[11]

Data on the number of home sales are obtained from the HMDA loan application registers provided by the Federal Financial Institutions Examination Council (FEIFC). Under HMDA, all lending institutions located within a metropolitan statistical area (MSA) with assets in excess of $10 million are required to file loan application registers with the FFIEC for each mortgage loan application they receive. Reported information includes the purpose of the requested funds (home purchase, refinance, or home improvement), the dollar amount of the loan request, whether the dwelling is owner occupied, the census tract in which the dwelling is located, and whether the application was approved or denied. Based on this information, we compute the number of home purchase loans that were approved in each MSA for each year between 1990 and 2009.

Our measure of supply constraints is the Wharton Residential Land Use Regulatory Index (WRLURI) from Gyourko et al. (2008). This is a measure of the strictness of local regulatory

[10] We exclude foreclosure sales from the three samples in order to focus on more ordinary bidding wars. In fact, the results turn out to be nearly identical when foreclosure sales are included. These results are reported in our Web Appendix.

[11] In 2008, OFHEO was combined with the Federal Housing Finance Board to create a new agency, the Federal Housing Finance Agency (FHFA). The housing index has continued to be produced by FHFA.

environment based on results from a 2005 survey of over 2000 localities across the country. It is scaled to have a mean of zero, a standard deviation of one, and is increasing in the amount of regulation.

The history of bidding wars

Bidding war frequency

This section documents the history of bidding wars using the NAR buyer, seller, and aggregate samples. Table 2 calculates the share of sales at or above list over the period 1986 – 2010. As discussed above, this is a lower bound for the share of sales involving multiple bidders, since the presence of multiple bidders is a necessary but not sufficient condition for sales price to exceed list price.

There are three important patterns in Table 2.[12] First, bidding wars were not too important in the 1980s and 1990s. For instance, the shares of sales we can identify as bidding wars in 1986 were 2.94% in the buyer sample, 4.80% in the seller sample, and 3.51% in the aggregate sample. In the buyer sample, where the data are richer, the share rose to 3.87% by 1995, with values always between 3% and 4% in the intervening years. The share of bidding wars was slightly larger for some years in the seller sample, as high as 6.25% in 1995, but these estimates are based on less rich data. The overall pattern, as seen in the aggregate data, is for the bidding war share to be between 3.23% and 4.51% over this period. This suggests a typical value of about 4%, which is about the same percentage that Merlo and Ortalo-Magne (2004) have in their data, also from the mid-to-late 1990s. It is therefore natural that prior research on time-on-market and related topics frequently assumed that the asking price was a price ceiling and that the actual seller reservation price was distributed on a support whose maximum was the asking price. Going forward, however, it is clear that bidding wars should not be ignored.

The second important pattern that can be seen in Table 2 is that bidding wars became much more important during the 2000s boom. Over the 2001-2006 period, the table's aggregate sample results show shares of sales where price exceeds list as being in the range of 12.46% (in 2003) and 15.52% (in 2005). The buyer and seller samples exhibit similar patterns.

[12] Table 2 excludes properties sold through foreclosures. In the web appendices, we present a similar table for the sample that includes foreclosure sales.

The third important pattern in Table 2 is that even after the bust, the share of bidding war sales remained larger than it was in the earlier periods. In 2009, the aggregate sample share of bidding wars is 7.64%, which is approximately twice as large as the share was in the early 1990s (4.51% in 1995 and 3.23% in 1993). The more sparse seller sample has a 2009 value of 5.68% which is actually smaller than the 1995 value of 6.25%, but is considerable larger than the 1991 and 1993 values of 3.10% and 3.17%, respectively. The share of bidding wars in the buyer sample in 2008 is 8.03%, which is roughly twice as large as the 1995 value of 3.87%.

Figure 1 presents the pattern of bidding war results (aggregate sample) in a graph, along with the time series of house prices (specifically, the FHFA house price index) and housing sales (from HMDA). Although popular perceptions of bidding wars tie them to booms, Figure 1 provides mixed support for such a hypothesis. The shapes of the price index and housing sales panels are familiar: a gradual rise from the early 1990s, the rate of increase growing in the early 2000s, the market peaking around 2006, followed by a collapse in both prices and volumes.[13] Although bidding war share was higher during the boom than previously, the shape of the bidding war graph is different in important ways. Bidding war share rises to a high level before the boom takes off, and it remains higher after the peak than it had been previously.

As noted above, Albrecht et al (2012) present a directed search model where list price is indeterminate in equilibrium. This means that one can potentially observe identical houses in the same market employing the contrasting selling strategies of negotiating-down from a high list price and the bidding war strategy, where the initial asking price is low and buyers compete by offering larger amounts. The data here show the two selling strategies coexisting in the market, which is consistent with AGV's theory. Also as noted above, the theoretical model does not make comparative static predictions about the relationship of bidding war frequency to housing booms. Casual analysis often links bidding wars and booms. The data presented here are only partly consistent with the casual analysis. It is true that bidding war share rose during the most recent boom, which is consistent with bidding wars being a boom phenomenon. However, bidding wars were roughly the same small and constant fraction of sales during prior booms and busts. Furthermore, the most recent bust witnessed only a partial decline of bidding wars. These

[13]The OFHEO national house price index shows a peak in nominal prices that is a few quarters later than in the Case-Shiller Index. Real prices peak in all series in 2006, and sales peak in 2005. Thus, the market peak is typically dated as 2006.

facts are inconsistent with there being a simple relationship between bidding wars and the real estate cycle. We will explore this relationship in greater detail below.

Bidding war premium and time-on-market

Table 3 further investigates the boom-bust pattern of bidding wars. As discussed in the data section, the NAR data are thinner before 2000 than after and are obviously thinner in any particular year than in a group of years. In Table 3, therefore, we consider the boom-bust pattern evidenced in the more recent years of the data by comparing market outcomes during the boom (2003-2006) with outcomes during the bust (2007-2010).

The first column of the table presents the share of bidding wars (aggregate sample) during boom and bust, which are respectively 13.78% in 2003-2006 and 8.70% in 2007-2010. The share of bidding wars is only slightly higher at the peak than during the period of rising prices (14.09% to 13.38%). The share of bidding wars drops sharply as the bust begins (to 8.66%), and then remains roughly constant (to 8.75%). We see the similarity within the periods as arguing that the four year periods are a sensible way to organize the data.

The rest of Table 3 considers other market outcomes. The second column of the table presents the percentage by which sales price exceeds list price. The first point to make about the premium is that the observed bidding war premiums of 10.01% and 17.89% (in 2003-2006 and 2007-2010 respectively) seem to us to be economically significant. The second point to make concerns the boom-bust pattern. The premium is higher in the bust than in the boom, and it, in fact, rises throughout the period covered by the table. This is surprising. As noted above, it is crucial in considering bidding wars to remember that there are two ways that a bidding war with price above list can occur. One is for the market to be sufficiently hot that many buyers are willing to pay above list. The other is for the list price to be sufficiently low that many buyers are willing to pay more than list. Table 3's evidence on the time series of the premium above list clearly establishes the importance of the second channel. The bust is identified by a decrease in sales price. That bidding wars showed a higher premium during the bust must therefore require that sellers have chosen lower list prices.

This pattern is inconsistent with the view that bidding wars are simply a boom phenomenon that takes place when sales price rises and list price is sticky. Such a model would predict a greater share of bidding wars in a boom. This is what we observe. It would also predict, however, that the share would fall in a bust and that the bidding war premium would also be procyclical. These predictions do not hold in the data. In order to more completely explain the observed data on bidding wars, it is necessary to recognize that list prices are endogenous.

The right side of Table 3 considers the seller sample. The boom-bust patterns of bidding war share and price premium are similar to the patterns in evidence in the aggregate sample. To be sure, the patterns are not identical. Price premiums are larger in the seller sample, especially in the bust period. Similarly, the share of bidding wars that take place are smaller, also especially in the bust period.

The reason that we focus on the seller sample here is to be able to say something about seller time-on-market. Column (5) gives time-on-market for the sales with bidding wars. Column (6) gives time-on-market for the no-bidding-war part of the sample. Looking at these more ordinary sales produces results that are consistent with prior research on time on market (i.e., Haurin, 1988). During the 2003-2006 boom, mean time-on-market for below list sales was 11.84 weeks, which rose to 16.20 weeks during the 2007-2010 bust. Sales were much more rapid when bidding wars took place, with boom and bust values of 5.84 and 9.46 weeks, respectively. The more disaggregate characterization of the boom and bust periods at the bottom of the table reveals a similar pattern. Consistent with accumulating data pointing to a very slow housing market recovery, time on market rose steadily during the period.

Table 4 further considers time-on-market by considering various points in the selling time distribution. This table, also based on the seller sample, shows that time on market is lower for over-list sales across the distribution. During the boom, the median time-on-market was two weeks for properties with bidding, while it was six weeks for transactions below list. At the 25th percentile, the values are one and two weeks respectively for the transactions with bidding and below list. At the 75th percentile, the values are six and fifteen weeks. The pattern persists during the bust, with the major change being that the properties that sell slowly have much longer times on markets. With bidding, the 75th percentile of time-on-market is eleven weeks. Without bidding, the value is twenty four weeks. All of these results together clearly establish one key fact about bidding wars: they take place quickly compared to below list sales.[14]

[14]The result that bidding war sales take place more quickly is consistent with motivated sellers setting low list prices as in Albrecht et al (2012) as discussed above. Another feature of this pattern is that although they take place quickly, bidding wars do not always take place immediately upon listing. This may reflect the simultaneous arrival

The most important stylized fact established thus far is that bidding wars have become a much more common transaction form in housing markets.   Although the share of bidding wars is clearly higher in a stronger housing market, their rise does not simply track the general rise of the housing market in the early 2000s, and their fall does not simply follow pattern of the general bust. In the rest of the paper, we will continue to consider the relationship of bidding wars to the boom-bust state of the housing market. We will also bring into consideration additional factors, including the use of the internet, consumer rationality, and land use regulation.

A market level analysis of bidding wars

Bidding wars in MSAs

We have thus far focused on the national pattern of bidding wars. Although there are national and international forces that impact all housing markets, there are also important differences between local housing markets. As Table 5 makes clear, one difference is in the incidence of bidding wars. In order to present MSA level estimates based on reasonably rich data, the table reports the share of bidding wars and numbers of observations in MSAs for which we have at least 300 observations.

The table shows the share of bidding wars during the 2003-2006 boom and during the 2007-2008 bust. The variation between MSAs in bidding war frequency is immediately apparent. During the boom, the share was 11.43% in Houston, while it was 29.10% in metropolitan Washington, DC.[15] During the bust, the shares for these cities were, respectively, 10.06% and 11.97%. Looking at other cities, one sees a very wide range of the share of transactions that involved a bidding war, both in the boom and in the bust.

There is clearly a relationship between the real estate cycle and bidding wars, but not an exact one. In order to classify in cities by their performance over the recent boom-bust episode, we will informally employ the taxonomy of Abel and Deitz (2010). They divide the boom-bust experience of MSAs into four categories: (I) Boom/No Bust; (II) Modest Boom or No Boom /

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of buyers, the decision by a buyer who had been waiting to actively bid when another potential buyer arrives, or even bidding that results after a previous sale agreement breaks down.

[15]As noted above, the NAR data do not allow us to observe payments by sellers to buyers (“seller subsidies”). To see how such subsidies might impact the calculations of bidding war frequency, it is instructive to consider Fairfax County, VA, which is close to Washington, DC. Here, the fraction of sales where the price net of subsidies exceeds list price is 28% over the boom period (calculations by Paul Carrillo using MLS data; see data description in Carrillo (2012a)). This figure is comparable to the calculations based on NAR data.

No Bust; (III) Modest Boom or No Boom / Bust; (IV) Boom / Bust.[16] Washington, DC, had a pronounced boom-bust cycle according to this taxonomy. So did Phoenix, but relative to Washington, in Phoenix the share of bidding wars was lower during the boom (16.70%), higher in the bust (15.69%), and less volatile between the boom and bust periods. Houston had a relatively modest boom and little bust. St. Louis' experience was broadly similar, but relative to Houston, it had a higher share of bidding wars during the boom (13.60%) and a lower share during the bust (7.98%). Having said that, other cities that had modest booms and no major bust such as Charlotte and Atlanta had patterns that were closer to that of Houston. Turning to cities that had booms but no busts, we see a share of bidding wars during the boom of 22.64% in Norfolk-Virginia Beach, but only 8.62% in New York. The bust shares fell to 6.30% and 4.83% respectively.

Bidding wars seem to have occurred more frequently in all MSAs. There seems to be some evidence suggesting that boom markets had more bidding wars, but the pattern is not clear cut. There does not seem to be evidence that an MSA's general economic growth is strongly associated with the rise of bidding wars. The history of bidding wars is quite different in Washington, DC and cities like Houston, Charlotte, and Atlanta despite the cities having all experienced general economic growth during the period of our data. All of this suggests that it would be potentially valuable to consider the pattern of bidding wars somewhat more systematically. The next section does so.

The distribution of bidding wars across markets

Table 6 considers the market level correlates of bidding wars more systematically by estimating a series of regression models at the market level. Most of the models include MSA fixed effects in order to control for MSA-level variables that might impact the frequency of bidding wars. The models also include time fixed effects. It is important to be clear that these models should be interpreted descriptively. Many of the regressors are clearly endogenous, and we do not have available any sort of natural experiment or instrumenting strategy that would enable us to make causal claims about the determinants of bidding wars. Observed sales

[16] Specifically, Abel and Deitz (2010) characterize a boom market as one where housing prices rose at an annual rate that was faster than the national average annual increase of 8.1% during the period 2000-2006. They define a bust market as one where prices fell at an annual rate larger than the national average annual decline of -0.3% during 2006-2008.

volumes and bidding war shares are both market outcomes, and results like these should be interpreted as characterizing the sorts of patterns that are observed in market equilibrium. Having said that, it is important to reiterate that the bidding war share depends on both the sales price of a particular house (which varies positively with how hot a housing market is) and the list price set for the house (which varies in a theoretically indeterminate way with the state of the housing market). This does not mean that there is no reason to be concerned with omitted variables here, but it does mean that omitted variables associated with market strength should not be interpreted as obviously increasing the likelihood of a bidding war.

The estimating equation takes the form

$$S_{jt} = a + \sum_{k=1}^{K} B_k X_{jkt} + z_j + z_t + \varepsilon_{jt} \qquad (1)$$

S_{jt} is the share of transactions that were bidding wars in MSA j at time t. a is a constant. z_j and z_t are MSA and time fixed effects. The vector X_{kjt} gives the values of the K market level correlates that we see as being potentially related to bidding war incidence. The vector B_k gives the corresponding coefficients. ε_{jt} is the error term.

The first column of Table 6 presents the most parsimonious model, including only sales, MSA fixed effects, and year dummies as regressors. The results of this model show a statistically significant positive relationship between sales and the share of bidding wars.[17] The results should be interpreted as showing that doubling sales would be associated with a 2 percentage point increase in the share of sales resulting in a bidding war. This result will prove to be qualitatively robust across the table's specifications. The result is consistent with the popular perception that bidding wars are more common during booms. However, the size of the coefficient shows that bidding wars are not simply a boom phenomenon.

The next column includes the change in sales over the previous year. This is meant to capture market momentum. This specification allows for a market to be hot in both the level of its activity and in the rate of change of its activity. In this specification, the sales coefficient remains significant and becomes somewhat smaller. The change in sales variable is positive and significant. This result will also prove to be robust. The quantitative interpretation of column

[17] Table 6 is calculated using the entire sample. Estimating over a restricted sample including only markets with more than five sales in a given MSA-year generates the same pattern of results.

(2)'s results is that a doubling of sales is associated with a short run increase of 1.4 percentage points and a long run increase of 2.7 percentage points in the share of bidding wars.

These results show that across our data there does seem to be a relationship between bidding wars and MSA level strength in housing markets. In order to look more closely at the bidding war – real estate cycle relationship, we will now look at some variables that characterize the strength of the local economy beyond the housing market. Ideally, we would like to use consumption and production amenities as indicators of demand. However, the difficulty in measuring their yearly variation leads us to rely on income and population instead. Both variables serve as good proxies for consumption and production amenities (Gyourko and Tracy, 1991).[18] Moreover, by adding the income growth and population growth, we can distinguish between the short run and long run effects of population and income.

The next two columns present the results on population and income. When the sales variable is not included, population has a positive and significant relationship with bidding war share, while the relationship with income is noisy. Including the rates of change of these two variables makes little difference. Including sales, however, renders the population coefficient insignificant. The magnitude of the sales coefficient remains similar to its value in the initial parsimonious model. It is worth pointing out that all of these models include MSA fixed effects, so the positive relationship of sales and bidding war share controls for range of metropolitan specific variables that might impact the bidding war share.[19]

Column (5) includes explicitly one such MSA variable, the stringency of land use regulation as measured by the Wharton Residential Land Use Regulation Index (WRLURI). As discussed in Section III, the WRLURI has been constructed to aggregate at the market level the many ways that governments regulate land use. Since the WRLURI is fixed over time at the MSA level, it is not possible to include MSA fixed effects in specifications that include WRLURI.

The degree of land use regulation – as proxied by the WRLURI – is positively related to the frequency of bidding wars. This is true even when other measures of the strength of the

[18] In a monocentric model, an increase in amenities will be associated with an increase in population and (if the amenity is a normal good) of income. More directly, in a monocentric model, an increase in population or income is associated with an increase in housing price (Wheaton, 1974).

[19] Local employment is also a sensible measure of local economic strength. We have estimated similar models using this variable and also employment growth. Results are similar to population, with employment being associated with an increase in bidding war frequency. However, the effects are smaller and insignificant. Results are presented in Table A3 in the Web Appendix.

housing market and the general economy are included.[20] The coefficient of 0.012 indicates that, everything else equal, moving from an MSA at the 25th percentile of the WRLURI (e.g., Iowa city, IA) to an MSA at the 75th percentile of the WRLURI (e.g., San Diego, CA) is associated with a 1.53 percentage point increase in the share of bidding wars. It is possible that this finding is simply another version of the result that there are more bidding wars in booms. It has been well-established (i.e., Glaeser et al, 2005) that land use regulation is positively related to housing prices. Furthermore, Glaeser et al (2008) show that land use regulation determines the degree to which a bubble manifests itself in volatile prices or in overbuilding. The positive relationship between WRLURI and the share of sales that involve bidding wars is, thus, consistent with a role of regulation in the boom-bust cycle. The estimated relationship is, of course, just a correlation.

The final set of results in Table 6 concern the correlation of an MSA's house price volatility during the recent boom-bust cycle and the share of bidding wars. These models include the MSA price growth during the bust of 2006-2009 as a regressor. All of the models in this table are to be interpreted as presenting stylized facts rather than causal relationships. This is especially true for the models in columns (6) - (9).

The idea of including this sort of variable is that bidding wars are thought to be related in part to lapses in buyer rationality. There are two reasons that a bidding war might encourage irrationality. The first is that bidding wars are similar to auctions, and participants may get carried away in the heat of an auction. This is the conclusion of Lee and Malmendier (2010), who examine online auctions. They consider a situation where objects are available simultaneously through bidding and by paying a posted price. Buyers sometimes pay more in the auction, even when the posted price is visible on the same web page through which the auction is conducted. Second, bidding wars are housing transactions, and thus are investment decisions made by non-professionals, with emotion perhaps trumping reason. It is difficult to look back at behavior during the recent boom – and even at prior behavior – and conclude that market participants are obviously fully rational agents in the sense of standard economic analysis. For instance, Bucchianeri and Miron-Shatz (2011) show, in an experimental setting, that owners tend to overvalue their houses. Similarly, Case and Shiller (2003) show that homeowners seem to have quite unrealistic expectations of future house appreciation. For both

[20] It is worth noting that including WRLURI does not affect the significance of the other variables. Sales remains the variable that seems to be most closely related to bidding war share. Its magnitude is slightly lower than in the other specifications, but this specification lacks MSA fixed effects.

of these reasons, it seems sensible to consider whether auction-like bidding wars also have an element of irrationality.

Ideally, we would be able to implement an empirical design similar to Lee and Malmendier (2010) by comparing the sales of identical houses with and without bidding wars. The NAR data do not allow this. A second best approach would be to include a variable that proxies for buyer irrationality in a market and at a given time. We do not have this sort of variable available in the NAR either. Our third best approach here is to suppose that markets are characterized by differing tendencies towards irrational bidding optimism. If this were true, then markets with more irrationality would have evidenced this by exhibiting a more pronounced pattern of boom and bust during the recent cycle. We capture this with the price growth during the bust period variable. A market where buyers were irrationally exuberant would have a stronger price rise during the boom and a stronger fall during the bust. It is worth noting that some markets (i.e., Detroit) have declined in a secular sense, with a large negative value of 2006-2009 price growth just like a market where the bust is a correction for the irrational boom. Since there is no reason to expect a secularly declining market to have more bidding wars, this will make this regressor less likely to be significant.

The results in Table 6 show a clear pattern: markets that fell hardest during the bust had higher shares of bidding wars over the entire period. This evidence is very loosely consistent with the common view that bidding wars have a component of irrationality. There are, of course, many other ways that one could explain the reduced-form empirical results. They definitely do not prove the existence of irrationality. They are presented here because they are the closest that the NAR data allow us to approach this issue (which is certainly important) and because of the consistent strength of the empirical pattern.

A transaction level analysis of bidding wars

Overview

The final set of models that we will estimate will be at the level of the individual house transaction. As discussed in Section III, the NAR survey asks about a number of individual characteristics of buyers and sellers that could potentially be linked to participation in a bidding war.

To uncover individual level patterns in the data, we estimate linear probability models of the following form:

$$P_{ijt} = a + \sum_{k=1}^{K} B_k X_{jkt} + z_j + z_t + \varepsilon_{jt} \qquad (2)$$

P_{ijt} is the probability of transaction i having a bidding war in MSA *j* at time *t*. The other notation is as above. We have chosen to estimate linear probability models rather than discrete choice models for several reasons. First, the linear probability models can be readily interpreted. Since the primary goal of the paper is to characterize the stylized facts of bidding wars, this seems important. Second, the occurrence of a bidding war is an equilibrium outcome reflecting the listing price chosen by the seller, the search and offer strategies of buyers, and the equilibrium sales price that results. This does not suggest a discrete choice framework, since the bidding war is not the choice of any one agent. We estimate the model separately for the buyer and seller samples since, as will become clear, the economic interpretations of the results differ in important ways.

Buyer sample

Table 7 presents results of the buyer estimates. The first column presents the results for ordinary transactions, with foreclosures excluded as in the rest of the paper. In the second column, we include both ordinary sales and also foreclosure sales. This allows us to say something about this increasingly important segment of the housing market.

The results at the top of Table 7 show a pattern of younger buyers being more likely to have purchased their houses through bidding wars than buyers in the omitted category (over 65 years old). For instance, a transaction from a buyer between 20-34 has an additional 18 percentage point likelihood of a bidding war. This effect grows steadily smaller for older buyers. In addition, first-time buyers have an 14 percentage point higher likelihood of having purchased their homes through winning in a bidding war in both the ordinary sales and ordinary sales plus foreclosures samples. In addition, Table 7 shows a decrease in bidding war likelihood associated with higher income homebuyers and with white homebuyers.

An interesting pattern emerges when these results are taken together. If we compare a 30-year old, nonwhite, first time buyer who has an income of $30,000 with a 65-year old, white, repeat buyer, who has an income of $60,000, the probability of having purchased through a bidding war is about 30 percentage points higher in the former case. Younger, first-time, non-white purchasers who have lower incomes are, thus, much more likely to have obtained their homes through bidding wars. This result has an interesting parallel to research on the recent boom that stresses the role of credit expansion (Mian and Sufi, 2009). Although the NAR data do not report information on loans that would allow us to infer their riskiness, Table 7's results on the individual correlates of bidding wars is certainly consistent with a role for high-risk credit in the recent boom and bust.

The results are quite strong for the foreclosure variable. A foreclosure sale has a probability of a bidding war that is 52 percentage points higher than one that is not. It is worth reiterating, however, that the previously documented historical patterns were for ordinary sales. So although foreclosure sales are more likely to be bidding wars (a fact that is new to this paper), the bidding war phenomenon is much broader. It is also worth pointing out that the results in the ordinary- and foreclosure-transaction columns are quite close. This is consistent with other robustness exercises that we have carried out, all of which have shown that including foreclosure sales does not change the basic pattern of results.

The individual model also allows us to examine other transaction level correlates of bidding wars. One of these is the use of the internet by homebuyers. In search theory (e.g., Pissarides, 2000), an improvement in matching technology will increase transaction volume. The use of the internet in housing transactions is clearly an example of such an improvement, and one would anticipate that internet use increasing the rate of home sales. Since the market level empirics discussed above find a positive relationship between the real estate cycle and bidding wars, it seems useful to see if internet use at the individual level also is associated with a greater fraction of sales taking place through bidding wars. That is exactly what Table 7 shows. A buyer's use of the internet is associated with a 4.3 point higher probability of a bidding war for ordinary transactions. The relationship is stronger, a 5.7 point higher probability, in the sample that includes both ordinary and foreclosure transactions. That the internet can potentially encourage bidding wars is consistent with two of the facts noted earlier. The first is that the rise of the bidding war coincided with the rise of the internet. The second is that the share of sales that took the form of bidding wars did not fall back to historical levels in the recent bust. Of course, we want to be clear that we are only suggesting the possibility of internet use as part of this process, not a complete explanation.

The new home coefficient is positive, very large, and significant. A buyer of a new home has a 31 percentage point greater likelihood of experiencing a bidding war in the sample of ordinary homes and a 25 point greater likelihood in the sample that also includes foreclosures. This result appears in a model with MSA fixed effects, so it is not simply picking up a boom operating at the metropolitan level. The technology of mass housing production means that new houses can be quite close substitutes for each other, so the result that there are many bidding wars in this market segment is somewhat surprising. One important way that a new home is different than an older home is that new homes are more likely to be sold by builders. If these builders have different marketing objectives, this may be manifested in their listing strategy and thus in the frequency of bidding wars that ensue.

The rest of the results in Table 7 are broadly consistent with the paper's earlier market level analysis. Bidding wars are 7.7 points more likely for individual buyers located in urban areas than in rural areas in the ordinary sales sample and 7.8 points more likely in the sample also including foreclosures. Suburban buyers are 5.2 and 6.2 percentage points more likely to experience a bidding war in the ordinary and ordinary plus foreclosures samples, respectively. The year coefficients (reported in the Web Appendix) also show that bidding wars were much more frequent at the peak of the boom and are much less likely during the bust. Having said that, Table 1 and the MSA level Table 5 both make clear that bidding wars continue to occur at higher levels than prior to the boom even after the market collapse.

Seller sample

Table 8 reports results estimated from the sample of sellers. As noted above, this sample is much smaller than the buyer sample, so the estimates here tend to be noisier. Many of the results are similar to those in the buyer sample. Bidding wars are observed more frequently for sellers who sold at the peak of the boom, for instance. Also, bidding wars are more frequent for urban sellers. Unlike buyers, where younger buyers are more likely to have purchased through bidding wars, there is no age effect for sellers. This difference is not surprising, since buyer and seller experience are likely to have different effects on how a house is transacted.

The most interesting result here concerns the role of real estate agents. The survey reports whether sellers employed an agent. We included this variable because of the possibility that an agent might be more interested in a quick sale than a seller marketing her own house.[21] This is the conclusion of Levitt and Syverson (2008), who show that agents selling their own houses have longer time-on-market and obtain higher prices than agents selling clients' houses.[22] Since encouraging the buyer to set a low asking price is more likely to lead to a rapid resolution (as shown earlier), this incentive issue may lead house sales involving agents to have more bidding wars. In Table 8, the agent variable has a coefficient associated with a 17 percentage point increase in the probability when an agent is used. This is certainly not a causal effect, since the sellers who use agents are quite possibly different than those who do not, as are their houses and their markets. It is, however, consistent with the incentive issue discussed above.

Conclusions

This paper has documented the rise of bidding wars and also their partial fall. It shows that bidding wars have become much more frequent over the last decade, which is consistent with the popular notion that bidding wars are more common in booms. However, the subsequent bust has not brought the frequency of bidding wars down to their historical levels. This, and the considerable variation in the occurrence of bidding wars across similar locations, suggests that bidding wars are not simply a boom phenomenon. The paper has provided evidence showing bidding wars are more likely when land use regulation is more stringent and in markets where one might suspect consumers to be less than completely rational. Bidding wars are also associated at the individual buyer level with the use of the internet and with the employment of an agent at the sales level.

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[21] This incentive problem is discussed by Geltner et al (1991), Anglin and Arnott (1991), and Arnold (1992) among others.

[22] Rutherford et al (2005) also find that agents selling their own houses obtain higher sales prices, but they do not find a longer time-on-market.

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Table 1: NAR summary statistics (1987-2010)

	Buyer Sample	Seller Sample
Transaction price ($)	245,956	252,054.6
	(822,947)	(370,928.4)
List Price ($)	248,916	261,203.7
	(541,746)	(282,216.8)
Above-list-price transactions (%)	9.98	9.78
	(29.97)	(29.71)
Age bracket [20, 34] (%)	39.79	22.89
	(48.95)	(42.01)
Age bracket [35, 44] (%)	24.43	29.07
	(42.97)	(45.41)
Age bracket [45, 54] (%)	17.27	22.02
	(37.80)	(41.44)
Age bracket [55, 64] (%)	11.31	15.85
	(31.68)	(36.52)
White (%)	62.96	72.91
	(48.29)	(44.45)
Married (%)	62.34	73.36
	(48.46)	(44.21)
English (%)	95.38	97.61
	(20.99)	(15.27)
Income ($)	86,055.38	102,121.8
	(49,498.45)	(55,186.9)
House size (square feet)	2,022.36	2,367.26
	(994.59)	(1,0218.1)
Small town (%)	13.94	12.70
	(34.64)	(33.29)
Urban/city (%)	19.88	19.22
	(39.91)	(39.41)
Suburban area (%)	56.49	57.45
	(49.58)	(49.44)
Resort area (%)	1.11	1.15
	(10.48)	(10.66)
Single family house (%)	68.58	77.98
	(46.42)	(41.44)
Find house through Internet (%)	22.33	24.00
	(41.64)	(42.71)
Desire to invest (%)	1.27	N/A
	(11.18)	
First home purchase (%)	42.12	N/A
	(49.38)	
New home (%)	20.31	N/A
	(40.23)	
Buy through agent (%)	81.11	N/A
	(39.14)	
Buyer time on the market (weeks)	15.22	N/A
	(19.29)	
Seller time on the market (weeks)	N/A	12.87
		(20.13)
Number of MSAs	336	314
Number of observations	73,123	19,577

Note: This table reports mean characteristics in the NAR samples. Standard deviations are reported in brackets.

Table 2: The history of bidding wars: mean percentage of sales-price-above-list-price transactions by year

		1986	1988	1991	1993	1995	2001	2003	2004	2005	2006	2007	2008	2009	2010
Buyers	%Transactions Above List	2.94	3.41	3.39	3.26	3.87	12.03	12.03	13.32	15.69	14.12	10.36	8.03	8.27	10.42
	Number of Observations	3026	3465	2951	1412	1188	4515	3300	7285	6596	6525	8928	8456	7284	7119
Sellers	%Transactions Above List	4.80	5.82	3.10	3.17	6.25	14.51	13.26	15.61	15.03	10.09	7.39	6.44	5.68	6.80
	Number of Observations	1356	1391	902	442	432	2212	1742	2313	2382	3250	3058	2717	2183	882
Aggregate	% Transactions Above List	3.51	4.10	3.32	3.23	4.51	13.11	12.46	13.87	15.52	12.78	9.60	7.64	7.67	10.02
	Number of Observations	4382	4856	3853	1854	1620	6727	5042	9568	8978	9775	11986	11173	9467	8001

Note: This table reports mean percentage of transactions for which sales price exceeds list price by years. The sample excludes properties sold through foreclosures. The data source is the National Association of Realtors homebuyer and seller surveys (1987-2010). The buyer sample contains reports from surveyed homebuyers on their home purchase experience. The seller sample contains reports on home selling experience from a set of surveyed homebuyers who had owned and sold a previous home.

Table 3: Bidding statistics in booms and busts

	Aggregate Sample		Seller Sample		Seller Sample	
	% Transactions Above List	Price Premium Above List	% Transactions Above List	Price Premium Above List	Mean time on market <weeks> (bidding)	Mean time on market <weeks> (no bidding)
2003-2006	13.78	10.01	11.07	21.89	5.84	11.84
	(33393)	(4601)	(17930)	(1984)	(1928)	(15521)
2007-2010	8.70	17.89	6.62	30.36	9.46	16.40
	(40627)	(3533)	(8840)	(585)	(567)	(8135)
2003-2004	13.38	7.59	14.60	7.46	4.97	10.57
	(14640)	(1959)	(4055)	(592)	(570)	(3352)
2005-2006	14.09	11.81	12.18	17.59	6.19	12.26
	(18573)	(2642)	(5632)	(686)	(659)	(4806)
2007-2008	8.66	15.75	6.94	30.47	9.75	15.65
	(23159)	(2005)	(5775)	(401)	(387)	(5287)
2009-2010	8.75	20.69	6.00	30.12	8.84	17.78
	(17468)	(1528)	(3065)	(184)	(180)	(2848)

Note: This table reports mean percentage of transactions for which sales price exceeds list price by years, and mean price premium in these transactions. The data source is the National Association of Realtors homebuyer and seller surveys (1987-2010). The sample excludes properties sold through foreclosures. See Section III for discussion of the aggregate and seller samples. Number of observations is reported in brackets.

Table 4: Distribution of seller time on market (in weeks)

	Seller Sample	25th	50th	75th
2003-2006	Above-List Transactions	1	2	6
	Other Transactions	2	6	15
2007-2010	Above-List Transactions	1	3	11
	Other Transactions	3	9	24

Note: This table reports the distribution of seller time on the market for above-list transactions and other transactions, respectively. The data source is the National Association of Realtors homebuyer and seller surveys (1987-2010).

Table 5: MSA-level variation in bidding wars: mean percentage of above-list transactions

MSA	% Transactions Above List Boom (03-06)	% Transactions Above List Bust (07-10)	MSA	% Transactions Above List Boom (03-06)	% Transactions Above List Bust (07-10)
Ann Arbor, MI	7.35 (340)	8.89 (90)	Louisville, KY-IN	10.92 (119)	7.51 (453)
Atlanta, GA	11.40 (228)	9.03 (454)	Memphis, TN-AR-MS	11.77 (340)	8.74 (721)
Austin-San Macros, TX	12.40 (379)	12.02 (541)	Middlesex, Somerset, Hunterdon, NJ	13.70 (146)	7.62 (210)
Baltimore, MD	22.44 (802)	9.69 (2404)	Milwaukee-Waukesha, WI	17.91 (1189)	7.04 (852)
Bangor, ME	3.76 (133)	7.56 (225)	Minneapolis-St. Paul, MN-WI	12.67 (647)	9.21 (1694)
Boston, MA	11.54 (468)	8.10 (716)	Monmouth, Ocean, NJ	8.72 (172)	5.06 (237)
Buffalo-Niagara Falls, NY	13.27 (113)	8.65 (601)	Nashville, TN	13.33 (833)	10.59 (699)
Charlotte-Gastonia-Rock Hill, NC-SC	11.47 (872)	8.75 (1268)	New York, NY	8.62 (58)	4.83 (373)
Chicago, IL	8.35 (647)	4.95 (1474)	Newark, NJ	16.67 (126)	8.78 (262)
Cincinnati, OH-KY-IN	1.97 (203)	8.31 (409)	Norfolk-Virginia Beach-Newport News, VA-NC	22.64 (265)	6.30 (127)
Cleveland-Lorain-Elyria, OH	9.76 (123)	7.60 (342)	Orlando, FL	18.38 (468)	9.03 (875)
Columbus, OH	7.94 (189)	8.08 (421)	Philadelphia, PA-NJ	14.25 (351)	6.74 (683)
Dallas, TX	10.95 (274)	9.34 (546)	Phoenix-Mesa, AZ	16.70 (461)	15.69 (204)
Dayton-Springfield, OH	7.54 (345)	6.29 (143)	Pittsburgh, PA	6.81 (191)	6.87 (364)
Denver, CO	10.92 (577)	8.81 (352)	Portland-Vancouver, OR-WA	18.65 (563)	13.46 (327)
Des Moines, IA	8.48 (295)	5.33 (75)	Providence-Fall River-Warwick, RI-MA	15.00 (400)	5.01 (579)
Detroit, MI	7.82 (243)	8.21 (414)	Raleigh-Durham-Chapel Hill, NC	7.94 (315)	9.42 (191)
Eugene-Springfield, OR	15.47 (362)	8.70 (46)	Richmond-Petersburg, VA	19.96 (461)	7.5 (80)
Fort Worth-Arlington, TX	11.83 (186)	8.85 (260)	Riverside-San Bernadino, CA	22.40 (192)	17.48 (143)
Hartford, CT	12.00 (325)	7.82 (435)	Rochester, NY	10.67 (75)	10.27 (370)
Honolulu, HI	20.00 (15)	18.49 (292)	St. Louis, MO-IL	13.60 (500)	7.98 (501)
Houston, TX	11.43 (700)	10.06 (676)	San Antonio, TX	7.90 (152)	12.05 (249)
Indianapolis, IN	7.72 (648)	5.55 (1189)	San Diego, CA	17.08 (363)	10.10 (99)
Kansas City, MO-KS	10.29 (515)	5.38 (186)	Seattle-Bellevue-Everett, WA	22.82 (517)	11.38 (378)
Las Vegas, NV-AZ	23.00 (187)	16.67 (318)	Tampa-St. Petersburg-Clearwater	11.88 (505)	7.94 (315)
Los Angeles-Long Beach, CA	26.05 (215)	15.27 (203)	Washington, DC, MD-VA-WV	29.10 (1499)	11.97 (2298)

Note: This table reports mean percentage of transactions for which sales price exceeds list price at the MSA level. The data source is the National Association of Realtors homebuyer and seller surveys (2003-2010). Only MSAs in which we observe over 300 transactions are reported. Number of observations is reported in brackets.

Table 6: MSA level regressions: correlates of bidding wars

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
lnSALES	0.3***	0.04***		0.04**	0.02**			0.02***	-0.002
	(2.6)	(3.0)		(2.5)	(2.29)			(4.01)	(-0.1)
ΔlnSALES		-0.02*		-0.02	-0.002				0.006
		(-1.7)		(-1.5)	(-0.2)				(0.2)
lnPOP			0.11***	0.01	-0.011		0.01**		0.02
			(3.1)	(0.2)	(-1.4)		(2.2)		(0.8)
ΔlnPOP			-0.09	-0.01	-0.04		-0.001		0.01
			(-1.6)	(-0.01)	(-0.8)		(-0.002)		(0.3)
lnINCOME			-0.02	0.111	0.01		0.14***		0.14***
			(-0.3)	(1.3)	(0.5)		(3.8)		(3.7)
ΔlnINCOME			0.06	-0.02	0.05		-0.09		-0.09
			(0.6)	(-0.2)	(0.5)		(-0.5)		(-0.05)
Wharton					0.01***		0.02*	0.03***	0.02*
Regulation Index					(3.0)		(1.9)	(3.1)	(1.9)
06-09 Price						-0.19***	-0.12***	-0.10***	-0.12***
Growth						(-5.76)	(-3.4)	(-2.9)	(-3.3)
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA Effect	Yes	Yes	Yes	Yes	No	No	No	No	No
Years	91-09	91-09	86-09	91-09	91-09	03-06	03-06	03-06	03-06
Obs.	1618	1618	1994	1613	1505	458	458	458	458

Note: This table presents the OLS regression results with the percentage of bidding wars among overall transactions in a given market as the dependent variable. The unit of observation is a market defined at the MSA-year level. Numbers in parentheses are t statistics. ***, **, and *denote statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 7: Transaction level regressions from the buyer sample

Sample	Ordinary Purchases	Foreclosures-Included
Age bracket [20, 34]	0.18*** (4.5)	0.18*** (4.5)
Age bracket [35, 44]	0.15*** (3.8)	0.14*** (3.5)
Age bracket [45, 54]	0.09** (2.3)	0.09** (2.3)
Age bracket [55, 64]	0.08* (0.04)	0.08* (2.0)
Income (in $1000)	-0.003*** (-3.0)	-0.003*** (-3.0)
Income Squared	6.39e-06*** (2.7)	7.13e-06*** (3.0)
White	-0.12*** (-6.0)	-0.13*** (-6.5)
Married	0.01 (0.7)	0.01 (0.7)
English	0.030 (1.3)	0.036 (1,0)
First purchase	0.14*** (7.0)	0.14*** (7.0)
Desire to Invest	-0.10 (-1.3)	-0.10 (-1.4)
Desire to Own	0.07*** (3.2)	0.06*** (3.1)
Internet search	0.04** (2.4)	0.06*** (3.4)
New home	0.31*** (15.5)	0.25*** (12.5)
Size (in 100 sqft)	-0.003 (-0.9)	-0.004 (-0.14)
Size Squared	0.00002 (0.3)	0.00003 (0.5)
Small town	0.01 (0.1)	0.02 (0.3)
Urban/city	0.077 (2.4)	0.078 (1.0)
Suburban area	0.052 (1.8)	0.062 (0.8)
Resort area	0.011 (0.1)	0.011 (0.13)
Single family house	0.06*** (3.0)	0.06*** (2.9)
Buy through agent	0.021 (0.9)	0.02 (0.8)
Sold through foreclosure		0.52*** (10.4)
# observations	48,547	49,797

Note: This table presents the OLS regression results with a dummy variable indicating whether a bidding war occurs as the dependent variable. The unit of observation is a purchase. Numbers in parentheses are *t* statistics. ***, **, and *denote statistically significant at the 1%, 5%, and 10% levels, respectively. The data source is the NAR (2003-2010). All specifications include MSA fixed effects and year dummies.

Table 8: Transaction level regressions from the seller sample

	Seller Sample
Age bracket [20, 34]	0.07
	(1.1)
Age bracket [35, 44]	0.11*
	(2.1)
Age bracket [45, 54]	0.09
	(1.4)
Age bracket [55, 75]	-0.02
	(-0.2)
Income (in $1000)	-0.003*
	(-1.9)
Income Squared	6.28e-06
	(1.4)
White	-0.15***
	(-3.0)
Married	0.002
	(0.05)
English	0.03
	(0.3)
Size (in 100 sqft)	0.02**
	(2.4)
Size Squared	-0.0004***
	(-2.7)
Small town	0.18*
	(2.6)
Urban/city	0.26***
	(3.7)
Suburban area	0.21***
	(3.5)
Resort area	-0.15*
	(0.8)
Single family house	-0.10***
	(2.7)
Sell through agent	0.17***
	(3.4)
# observations	13,035

Note: This table presents the OLS regression results with a dummy variable indicating whether a bidding war occurs as the dependent variable. The unit of observation is a sale. Numbers in parentheses are *t* statistics. ***, **, and *denote statistically significant at the 1%, 5%, and 10% levels, respectively. The data source is the NAR (2003-2010). All specifications include MSA fixed effects and year dummies.

Figure 1: history of bidding wars, house prices, and home sales