Emotions, Uncertainty, Gender and Residential Real Estate Prices: Evidence from a Bubble Market

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Abstract

This paper investigates the impact of valuation uncertainty on residential property prices near the peak of a bubble. Our hand-collected sample comprises the sequence of bids and gender of the participating bidders at Irish residential real estate auctions, prior to the collapse of a bubble, which when it burst had disastrous implications for the banking system and the economy itself. Portfolios of practitioner- and hedonic pricing model-selected self-similar properties provide benchmark property price estimates and uncertainty is calculated by reference to various measures of dispersion related to prices achieved for comparable properties. We find, in aggregate, auction winners do not shade bids with increased valuation uncertainty. In addition, winning female bidders, in contrast to findings in the extant literature across a wide range of academic disciplines, including experimental bubble markets, are not less risk averse, or more likely to shy away from competitive situations than their male counterparts.

Key words: *auctions, competition, emotional finance, female bidders, real estate bubble, valuation uncertainty*

JEL classification: D44, D81, D91, G01, G41, R31, J16

Introduction

This paper draws on insights from *emotional finance* (e.g. Taffler 2018), arguing in residential property bubbles valuation uncertainty may not play a role in property prices achieved at the *height-in-bubble* phase. Emotions and their asset pricing consequences have relevance in real estate transactions in general (e.g. Salzman and Zwinkels 2017: 94-97) and may have particular significance in bubble markets. Drawing on data from Irish residential real estate auctions near the peak of a bubble, we conjecture that auction bidders will not shade their bids in line with property price uncertainty. In addition, we explore whether the gender composition of auction bidders impacts on price outcomes. The only two extant studies on gender conducted in bubble market conditions are in experimental settings (Cueva and Rustichini 2015, Eckel and Füllbrunn, 2015), who report that increasing the proportion of female participants reduces the magnitude of bubbles. However, as the extant literature finds emotional aspects associated with house purchase decisions affect both female and male market participants (e.g. Levy et al 2008), we speculate the findings of Cueva and Rustichini (2015) and Eckel and Füllbrunn, 2015) may not hold in residential real estate markets.

Bubbles are ubiquitous in financial markets (e.g. Reinhart and Rogoff 2008). It is universally recognized that real estate, and the US housing bubble in particular, played a leading role in the Global Financial Crisis (e.g. Geanakoplos et al 2012, Scherbina and Schlusche, 2012, 2014). In comparison to other asset pricing bubbles, the banking and macroeconomic impact of residential real estate bubbles are particularly damaging to both the banking system and the wider macroeconomy (e.g. Bengtsson, Grothe and Lepers, 2018, Carmichael and Coën, 2018). Scherbina and Schlusche (2012) argue that bubbles are pervasive in residential real estate markets as such markets are dominated by financially unsophisticated households who often develop optimistic views by over-extrapolating from a time- series of past price movements. The authors argue anomalies are difficult to arbitrage away in real estate markets due to (1) high transaction costs, and (2) the inability to sell short in such markets.[1]

Given the prominence of the collapse of the US housing bubble to the Global Financial Crisis (GFC) it is not unsurprising that there has been significant research on residential real estate bubbles in recent years. The research finds that changes in the level and volatility of house prices exceed that which would be predicted by changes in economic fundamentals. (e.g. Mikhed and Zemčík 2009, Lai and Van Order 2010, Park et al 2010, Glaeser, Gottlieb and Gyourko 2013, Huang, 2013, Hattapoglu et al 2014). For instance, Glaeser, Gottlieb and Gyourko (2013) find that interest rate declines explain just 20% of the rise in house prices over the long 1996- 2006 boom. Building on the seminal *survey* study of Case and Shiller (1988), a significant corpus documents the most important factor driving home purchasers' expectations of future price changes is by extrapolating from past price movements. Jurgilas and Lansing (2013) find that investors in housing appear to expect high future returns on real estate even after a sustained run up in the price rent ratio.[2] Case, Shiller and Thompson (2012) conclude that 12- month expectations of future house price changes are fairly described by lagged actual 12-month price changes. In a recent study of 36 countries (including Ireland) Aizenman and Jinjarak (20143) find that past price changes are the most important factor determining subsequent real estate price appreciation, concluding that the concerns of Shiller (2000) regarding irrational exuberance apply globally. Gelain and Lansing (2014) find that fully rational expectations models significantly under-predict the volatility of the US price-to-rent ratio for

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[1] Ikramov and Yavas (2012) find in experimental real estate markets such limits to arbitrage impact on the magnitude of bubbles.

[2]They argue *survey-based* evidence on people's expectations of future house prices based on the extrapolation of past prices can provide insight to distinguish a bubble from a rational response to fundamentals.They conclude that their findings are directly at odds with the idea that a decline in the risk premium of rational investors is the explanation for the run up in house prices. In this regard they are addressing the concern of Cochrane (2008) that it is difficult to distinguish an asset pricing bubble from a situation in which rational investors have low risk premiums and hence low discount rates.

reasonable levels of risk aversion. However, they find that they can approximately match the volatility of the price-to-rent ratio if agents employ a moving average forecast rule for the price-to-rent ratio that places a large weight on most recent observations, which they refer to as "*backward looking, extrapolative – type expectations*".

The weight of this evidence suggests that home buyers may be more likely to extrapolate past price trends rather than to base decisions on the discounted present value of housing using fundamentals. It appears factors driving backward-looking non-fundamentals based expectations as well as social dynamics help to explain housing bubbles. However, Glaeser and Gottlieb and Gyourko (2013) point out that little is known about the process that generates and sustains such non-fundamental based explanations in the housing market. We conjecture insights derived from emotional finance (e.g. Taffler 2018) may shed light on prices in the *height-in-bubble* phase of residential real estate bubbles. Specifically, as we argue below prices throughout this period may be driven up by "excitement" and "mania" creating a self- propagating trajectory of upward price movements. In such an environment standard financial measures of risk may not impact on prospective purchaser decision making as prices rush to a peak.

Emotions have an important role to play in bubbles in general (e.g. Tuckett and Taffler 2008, Shiller 2014, Aliber and Kindleberger 2015, Andrade 2016, Breaban and Noussair, 2017, Taffler, 2018)[3] and, as we shall argue below, be potentially more salient in residential real estate market bubbles in particular. Shiller (2014) offers the following definition of a bubble, which he frames, using emotional terminology:

[3] Aliber and Kindleberger (2015) in characterizing bubbles give examples of the various emotional terms used to describe the euphoric state (*manias…insane land speculation…blind passion… financial orgies…frenzies…feverish speculation…epidemic desire to become rich quick… wishful thinking… intoxicated investors… turning a blind eye.. people without ears to hear or eyes to see…"* p.41) that arises at the peak of a bubble and the panic (*uneasiness, apprehension, tension, stringency, pressure, uncertainty, ominous conditions, fragility"* p. 91) that ensues when the bubble bursts.

A situation in which news of price increases spurs investor enthusiasm which spreads by psychological contagion from person to person, in the process amplifying stories that might justify the price increases and bringing in a larger and larger class of investors, who, despite doubts about the real value of an investment, are drawn to it partly through envy of others' successes and partly through a gambler's excitement (page 1487).

Drawing on psychoanalysis, Taffler, Obring, and Agarwal (2018), build on the five- stage path- dependent trajectory model of Aliber and Kindleberger (2015) framing bubbles from an emotional perspective. These five stages are: displacement, boom, euphoria, profit-taking and panic.[4] Taffler et al (2018) find that bubbles are highly-charged emotional episodes. Investors are driven by powerful emotions such as excitement and mania as prices as proceed through the 'euphoric' stage and by anxiety as 'external reality'[5] intrudes and prices collapse in the 'panic' stage. As prices escalate upwards from 'boom' to 'euphoria' investors engage in 'wishful thinking' and powerful ' psychic defense mechanisms'[6] are employed distorting the markets sense of reality to dynamically

[4] This is not to say that favorable fundamentals e.g. low interest rates or relaxed credit conditions do not play a role in generating bubbles in addition to emotions. In a recent survey of the literature on housing bubbles Glaeser and Nathanson (2015) conclude that easy credit is a necessary but not a sufficient cause of housing bubbles. From an emotional finance perspective such factors contribute to the *displacement* stage of the Aliber and Kindleberger (2015) 5 – stage model.

[5] In psychoanalysis a distinction is made between 'external' reality' and 'psychic reality'. External reality is comprised of actual, physical events. In contrast, psychic reality is internalized and based on fantasy, wish, fear, memories and anticipation. It contains representations of the world that the subject has formed, with fantasies stemming from unconscious desires. Tuckett and Taffler (2008: 398-402) discuss these distinctions in the specific context of bubble markets.

[6] A range of psychic defense mechanisms can be employed including *splitting*, mentally separating the good and bad feelings, with the latter being suppressed and rendered unconscious through a number of processes including *idealization* (the unrealistic exaggeration of attributes or qualities), *projectio*n (unconsciously attributing unwanted feelings and attaching blame to others), and critically *denial* (the repudiation or disavowal of aspects of external reality the individual does not want to know about to diminish or avoid painful effects associated with that reality) e.g. (Auchincloss and Samberg, 2012).

render unconscious any anxieties associated with asset purchase decisions (Tuckett and Taffler: 2008: 398-402). Emotional conflict about taking on risk is eliminated by splitting off from conscious awareness information that creates ‘bad’ feelings. This leads to an associated denial and repression of valuation uncertainty (Tuckett and Taffler 2008; Taffler 2018).

Han and Strange (2014) find that in real estate markets *bidding wars* are more common in boom periods which they attribute in part to buyer irrationality driven by *“emotion perhaps trumping reason”* (page 23). Shi and Kabir (2018) attribute the increased use of the auction mechanism to sell properties during boom periods to irrational exuberance and “animal spirits” in such market conditions. Independently of the existence of bubble-like conditions there is a corpus that emotions in general impact on property purchase decisions in the real estate literature as well as in economic sociology, psychology, and human geography (e.g. Levitt and Dubner 2005, Christie et al 2008, Levy et al 2008, Munro and Smith 2008, Seiler, Madhavan and Liechty 2012, Besbris 2016, Jørgensen 2016, Gillon and Gibson, 2018). For instance, Levitt and Dubner (2005) find buyer behavior and prices are dependent on feelings that purchasers attach to words in advertisements. Jørgensen, 2016 using qualitative interview data find “*homeownership is… an emotional investment through financial and material means in the future of the family* [and that] *markets are saturated with emotions such as love, desire, fear, anxiety and hope”* (page 98). Seiler, Madhavan and Liechty (2012), using ocular tracking methods, find that when browsing property webpages people are viewing the image of a listing most of the time and far less time and effort are spent on quantitative information provided on the webpage. Munro and Smith (2008, page 359) shows that prices are often determined by feelings. Besbris (2016) drawing on fieldwork observing interactions between real estate agents and homebuyers demonstrate how market intermediaries deliberately evoke emotions in buyers influencing their property purchase decisions.

Thus, in bubble markets, and in residential real estate bubbles in particular, standard finance models of risk, such as standard deviation, may not impact on buyer decision making, with powerful emotions such as excitement dominating as prices accelerate to a peak. As such we hypothesize that there may be no relationship between pricing and risk in housing markets in the *height-in-bubble* phase of a real estate bubble.

Hypothesis 1: *Real estate buyers will not shade their bids relative to valuation uncertainty in the height-in-bubble phase of a residential real estate bubble.*

Hidalgo and Hernandez (2001) find, in addition to economic considerations, men and women have a physical, social and emotional attachment to three spatial levels: the house, the city, and the neighborhood, though the weight placed on each differs by gender. Levy, Murphy and Lee (2008) note that woman and men are driven by the social and emotional aspects of houses. Women are more concerned about issues relating to the family and how they would live in the home whereas men are concerned with the location, prestige value, and maintenance aspects as well as the size and aesthetics of the lawn. The authors report women tend to rely on their feelings in making a property purchase decision quoting from one of their questionnaire respondents "*I"ve got no idea why this house is nicer than others… it just feels right. It really just feels right"* (page 286). Dowling (1998) finds that apart from financial considerations a major factor for men in property transactions is social status whereas women are more concerned with familial aspects. These findings suggest that in relation to residential real estate women and men are equally prone to emotions in decision making in relation to residential real estate purchase transactions. We speculate therefore that female bidders will behave no differently to men in the prices they pay in for properties and in their degree of risk aversion and their willingness to engage in competitive bidding behavior. This speculation potentially contrasts with a significant literature on gender which finds that women shy away from competition (Gneezy et al 2003, Niederle and Vesterlund 2007), and are more risk averse across a wide range of contexts (Byrnes et al 1999).

There is very limited research on the relative responsiveness of men and women in bubble market conditions. As far as we are aware there are only two extant studies on the relative performance of males and females in bubble market conditions. These are conducted in experimental settings (Cueva and Rustichini 2015, Eckel and Füllbrunn 2015). The purpose of these studies is to explore whether with more female market participants the incidence of risk- taking behavior, and hence the magnitude of bubbles could be reduced. Both studies find an inverse-relationship between the magnitude of price bubbles and the frequency of female traders in the market. However, these studies do not e*xplicitly* test the impact of competition and uncertainty on decision making in the experiment itself. Rather they conduct surveys on their participants' attitude to competition and uncertainty *prior* to conducting their experiments. They find, consistent with prior research, that women are more risk averse and are less likely to engage in competitive behavior. Hence they interpret their findings that the inverse relationship between the magnitude of bubbles and the frequency of female traders is consistent with women being more risk averse and being less competitive than their male counterparts. However, do not explicitly test this *within* the dynamics of the experiment itself by letting both uncertainty and the number of competitive bidders vary in their experimental design.

We question the interpretability of these experimental results in the emotional context of a live bubble, and in terms of a residential property bubble in particular. George and Dane (2016: 52) in their review article published in *Organizational Behavior and Human Decision Processes* on the extant research on the impact on emotions on decision making argue: "*fine grained experimental studies can isolate specific factors but at the same time are lacking in realism and do not come close to approximate the complexity involved in making decisions…"*

One such 'complexity' is the time period over which emotional intensity may build up. Aliber and Kindleberger (2015) argue in their 5- stage model suggests that there may be an elongated time period associated with the build- up of behavioral and emotional factors in bubble markets.

Thus, the concentrated time period over which experimental studies are conducted may not be able to adequately capture the richness associated with the evolution of the psychological processes at work as actual bubbles unfold. In addition, the nature of the asset itself that is the subject of the experimental setting in both of these studies is not real estate but rather hypothetical shares that pay dividends and cash. Such an asset may not adequately replicate the emotions associated with an actual property- related transaction.

In contrast to the experimental studies of Eckel and Füllbrunn (2015) and Cueva and Rustichini (2015) who explore the magnitude of bubbles, conditional on the gender composition of their participants, we focus on the bidding behavior of male and female bidders in a field study *within* what turns out to be a period coinciding with the peak of a residential property bubble. We address a number of interrelated research questions. Are female bidders, where they win, likely to pay lower prices than their male counterparts as found in Eckel and Füllbrunn (2015) and Cueva and Rustichini (2015)? Does the presence of more women in the bidding process have a dampening effect on auction prices? Do winning female bidders shade their bid with respect to: (1) the uncertainty associated with property values, and (2) the number of competitive bidders?

These conjectures lead to our set of gender- related hypotheses.

Hypothesis 2a: *Winning females bidders pay no less than their male counterparts for comparable properties in the height-in-bubble phase of a residential real estate bubble.*

Hypothesis 2b: *Increasing the proportion female bidders in an auction will not have a dampening effect on prices in the height-in-bubble phase of a residential real estate bubble.*

Hypothesis 2c*: Winning female bidders are no less likely to shade their bids with respect to valuation uncertainty and competition than their male counterparts in the height-in-bubble phase of a residential real estate bubble*.

Our sample consists of residential real estate auctions in the Dublin market over the 18- month period from September 2004 to February 2006, a period coinciding with near the peak of our bubble.[7] During the period from January 1994 to early 2007 Irish residential real estate prices nationally rose in excess of 500% and then in April 2007 they started to collapse, with a sustained decline continuing for almost six years eventually stabilizing in March 2013. In the region of the capital city, Dublin and its hinterland the comparable rate of price increase was in excess of 510%. From peak to trough this fall (both nationally and in the Greater Dublin region) was in excess of 50% and in modern times is second only to Japan in terms of magnitude. [8]

In our study we exclusively use auction data as transaction data on private treaty dealings is

[7] During the period of our study the news media actively propagated the notion of property purchase. The hype was such that newspaper articles frequently compared rates of return on property directly with those of bank deposits (Mercille, 2014). This may have implied that property was a one way bet. What is also noticeable in the media coverage is the way emotional terms are used to talk about real estate in newspaper property supplements. Expressions such as *"living the dream", living the lifestyle", "opulent living" , "show stopper", "sheer opulence", "the spirit of gracious living", " a perfect setting, "a perfect lifestyle"* abound. Shiller (2002) argues that such media attention amplifies feedback trading tendencies in an emotionally charged market.

[8] The first warning that the Irish residential property market was significantly overvalued came in April 2003 (IMF, 2003) with further warnings made in quick succession (IMF, 2004; Economist, 2005). When the property bubble finally burst it had disastrous consequences not only for the housing market, but also for the banking system and critically the entire Irish economy eventually triggering a €64bn bailout from the IMF, European Commission and European Central Bank in November 2010 (Nyberg, 2011). Such was the dominance of the real state sector in terms of the performance of the Irish economy during the bubble period that it distorted macroeconomic aggregates, including importantly the interpretation of GDP growth (e.g. Donovan and Murphy, 2013).

not publicly available.[9] Using auction data does, however, have a number of features from our perspective. First, the *auction fever* literature finds that competitive bidding in an auction setting, where other bidders are physically or virtually present (such as in internet auctions) is more intensely emotionally driven, enhanced by such factors as time pressure, hype, social facilitation[10] and a desire to win, which impairs bidders' decision making pushing them to bid beyond their limits (e.g. Jones 2011, Malmendier and Lee 2011, Adam et al 2015, Ehrhart, Ott and Abele 2015). This potentially compounds any emotional aspects of a bubble market itself.[11] Second, in auctions all bidders are physically present in the auction room, and the number of competitive bidders and their gender can be directly observed.

We find that winning auction bidders do not shade their bids with respect to house price uncertainty. Thus it appears that conventional measures of dispersion used in financial markets do not appear to impact on pricing outcomes in the *height-in-bubble* phase of a housing bubble. Our findings are consistent with an emotional finance perspective whereby excitement dominates as prices

[9] Prices achieved at auctions were publicly disclosed in the weekly property supplements of the main newspapers. They are a matter of public record. In contrast, prices achieved via negotiated sales transactions were not publically disclosed. They would have been known solely to those who participated in such transactions. This lack of price transparency about otherwise similar properties and the potential impact on market prices both in auctions and in other negotiated sales transactions attracted media attention over the period (e.g. "Can bidding be more transparent?: Bidding on a private treaty sales is a game of bluff and bluster", *Irish Times*, 5th February, 2004). This eventually lead, after a considerable lapse of time, driven by arguments about confidentiality of price information, (e.g. "No easy solution to price disclosure", *Irish Times*, 22nd May, 2008) to the enactment of the Property Services Regulation Act, 2011. This Act ensured that, inter alia, prices achieved in negotiated sales transactions (private treaty sales) be made available via an online register.

[10] Social facilitation is where the physical presence of a live audience may increase emotional arousal (Zajonc, 1965).

[11] Shi and Kabir (2018) report, using data from the New Zealand market, the proportion of residential properties auctioned increases as a proportion of the total volume of property transactions in boom periods which they attribute to a manifestation of 'animal spirits'. In this regard, it is worth noting that in the years following the collapse of the Irish residential property bubble, starting in mid- 2007 up to the present day, there has been a virtual collapse in the use of the auction mechanism to sell residential property in the Irish market.

accelerate to a peak. In addition we find that gender has no impact on differential bidding behavior in residential real estate auctions. In particular, we find that winning female bidders pay similar prices for an auctioned property as their male counterparts. In addition, the participation of women, as measured by the proportion of female bidders to total auction bidders in each auction, has no dampening impact on final prices. This is in contrast to the experimental findings of Eckel and Füllbrunn (2015) and Cueva and Rustichini (2015). In addition, we find that winning female bidders are no less likely to shade their bids in the presence of valuation uncertainty or auction competition than their male counterparts. These findings, in aggregate, contrast with those of Eckel and Füllbrunn (2015) and Cueva and Rustichini (2015) and are suggestive that winning female bidders in a live residential real estate bubble situation appear to behave differently than in extant experimental studies.

The remainder of this paper is organized as follows. In the next section we set out the mechanics of the residential auction process in the Dublin auction rooms as well as a description of our sample of observed auctions and auctioned properties. In the following section we present our methodology to infer property price uncertainty and levels of competition. In the next section we present our results. In the final section we conclude.

Mechanics of the Auction Process in the Dublin Auction Rooms and Sample Characteristics

Irish residential real estate auctions are conducted via the English open outcry (ascending bid) auction mechanism and may be characterized as common value auctions (e.g. Lusht 1996, Shi and Kabir 2018). [12] [13] The auctions are held in a public auction room and the results are published in

[12] Residential real estate auctions may have some features of private value auctions which relate to assets that appeal to bidders' aesthetic sense. Auctioned real estate property values, however, also have a substantial common value element. The cross section of international property values can be largely explained by objectively observed property features and traits

national newspapers. In English style auctions the auctioneer opens the auction typically by inviting offers for the property at the auction guide price and if there are no bids he/she then reduces the bidding until a starting bid is received. At that stage the auctioneer suggests a level for the second bid and bidding would proceed with the auctioneer announcing the next price level.[14] When the bidders complete bidding the auctioneer looks around the room to all previous bidders to encourage further participation. If no further bids are forthcoming the auctioneer announces “going, going twice, sold” or alternatively the auctioneer indicates that the vendor’s undisclosed reserve price has not being reached and that the property is withdrawn. In such circumstances the auctioneer indicates the highest

(Sirmans et al. 2006), and the Dublin auction rooms for residential real estate, even at the height of a so-called bubble market, are shown in this paper to be no exception to this general rule.

[13] Cramton (1998) shows that an English open outcry ascending bid auction mechanism dominates the use of sealed bid auctions and leads to greater efficiency and higher price outcomes in a common value auction, such as a property auction. The argument in Cramton (1998) is that in such an auction setting bidders can add to their own information set about common value by observing the bidding behavior of other bidders. Thus, open-bidding, especially by a large number of bidders, potentially reduces but does not eliminate uncertainty by imparting information which the bidders can use to update their estimates of value, leading them to bid more aggressively. However, as Shi and Kabir (2018) note, using residential real estate data, observing other bidders can provide false comfort about value and may reinforce bidding strategies that move prices from fundamentals, particularly in auction markets, where emotions are high. Rational bidders should take this into account in their bidding strategies and hence shade their bids in the face of valuation uncertainty. Shi and Kabir (2018) motivate their arguments by reference to the concept of affiliated values (Milgrom and Weber (1982) whereby bidders’ valuations for a common value object could be a function of other bidder’s bidding. Such arguments are consistent with the literature on auction fever (e.g. Adam et al, 2015). In a parallel setting Eriksen and Kvaløy (2017) find in tournaments that more competition increases risk seeking behavior, concluding that “*people more or less atomically take risk in competitive situations*” (page 1343).

In addition, the arguments of Cramton (1998) need to be tempered in the context of the particular circumstances of the Irish residential property market where prices from negotiated sales transactions are not available (footnote 9). Thus, when bidders drop out of the bidding process it is difficult for remaining bidders to infer whether they dropped out because they reached their reservation price, or alternatively their last bid price may have exceeded a price from a negotiated sales transaction for a similar property that they may have been involved in. (See footnote 20). In such circumstances bidders should rationally shade their bids in the presence of this uncertainty.

[14] In some cases bidders would pre-empt the auctioneer and announce a bid in excess of the previous pattern of increment increases

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unsuccessful bidder at that stage would for a certain time period (typically a day or so), have exclusive rights to negotiate with the vendor following the auction. There is no requirement to publicly disclose the reserve price and it is not done in Irish residential real estate auctions during our sample period.[15] Vincent (1995) argues that in common value auctions, non-disclosure of the seller's reserve price is optimal as it encourages the entry of more bidders to the auction.

In the event of a successful auction the highest bidder is immediately invited to meet the vendor and sign a contract and pay a non- refundable deposit of 10% of the sales price and sign contracts normally within six weeks of the auction date. As Dublin real estate auctions require the successful bidder to pay the deposit for the property immediately after the auction a potential bidder is likely to have spent funds on a property survey and a title search prior to the auction. In comparison, in negotiated private treaty sales the deposit is refundable up to the date contracts are signed, normally four-to-six weeks after the price is agreed.

In an English auction each bidder has a valuation for the item being sold. A second bidder will drop out of the bidding as soon as the price exceeds her/his own valuation of the item. Thus, the highest valuation individual wins the bidding and only pays the price equal to the valuation of her/his last remaining rival, or one bid increment above this price level. Usually this will be below her/his own maximum valuation of the item. This implies that only the successful bidder knows how much economic value she/he receives because only she/he knows her/his own valuation.

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[15] Even in those jurisdictions where seller reserve prices are disclosed, the reserve price is an imperfect proxy for value. The real estate literature finds that buyers are in general better informed than sellers about value whereas the seller has more information about the condition of the property (Levitt and Syversen 2008). This asymmetry in relation to condition can be resolved by a property inspection or a survey prior to the auction.

Sample Properties

Our sample consists of the 18- month period from September 2004 to February 2006. This is a potentially fruitful period to explore for the bidding behavior of female and male auction participants with respect to uncertainty as it was during a market that was on a continuous upward trajectory since January 1994. Our time period ended fourteen months prior to the start date of the unravelling of the bubble in April 2007. Prices in September 2004, the start date in our sample period, were up in excess of 375% of prices in January, 1994. Our sample period thus coincides with the *height-in-bubble* phase of the bubble's trajectory. There was no quarter over that entire period (1994 to April 2007) where prices did not register positive movements.

[Please insert Figure 1 about here]

During the period of our study there were a total of 1565 auctions of which 666 (44% of the total) resulted in a successful sale at the time of the auction. The authors attended 210 of these auctions. These 210 auctions were chosen randomly from a selection of residential real estate auctions in the Dublin area.[16] The auctions were held mid-week usually on Tuesday, Wednesday and Thursday afternoons in the offices of the real estate agents with a number of auctions taking place in sequence. The auctions generally occurred at concurrent times in the different auction houses. Auctions from both the large and smaller real estate agencies were attended so as to minimize any potential bias from concentration on the bigger estate agents. Of the 210 auctions 106 of these resulted in a successful auction. Ultimately we restricted our sample from 106 to 87 as we needed to be able to compare the prices achieved at our sample auctions with a portfolio of self- similar properties and derive a measure of price uncertainty.

[Please insert table 1 about here]

[16] The city and its region account for almost 1/3 of the population of Ireland and generate close to 40% of GDP.

Methodology

In order to test the impact of uncertainty on auction prices we require robust estimates of an auctioned property's fundamental value to act as a reference point. We adopt a dual approach, discussed below.

The first benchmark price we use is the average price of similar properties to the property being auctioned, which we will refer to as the mean price of *self-similar* properties. Senior professional real estate agents are consulted to identify the comparable properties. Our second benchmark price is obtained from the predictions of a hedonic asset pricing model (HAPM).

Mean Price of Self- similar Properties

To calculate the mean (average) value of the self-similar properties we proceed as follows. We commence with the 106 successful auctions that were attended by the authors. We construct a portfolio of self-similar real estate properties and note their prices for each of our attended auctions in the following way:

1. We arrange all 666 successful auctions, which are a matter of public record (table 1) according to the criteria: Time period of the auction, location, house type, area (square feet), number of bedrooms, and the condition of the property. By "time period of the auction" we mean that in order to be a potential candidate as a self-similar property the property must have been successfully auctioned no longer than one month prior to that of our sample auctioned property.[17] The "location" match requires that the property must be located in the same postal district as our sample of auctioned

[17] Employing a longer window, such as two months would have increased the number of comparable self-similar properties. However, adopting a longer window also potentially increases the likelihood that prices may be potentially stale.

properties.[18] The area (square feet) criterion is satisfied by properties within 100 square feet of the observed auction property. The other criteria are defined in table 2. The identification of these select criteria, and their relative importance, were indicated by two experienced senior auctioneers (one a current director and one a former director of a major real estate agency). They considered these variables and their ordering to be the key variables in identifying self-similar properties in the first instance. [19]

2. According to these criteria, a portfolio of self-similar properties was identified in respect to the 106 successfully auctioned properties. The matched portfolios of self-similar properties were checked by each of the auctioneers independently for consistency and to spot any anomalies. At this stage some of our sample properties were excluded if, in the opinion of our auctioneers, there were distinguishing features (unique characteristics) in relation to those candidate comparable properties or, indeed, if our sample properties were e.g. corner sites, a house sold with planning permission for extension already obtained, south facing garden etc. This can make such properties inappropriate for matching purposes.
3. The mean of the auction price of self- similar properties is calculated. As a result of the matching process we reduce our sample of successful auctions from 106 to 87 as we required at least three self-similar properties in order to make an appropriate price comparison and to calculate a measure of price uncertainty. [20]

[18] The criteria are more restrictive conditions than adopted in our HAPM specification where we amalgamate postal districts into discrete areas for the location variable and we use quarterly dummies for time.

[19] The criteria selected by the two independent auctioneers all proved to be statistically significant factors in our HAPM specification.

[20] For these 87 properties we also asked the auctioneers to identify using the same criteria is in 1 above, comparable properties that would be on offer via negotiated sales transaction in a two month period prior to the date of our sample auctions. In each of these cases a minimum of four such properties were identified, prima facie evidence of potential information asymmetries in relation to our sample auctions.

Hedonic Asset Pricing Model

Our HAPM model specification is estimated in log form (Sirmans, MacDonald, Macpherson and Zietz, 2005). The following regression is run:

$$In\ (p_i) = \alpha + \sum \beta_i X_i + \varepsilon_t \qquad (1)$$

where the selling price of property i (p_i) is expressed in log form, α is a constant term, β_i is the regression co-efficient for the i- th housing characteristic, X_i, and ε_t is the residual error term.

The properties evaluated in the model are disaggregated into their physical characteristics: property size, bedrooms, bathrooms, garden, type of property, property condition. In addition, we explore the properties location, the size of the real estate agent marketing the property and the time period in which the property is auctioned. The characteristics are defined in table 2.[21] [22]

[Please insert table 2 about here]

In table 2, the results of the hedonic model are reported. We would expect with the exception of the garden variable (expectation of negative and significant) that the coefficients on the physical property characteristics such as property size, bedrooms, bathrooms etc. would be positive and significant. The reported coefficients are in line with expectations with many of the variables significant at the 1% level. The property types are all significant with the exception of the apartment category. In relation to the location dummy variables they are all significant with the exception of

[21] The data for the condition variable was extracted from the estate agents brochures for the auctioned properties and, where these were not available, from the agent websites or from the property descriptions in the national newspapers. In regard to the property type variable, the property type dummy excluded is the period property.

[22] Location is dominated by two key submarkets namely South Dublin and South County Dublin. These are the two most highly priced broad areas in Greater Dublin. In regard to the location variable, the location dummy excluded is North county Dublin.

Dublin Central. The south County Dublin area is highly significant. The real estate agent dummy variable is not significant. The time dummy variables are all negative and significant with the exception of the May to July 2005 period which though negative falls slightly short of significance at the 10% level. The negative coefficients on the time dummies are reflective of a rising property market over the period. It is noteworthy that the R^2 associated with the model is 64.3%. This indicates a good fit and is suggestive that residential real estate auctions contain a substantial common value component, where a winner's can manifest. In that regard the reported R^2's are broadly comparable to the magnitudes reported in the literature on the relationship between property characteristics and prices (e.g. Sirmans, Mac Donald, Macpherson, and Zietz 2006).

Model

Our dependent variable, in our baseline model specification, is the deviation, B_t, of the winning bid price, from its reference price, p_m, in the t^{th} auction. It is determined as follows:

$$B_t = ln\left[\frac{P_t}{P_m}\right] \qquad (2)$$

We seek to explain the influence of price uncertainty (U_t) on the deviation of the winning auction bid from a reference price (B_t). We also examine if the gender of the winning bidder (G_t) is associated with the bid price relative (B_t). We also include a measure of the intensity of auction competition (C_t) (discussed below). As a result, we estimate the following equation:

$$B_t = \gamma_0 + \gamma_1 U_t + \gamma_2 C_t + \gamma_3 G_t + \varepsilon_t \qquad (3)$$

The γ's are regression parameters to be estimated. The stated regression model is in line with the approach followed in Tse et al (2011).[23]

Valuation Uncertainty

In order to test for the behavior of bidders in the face of price uncertainty and to test whether female bidders behave differently to their male counterparts in the face of uncertainty we need a measure of *ex ante* price uncertainty for our sample of attended auctioned properties. We adopt a methodology to quantify price uncertainty (U_t) of residential real estate by constructing portfolios of properties with similar characteristic traits. Our main measurement of a property's price uncertainty is calculated as the coefficient of variation of the portfolio of self-similar properties that sold via the auction mechanism.[24] [25] It is measured as the ratio of standard deviation to the mean of self-similar portfolio property prices as outlined in the section on *Mean Price of Self-similar Properties*. The coefficient of variation is often regarded as a superior proxy for uncertainty than

[23] An advantage of using this specification is that a regression coefficient on a dummy variable can be interpreted in percentage terms when multiplied by 100.

[24] This is a publically available measure of price uncertainty as the prices achieved via otherwise equivalent negotiated sales transactions are not disclosed.

[25] In an ideal world a true measure of uncertainty would be to obtain each bidder's estimate prior to the auction of the price of the property. However, due to the nature of our property auctions this is not possible for a number of reasons First, as a number of consecutive auctions take place in the same auction room on the same day it is not possible prior to bidding who the potential competitors are for each individual auction. Second, bidders are unlikely to be willing to disclose their bidding intentions publicly. Such lack of access to individual bidder valuations as in the case of those studies evaluating valuation uncertainty in auction markets necessarily means that we use a proxy. For instance, Boone et al (2009) in studying takeover markets employ the proportion of intangible assets to total assets as a proxy for valuation uncertainty. Other proxies that have been employed in the takeover literature include idiosyncratic volatility, turnover of the target's stock and Tobin's q.

variance of the distribution, and is the method adopted in Tse at al (2011). Our measurement of the coefficient of variation proceeds as follows:

1. For each of the attended 87 auctions we compute the mean, $\bar{x}$, and standard deviation, s, of the auction prices achieved by the self-similar properties.

2. We then compute a normalized measure of dispersion, the coefficient of variation, $\hat{c}_V$, and an adjusted coefficient of variation, $\hat{c}_V{}^{adj}$.

$$\hat{c}_v = \frac{s}{\bar{x}}$$

$$\hat{c}_v^{adj} = \left[1 + \frac{1}{4n}\right]\hat{c}_v \qquad (4)$$

The adjusted coefficient of variation is, for normally distributed data, an unbiased estimator of the coefficient of variation for a sample size, *n*, and is a superior measure than the co-efficient of variation when the sample size is small (Sokal and Rohlf, 1995). As a robustness test we also employ two other methods: mean absolute deviation and standard deviation.

Competition and Gender

We include competition for two reasons. First, an extensive auction literature finds more auction competition triggers higher price outcomes, for instance Holt, (1979), Harris and Raviv, (1981), Milgrom and Weber, (1982) as well as in empirical research in the real estate literature such as Lusht, (1996). Second, we seek to explicitly test whether winning female bidders behave differently in competitive environments than their male counterparts. Prior auction research has consistently demonstrated higher competition leads to higher auction prices and has both rational and psychological drivers. Bazerman and Samuelson (1983) interpret competition in terms of its impact on auction participants bidding to their own reservation price. In their model, as the number of bidders' increases the bidder will bid closer to her own reservation price and the expected sales revenue increases. In the absence of competition there are fewer incentives for bidders to bid up to their own valuation prices and it would be less likely that there will be a successful sale. Thus in their model bidders *rationally* respond to the number of bidders at the auction. Other models of competition argue that the competitive process itself may generate its own momentum triggered by behavioral and emotional factors causing prices to detach from fundamentals (e.g. Ku et al 2006, Adam et al 2015). Eriksen and Kvaløy 2017 find that less intensive competition reduces risk seeking behavior.

For robustness purposes we employ two measures of competition "C_t": the first proxy is the number of bidders who submitted at least one bid for the property at the auction[26], whilst the second proxy is the average number of bids per bidder that an auction takes to reach its conclusion from the initial bid (Tse et al, 2011). The average number of bids per bidder is thus the total number of bids in the auction divided by the number of bidders at the auction. [27]

The real estate bidder variable "G" takes on the value of 1 if the winning bidder is a female bidder and zero otherwise.

[26] In the real estate agents' premises a number of auctions may be run consecutively. Thus attendees may be there for one or more auctions, may not bid, or may simply be observing. We draw our measure of bidding from the number of active participants in each individual auction.

[27] The average number of bids per bidder may capture a different aspect of competitive dynamics at an auction. Ku et al (2006) argue that the more bids that a person makes the more committed he is to win the auction; he accumulates sunk costs in time and energy. Each time he bids he is for a moment the new owner of the property. For that moment he may be the subject of the *endowment effect*. When he is outbid his sunk costs and the endowment effect may encourage him to escalate his commitment and bid more. The endowment effect associated with auction fever is particularly pronounced in situations of valuation uncertainty (Ehrhart, Ott and Abele, 2015).

Results

Table 3 presents summary statistics on the various proxies we use for our key variables: valuation uncertainty, the gender of the auction winner and competition. Panel A shows the summary statistics on valuation uncertainty and the gender of the winning bidder. The average valuation uncertainty as measured by the co-efficient of variation is 0.15 Summary statistics on our alternative price uncertainty measures are also reported. Of the 87 auctions, 17% of these are won by female bidders. Panel B shows the data on competition. It shows that the average number of bidders across the 87 auctions is 3.2, the maximum is 6 and the minimum is 2. The average number of bids per bidder is 5.81.

[Please insert table 3 about here]

In table 4, we report the pairwise correlation matrix of the proxy variables presented in table 3. Our two dependent variables, the mean price of self-similar properties and the HAPM bid price relatives, are highly correlated (correlation coefficient 0.55; t-statistic 6.13). At the same time, they are evidently complementary. They relate to different information as shown by the significant distance of this correlation coefficient to one. Our two measures of competition, number of bidders and average number of bids per bidder, are also highly correlated (t-statistic = 2.74). All four of our measures of uncertainty, the adjusted coefficient of variation, the coefficient of variation, the mean absolute deviation and standard deviation, are highly correlated with associated large t-statistics. We find that both measures of competition and gender are not correlated.

Interestingly, we find no statistically significant correlation between any of our four measures of uncertainty and our two bid price relatives. This is indicative that winning bidders do not shade their bids in the presence of increased uncertainty. This finding is consistent with the predictions of emotional finance whereby conventional measures of risk are not factored into bidder decision making in the *height-in-bubble* phase of a property bubble. We also report that gender is correlated negatively with both of our bid price relative though the co-efficients are not even close to being significant. This suggests that in line with our expectation in hypothesis 2a female bidders pay similar prices to their male counterparts. Also though the correlation between both of our bid price relatives and competition is positive and significant in line with auction theory, the correlation between gender and both competition and uncertainty are also negative they also are not close to being statistically significant. In fact, taking our preliminary finding on the positive correlation between auction bid price relative outcomes and competition together with our preliminary finding on the gender of the winning bidder and competition and uncertainty, it would appear that female winning bidders do not actually behave any differently than their male counterparts. This result is in contrast with the extant literature on gender, across a wide range of decision making contexts which finds that females are more risk averse across a wide range of decision making contexts (e.g. Byrnes et al 1999), and tend to shy away from competition (Gneezy et al 2003). As these are univariate preliminary correlations we test our hypotheses more formally in the multivariate regression equations below.

[Please insert table 4 about here.]

In tables 5 and 6, we present our initial empirical findings on the effects of valuation uncertainty, gender and competition of the auction winner on realized auction prices scaled by benchmark prices, testing hypotheses 1 and 2. Table 5 presents the results with the level of auction competition proxied by the number of bidders at the auction and table 6, as a robustness test, presents the results with competition proxied by the average number of bids per bidder. Though the adjusted co-efficient of variation is our preferred measurement of price uncertainty, we also test three other measures of price uncertainty. These are the unadjusted co-efficient of variation, the standard deviation and the mean absolute deviation as robustness tests in tables 5 and 6.

In table 5, we show, using either the mean price of self- similar properties or the HAPM estimated price as a benchmark price for the winning bid price, that the adjusted co-efficient of variation is not even close to being a statistically significant explanation. Further, this result holds as we use the coefficient of variation, the mean absolute deviation and the standard deviation as alternative measures of property price uncertainty. Hence, we conclude that buyers in general at an auction do not shade their bids relative to price uncertainty. Turning to hypothesis 2b and our test that winning bids of female bidders, relative to benchmark prices, will be equal to those of their male counterparts. Our findings in table 5, in relation to winning female bidders, is that when they win they do not pay less than their male equivalents. This result holds irrespective of our choice of benchmark price, using the HAPM or the mean price of self-similar properties to obtain a reference price.

Turning to the level of competition in the auction setting, as proxied by the number of active bidders. The impact of one additional bidder using the mean price of self- similar properties as the reference price is a 6 percentage point increase. Using the HAPM, to provide an alternative benchmark price, the addition of one bidder also increases the final auction price by 6 percentage points. These co-efficients are both significant at the 1% level, and indeed the result holds irrespective of which measure we use to account for price uncertainty as a control variable. Such results are consistent with auction theory whereby higher competition generates higher prices.

[Please insert table 5 about here.]

As a robustness test, table 6 presents comparable results to those reported in table 5 but it uses the average number of bids, instead of the number of bidders, as the specified competition proxy. The reported results in table 6 are substantively identical to those reported in table 5. Winning bidders in aggregate do not shade their bids in respect to price uncertainty and our results are invariant to how we proxy for price uncertainty and how we impute benchmark prices. Further, we confirm that winning bids of female buyers, relative to benchmark prices, are no lower than those of male buyers. In addition, our results are invariant to the competition proxy employed.

[Please insert table 6 about here.]

Table 1 reports that 53% (=831/1565) of properties did not sell at auction, though 35% of these (293 cases) sold immediately after the auction to the highest unsuccessful bidder. By way of an additional robustness test, we investigate in our observed sub-sample of withdrawn auctions (62 withdrawn auctions where the authors were present), whether the results of equation 3 are still manifest in those properties that are withdrawn at auction. In other words, even if the auction is not successful do bidders behave in the same way in relation to auction uncertainty as in successful auctions? To measure B_t in the case of withdrawn properties, we employ the withdrawn price as the numerator variable in lieu of the auction price achieved. We find that our results are consistent with those reported in tables 5 and 6 with an insignificant coefficient on the uncertainty variable (Ut) and the coefficient on the competition variable (Ct) being positive and significant.[28] We asked our experienced real estate professionals in relation to these properties. The explanation they offered is that the seller's (non-disclosed) reserve price was probably unduly optimistic. They also indicated that in the case of the 19% of properties sold immediately after auction (Table 1) that these were exclusive negotiations between the highest unsuccessful bidder at the auction and the seller with the price ultimately agreed being typically "in the region of" the last auction bid typically accompanied by a

[28] To perform this test we adopt the same methodology to calculate the mean prices of self-similar prices as that adopted for the portfolio of successful auctions. In terms of our sample auctions attended though there were 62 withdrawn properties, we finally reduced our sample to 40 to obtain at least three comparator properties. Thus, we had to drop a third of the total sample. This is versus only 17% (106 to 87) in the case of successful auctions. Our experienced auctioneers indicated that the lack of matching of comparable properties could be attributed to auctions taking place in postal districts that did not have a tradition of properties offered for auction, or that the properties auctioned were not of a type traditionally offered for auction e.g. two bedroom townhouses. We checked these explanations by reference to the characteristics of the portfolio of 666 successful auctions and the explanations received appear reasonable.

compromise on the "undisclosed" reservation price by the property seller. We conclude that even in the auctions which were withdrawn the highest bidders did not bid shade with respect to uncertainty.

Our results so far confirm that winning bidders do not shade their bids in the face of price uncertainty. In addition, female bidders pay the same price for comparable properties as their male counterparts. One potential concern is that though winning female bidders they may pay similar prices to their male counterparts it may be that female bidders may drop out of an auction more frequently than their male counterparts. If this is indeed the case then female bidders may be argued to take action to avoid paying high prices by dropping out of the auction following earlier rounds of bidding.

Across our sample auctions, female bidders win 17% of our 87 auctions. An analysis of the auction bidding data reveals that they constitute 22% of the total bidding population. These proportions are very similar providing prima facie evidence that female bidders win at the sample auctions proportionate to their representation in the bidding population. We address this issue more formally by conducting two additional tests. First, we run a logit regression with the dependent variable (Y) taking on a value of one if the winning bidder is a female bidder and zero otherwise. Our dependent variable is the proportion of the bidding population in each auction that is female. Additionally, we run a chi-squared test exploring whether there is any difference in the number of auctions won by female bidders versus male bidders, conditional on the proportion of bidders that are female in each auction. The results of these tests confirm that the proportion of auctions won by female bidders are proportionate to the percentage of female bidders that participate in each of our sample auctions.

Next, we investigate whether irrespective of whether a female bidder wins an auction does the presence of female competitive bidders in an auction impact on final auction prices (hypothesis 2c). In this way we are able to test whether the experimental findings of Eckel and Füllbrunn (2015) and Cueva and Rustichini (2015) that increasing the number of female participants dampens the impact of a bubble. In other words, does the presence of female bidders lead to a dampening of the final auction price vis-à-vis those auctions that are more dominated by male bidders. Specifically, we run the following regression:

$$B_t = \gamma_0 + \gamma_1 U_t + \gamma_2 C_t + \gamma_3 \%G_t + \varepsilon_t \qquad (5)$$

where the variables are identical to those of equation 3, except that G_t is replaced by $\%G_t$. $\%G_t$ is the proportion of the total population of bidders in auction t that are female bidders.

Our results are presented in table 7 and 8. Table 7 reports our results employing the number of bidders in the auction as the competition proxy, and table 8 presents our results using the average number of bids per bidder as the competition proxy.

[Please insert table 7 and table 8 about here.]

Our reported results in table 7 and 8 are identical to those reported in tables 5 and 6, indicating that auction price outcomes are not impacted by the presence of female bidders participating in the bidding process across our sample auctions. [29]

Overall our results thus far indicate that winning female bidders pay the same prices for comparable properties as their male counterparts. In addition, in those auctions where female bidders constitute a greater proportion of the total number of bidders there is no dampening effect on auction prices. This is in direct contrast to the experimental findings of Eckel and Füllbrunn (2015) and Cueva and Rustichini (2015) who find increasing representation by female bidders

[29] We also investigate whether the proportion of female bidders relative to the total population of bidders in a given auction in our sample of withdrawn auctions differs to the proportion of females in successful auctions. To do so we conduct a difference-in-means test of $\%G_t$ across both auction types and find that the difference- in- means is not significant. We conclude that female participation in the bidding process was not a factor leading to auctions been unsuccessful.

in mixed groups dampens the magnitude of a bubble. In addition, we find the proportion of the bidding population represented by female bidders is a reliable predictor of the likelihood of a female winning the auction, and correspondingly for male bidders. In other words, female bidders appear no less likely than their male counterparts to drop out of bidding in the auction.

However, interestingly, we also find that female bidders represent only 22% of the bidding population. Thus, women appear, on a prima facie basis, to be less likely to bid at all in an auction setting than their male counterparts.

We now turn to test hypothesis 2c, as to whether the findings across a wide range of decision making contexts, that females tend to be more risk averse and less likely to compete when competition is intense is also valid in a residential real estate context in bubble market conditions. Specifically, we test whether in a residential real estate bubble bid shading differs across female and male buyers in the presence of uncertainty and the intensity of competition. We extend our parsimonious model specification to include suitable interaction terms to conduct this hypothesis test. Specifically, we run the following regression:

$$B_t = \gamma_0 + \gamma_1 U_t + \gamma_2 C_t + \gamma_3 G_t + \gamma_4 G_t * U_t + \gamma_5 G_t * C_t + \varepsilon_t \qquad (6)$$

This model specification is identical to that of equation 3 except for the inclusion of the interaction of gender (G_t) with both the uncertainty variable (U_t) and with the competition variable (C_t). The objective is to test whether the co-efficients on the competition and uncertainty variables vary according to whether the winning bidders are female or male. Thus we are testing whether female winning bidders relative to male winning bidders shade their bids in the presence of competition and uncertainty.

Our results are presented in table 9, panel A and panel B. In line with table 5 (table 6), panel A (panel B) employs the number of bidders at the auction (average number of bids per bidder) as the proxy for the level of competition in the auction setting.

[Please insert table 9 about here.]

We find the co-efficients on the specified interaction terms are not significant across all the models reported in table 9. Our results are thus consistent with no difference in the exposure of female winning bidders, vis-à-vis their male counterparts. Specifically, when we allow the response of winning bidders to price uncertainty and to competition to vary across gender, we find, across all models, no differences relative to inferences in tables 5 and 6, where we do not explicitly differentiate between the gender of the winning auction participants.

A potential concern is that this result may be due to multicollinearity which spuriously arises due to small sample size or, indeed, true co-movements between the interaction terms and our gender dummy variable or our price uncertainty and competition proxies.[30] As a result, we conducted several additional model building exercises with more parsimonious specifications. We perform again the eight regressions in table 9, by excluding the "gender" variable. We also perform these regressions by dropping each of the interaction terms sequentially. Invariant to the model specification adopted the coefficient on the interaction term remained indistinguishable to zero.[31] We therefore conclude that there is no differential impact on the trading behavior of winning bidders, conditional on their gender.

Our overall results are consistent with winning auction bidders in aggregate not taking action to reduce their bidding in the face of uncertainty. This is consistent with survey evidence (e.g. Case and Shiller, 1988) whereby the predominant influence on households is optimism about the prospects for future home prices following a sequence of recent price increases. Irish residential real estate prices had been on a sustained upward trajectory for a decade prior to the commencement of our sample period. Thus, owner occupier willingness to shade their bids in the face of uncertainty may have been tempered by the expectation that

[30] This co-movement reduces the amount of independent variation available from which we can make inference using a least squares estimator. In short, this effect can result in large standard errors and, thus, Type II statistical errors in our inferences.

[31] The results are not reported for brevity but are available on request.

failure to buy now may mean having to pay higher prices in the future.[32] In the case of winning female bidders, they appear to behave consistent with their male counterparts. They do not pay less than their male equivalents for comparable properties. They do not behave differently in the face of competition or uncertainty than male winning bidders.

Conclusion

This paper tests for the relationship between prices and value uncertainty in a bubble market. Our empirical context is the Irish residential real estate auction market in what turns out to be approaching the peak of the bubble. Residential real estate markets are an interesting research context to explore, as such markets are particularly prone to anomalous behavior (Scherbina and Schlushe, 2015), and have significant spillover effects into the banking system (Carmichael and Coën, 2018), and the wider economy (Bengtsson, Grothe and Lepers, 2018). We conjecture that in the *height-in-bubble* phase of such markets bidder decision making is likely to be dominated by feelings of excitement and mania such that conventional measures of financial risk will not impact on pricing outcomes. The extant literature reports that emotions play a role in property purchase decisions, even in the absence of bubble market conditions (e.g. Gillon and Gibson 2018). Auction markets themselves by their nature may be particularly prone to emotional arousal (e.g. Adam et al 2015). Thus testing the relationship between prices and valuation uncertainty in (1) residential real estate, in (2) an auction market, and (3) at the height of a bubble, provides a perfect empirical setting to explore the impact of emotions on pricing outcomes.

We find consistent with the predictions of emotional finance that winning bidders do not

[32] In fact many newspaper articles appeared during the course of our study period and indeed prior to that period discussing price escalation in the residential property market. Many of these articles encourage purchasers to buy now before prices escalate further. A main point of these media articles is on declining housing affordability and urging government action to improve affordability by tax reductions, reducing stamp duty on property transactions as well as other measures (e.g. Mercille, 2014).

shade their bids in the face of valuation uncertainty. This finding is consistent with the psychoanalytic understanding of the human mind whereby an individual's unconscious feelings, fantasies and needs determine psychic reality. Investing provokes conflicting feelings of both excitement and anxiety and the emotional consequences associated with having to engage in a necessarily ambivalent relationship with an asset that may let him or her down. In the *height-in-bubble* phase, the excitement associated with property ownership dominates leading to an associated denial of uncertainty rendering it dynamically unconscious. The highlights the need for models in economics developed to explain bubbles, and real estate bubbles in particular, to take account of emotional factors.

Interestingly, the arguments of Scherbina and Schlushe (2015) are couched in terms of real estate markets been dominated by unsophisticated households and that *limits to arbitrage* prevent more 'rational' experienced individuals take *action* to drive prices back to equilibrium. However, the findings of Cheng et al (2014) who report that experienced Wall Street bankers got caught up investing in property portfolios in similar ways to those that they were selling loans to may cast some doubt on the predictions of Scherbina and Schlushe (2015). We speculate that people's emotional attachment to residential real estate may potentially explain the actions of these Wall Street bankers and is consistent with "experts" getting caught up in the same emotional processes as their less expert counterparts.

We also explore whether winning female bidders pay similar prices for comparable properties as their male counterparts and whether winning female bidders shade their bids in the presence of increased valuation uncertainty and more robust competition. Prior research on the responsiveness of male and female bidders in bubbles is exclusively conducted in an experimental setting (Cueva and Rustichini 2015, Eckel and Füllbrunn 2015). These studies find that increasing the number of female participants has a dampening effect on the magnitude of bubbles. We argue, however, that an experimental setting may not fully capture the richness and complexity of the factors impacting on decision-making in an actual bubble. We find, in contrast to those studies conducted in an experimental setting, winning female bidders are equally as likely to pay high prices as their male counterparts for comparable properties. We also find, increasing the proportion of female bidders in an auction does not deflate auction prices. In addition, we report, contrary to the findings across a broad range of decision contexts, that winning female bidders do not behave differently with respect to competition and uncertainty than their winning male counterparts. Cueva and Rustichini (2015) and Eckel and Füllbrunn (2015) use their findings to justify that the presence of more women in financial markets would reduce the magnitude of bubbles. Our findings in the specific context of real estate indicate the presence of females in bidding wars in the residential real estate market would have no such dampening effect on prices.

We offer three suggestions for future research. First, are our results in a bubble market setting robust to negotiated sales transactions as well as in the case of auction markets? Auction markets are susceptible to *auction fever* and may be more intensely emotionally driven, enhanced by such factors as the physical presence of other bidders, time pressure and hype impairing bidders' decision making pushing them to bid beyond their limits (e.g. Ehrhart, Ott and Abele 2015)? However, the findings of Han and Strange (2014) who analyse the "quasi- auction", called bidding wars find that such wars are popular during housing booms and that the bidding process is associated with buyer's "irrationality". This may, prima facie, be indicative that our results may also hold in the case of negotiated sales transactions in a bubble market, were the granular data available to test this.

Second, though we find that female bidders behave in an indistinguishable way to male bidders across our sample auctions, the proportions of female bidders participating in auctions is less than the proportions of male bidders, being circa one quarter of the total bidder population. Thus, there appears, on a face value basis, less willingness for females in the population to participate in bidding in an auction setting. Are there particular characteristics of our participating female bidders that may encourage them to self-select to engage in competitive bidding in auctions? In this regard as our sample auctions are high value properties (footnote 22), our auction participants are in all likelihood homogeneous in terms of income and wealth. However, such characteristics as well as other factors such as age, experience, educational attainment and task familiarity have been shown in prior research not to impact on the risk aversion of females (e.g. Powell and Ansic, 1997, Estes and Hosseini, 1988).

Finally, are our findings with respect to residential real estate replicable across other asset classes? Are there unique emotional features associated with real estate which may impact on the decision making of male and female bidders that may not be salient in other long lived asset classes, such as equities or bonds?

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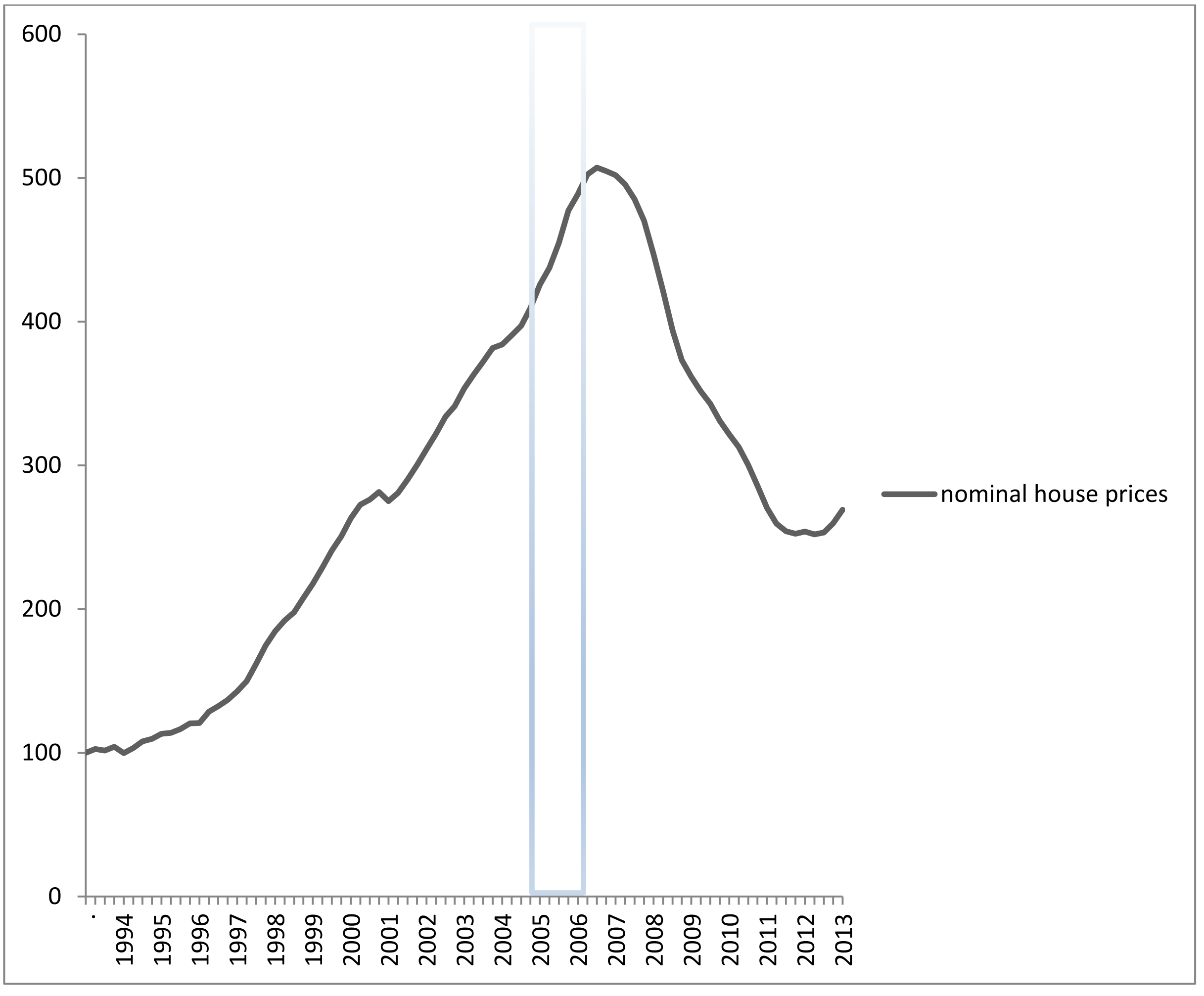
Figure 1 ■ Graph of Irish residential real estate prices 1994-2013. This figure presents the trajectory of Irish residential real estate prices over the period 1994-2013. The rectangular box highlights the time interval of our observed auctions, from September 2004 to February 2006.



Source: OECD.

Table 1 ■ Auction descriptive statistics for September 2004- February 2006

This table presents descriptive statistics on the total population of auctions that took place in the Dublin residential real estate market over the period September 2004 to February 2006.

Period	Total auctioned	Total sold at auction	Sold prior to auction	Sold directly after auction	Withdrawn and sold within six weeks of auction
September to December 2004	405	155	15	61	174
January to April 2005	331	158	6	77	90
May 2005 to August 2005	421	179	30	83	129
September 2005 to February 2006	408	174	17	72	145
Total	1565 (100%)	666 (44%)	68 (3%)	293 (19%)	538 (34%)

Table 2 ■ Hedonic asset pricing model

This table presents the results of the hedonic asset pricing model regression (HAPM), equation 1. The model is estimated in log form (Sirmans, MacDonald, Macpherson and Zietz 2005). The properties evaluated in the model are broken down into their physical characteristics (property size, bedrooms, bathrooms, garden, type of property, property condition) and in addition we include the properties location, the size of the real estate agent marketing the property and the time period in which the property is auctioned. Property size is measured by the log of the square feet of the property. In relation to garden we adopt a dummy variable approach taking on a value of 1 if the garden size is under 50 feet in length and zero otherwise. The property's condition is also evaluated using a dummy variable approach. Condition takes on a value of 1 if the property is in excellent or good economic condition and zero otherwise. In relation to property type these were broken down into four categories: apartment, semi-detached, detached, period property. The property type dummy excluded is a period property. A dummy variable approach was adopted in relation to the size of the real estate agency marketing the property. The top six real estate agencies account for over 70% of auctions and a dummy variable was set equal to 1 if the auctioned property was sold through one of these agents and zero otherwise. In relation to location the Greater Dublin area is divided down into the Dublin Central, North Dublin, South Dublin and South County Dublin. These areas are identified by postal codes (zip codes) and are grouped accordingly. The location variable excluded is North Dublin. Time dummies are also included to capture changes in prices over the period. These time periods are September to December 2004, January to April 2005, May to August 2005 and September 2005 to February 2006. The time dummy excluded is September 2005 to February 2006. Dummy variables are denoted by †. The level of significance is denoted by *** $p \leq 0.01$, ** $p \leq 0.05$**, * $p \leq 0.10$. We use Newey-West standard errors.

Variable	Coefficient	T-statistic
Constant	9.75	26.71***
Square feet†	0.54	9.90***
Bedrooms	0.07	3.31***
Excellent condition†	0.09	2.84***
Small garden†	-0.23	- 6.67***
Apartment†	0.19	1.53
Semi-detached†	-0.19	- 4.88***
Detached†	0.079	1.92*
Bathrooms	0.048	2.77***
Dublin Central†	0.011	0.14
South Dublin†	-0.44	-2.95***
South County Dublin†	0.23	5.05***
Big agent†	- 0.05	-1.11
Sept-to- Dec04†	- 0.22	-4.91***
Jan-to- April05†	- 0.12	-2.87***
May-to-Aug05†	- 0.06	-1.51
R^2 adjusted	64.3%	

Table 3 ■ Descriptive statistics of winning bid price relatives, valuation uncertainty and competition

This table presents, in panel A, descriptive statistics on the winning bid prices relative to benchmark prices, reference prices are computed: (1) from portfolios of similar properties or (2) from the estimated hedonic asset pricing model. It presents, in panel B, descriptive statistics on our measures of valuation uncertainty: (1) adjusted co-efficient of variation (adj-CV), (2) coefficient of variation (CV), (3) mean absolute deviation (MAD) or (4) standard deviation (Stdev), in respect to self-similar property prices. It also presents data, in panel C, in relation to our two measures of competition: (1) number of bidders at the auction, and (2) average number of bids per bidder. The number of bidders is the number of bidders bidding at each auction irrespective of the number of times they actually bid at the auction. The average number of bids per bidder is the total number of bids at each auction divided by the number of bidders at the auction.

		Panel A. Bid Price Relatives		Panel B. Valuation Uncertainty				Panel C. Competition	
Characteristics		Mean price of self-similar property	HAPM	Adjusted co-efficient of variation	Co-efficient of variation	Mean absolute deviation	Standard Deviation	Number of Bidders at Auction	Average number of bid per bidder
Average		1.08	1.03	0.15	0.14	207329	276019	3.2	5.81
Median		1.06	1.04	0.13	0.12	148889	210517	3.0	5.3
Standard deviation		0.20	0.13	0.09	0.09	211415	279197	1.0%	3.0%
Maximum		1.76	1.51	0.44	0.41	1000000	1343503	6.0	21.5
Minimum		0.63	0.75	0.01	0.5	10000	14142	2.0	2.3
Female winning bidder percentage	17%								
Number of Auctions	87								

Table 4 ■ Correlation Matrix

This table summarises the correlation co-efficients between our independent and dependent variables. The level of significance is denoted by *** p≤ 0.01, ** p≤ 0.05**, * p≤ 0.10.

	Mean price of self-similar properties bid price relative	HAPM bid price relative	Number of bidders	Average number of bids per bidder	Adjusted co-efficient of variation	Coefficient of variation	Mean absolute deviation	Standard deviation	Gender
Mean price of self-similar properties bid price relative	1								
HAPM bid price relative	0.55 (6.13)***	1							
Number of bidders	0.33 (3.20)***	0.48 (5.09)***	1						
Average number of bids per bidder	0.31 (3.05)***	0.46 (4.78)***	0.28 (2.74)***	1					
Adjusted co-efficient of variation	-0.09 (-0.82)	0.03 (0.25)	0.05 (0.44)	0.14 (1.27)	1				
Coefficient of variation	-0.10 (-0.88)	0.02 (0.21)	0.05 (0.43)	0.13 (1.23)	1.00 (27.5)***	1			
Mean absolute deviation	0.12 (1.08)	-0.02 (-0.21)	0.00 (-0.03)	-0.06 (-0.54)	0.46 (4.73)***	0.45 (4.68)***	1		
Standard deviation	0.14 (1.34)	0.00 (0.00)	0.00 (0.02)	-0.05 (-0.48)	0.46 (4.71)***	0.45 (4.66)***	1.00 (10.66)***	1	
Gender	-0.10 (-0.94)	-0.01 (-0.06)	-0.02 (-0.06)	0.02 (0.17)	-0.15 (-1.44)	-0.15 (-1.37)	-0.06 (-0.22)	-0.02 (-0.22)	1

Table 5 ■ Winning bid price relative regressions using number of bidders as the competition proxy

This table presents the results of equation 3 estimated using ordinary least squares. In the HAPM regressions the reference price is the price generated from the HAPM regression reported in Table 2. In the case of the "Mean price of self-similar properties" regressions, the reference price is the mean price of similar properties that were successfully auctioned in the same time period as our sample of 87 auctions using a number of the characteristics from the HAPM model (table 2). These characteristics were identified by Dublin based senior real estate professionals. Specifically: the time period of the auction, location, house type, square feet, number of bedrooms and the condition of the property. The dependent variable in both sets of regressions is the deviation of the winning bid from a reference price. In both cases the actual winning bid is divided by the reference price and the natural log is calculated. The competition variable is the number of bidders at the auction. The uncertainty variable is modelled using four methods: (1) adjusted co-efficient of variation (adj-CV), (2) coefficient of variation (CV), (3) mean absolute deviation (MAD) or (4) standard deviation (Stdev), in respect to self-similar property prices. The gender variable is a dummy variable (†) taking on a value of 1 if the winning bidder is a female bidder and 0 otherwise. The level of significance is denoted by *** p≤ 0.01, ** p≤ 0.05**, * p≤ 0.10.

Variable	Mean price of self- similar properties				HAPM			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Constant	-0.12	-0.11	-0.17	-0.17	-0.22	-0.22	-0.22	-0.22
	(-1.06)	(-1.58)	(-2.35)***	(-2.43)***	(-5.06)***	(-5.05)***	(-5.10)***	(-5.16)***
Comp (C)	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
	(3.23)***	(3.23)***	(3.19)***	(3.20)***	(5.04)***	(5.04)***	(5.06)***	(5.05)***
Adj- CV	-0.20	-	-	-	0.13	-	-	-
	(-1.01)				(0.20)			
CV	-	-0.23	-	-	-	0.02	-	-
		(-1.08)				(0.17)		
MAD	-	-	0.01	-	-	-	- 0.01	-
			(1.13)				(-0.25)	
Stdev	-	-	-	0.01	-	-	-	-0.01
				(1.40)				(-0.03)
Gender (G)†	0.01	0.01	-0.01	-0.01	- 0.04	-0.04	-0.03	- 0.03
	(0.11)	(0.11)	(-0.11)	(-0.11)	(-1.05)	(-1.04)	(-1.04)	(-1.02)
R^2	11.8%	8.9%	8.9%	9.7%	21.6%	21.6%	21.7%	21.6%

Table 6 ■ Winning bid price relative regressions using average number of bids per bidder as the competition proxy

This table presents the results from equation 3 estimated using ordinary least squares. In the HAPM regressions the reference price is the price generated from the HAPM regression reported in Table 2. In the case of the "Mean price of self-similar properties" regressions, the reference price is the mean price of similar properties that were successfully auctioned in the same time period as our sample of 87 auctions using a number of the characteristics from the HAPM model (table 2). These characteristics were identified by Dublin based senior real estate professionals. Specifically: the time period of the auction, location, house type, square feet ,number of bedrooms and the condition of the property. The dependent variable in both sets of regressions is the deviation of the winning bid from a reference price. In both cases the actual winning bid is divided by the reference price and the natural log is calculated. The competition variable is the average number of bids per bidder at the auction. The uncertainty variable is modelled using four methods: (1) adjusted co-efficient of variation (adj-CV), (2) coefficient of variation (CV), (3) mean absolute deviation (MAD) or (4) standard deviation (Stdev), in respect to self-similar property prices. The gender variable is a dummy variable (†) taking a value of 1 if the winning bidder is a female bidder and 0 otherwise. The level of significance is denoted by *** p≤ 0.01, ** p≤ 0.05**, * p≤ 0.10.

Variable	Mean price of self- similar properties				HAPM			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.03	-0.02	-0.08	-0.08	-0.13	-0.13	-0.14	- 0.14
	(-0.45)	(-0.42)	(-1.71)*	(-2.42)**	(-4.27)***	(-4.26)***	(-4.55)***	(-4.65)***
Comp (C)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(3.62)***	(3.64)***	(3.46)***	(3.13)***	(4.15)***	(4.15)***	(4.24)***	(4.24)***
Adj- CV	-0.26	-	-	-	-0.03	-	-	-
	(-1.27)				(-0.19)			
CV	-	- 0.22	-	-	-	- 0.03	-	-
		(-1.23)				(-0.23)		
MAD	-	-	0.01	-	-	-	0.01	-
			(1.30)				(0.02)	
Stdev	-	-	-	0.01	-	-	-	0.01
				(1.56)				(0.22)
Gender (G)†	0.03	0.07	- 0.01	- 0.01	-0.04	-0.04	-0.04	-0.04
	(0.07)	(0.07)	(-0.09)	(-0.09)	(-1.09)	(-1.09)	(-1.13)	(-1.33)
R^2	8.4%	8.6%	8.5%	9.3%	19.6%	19.6%	19.6%	19.6%

Table 7 ■ Winning bid price relative regressions, incorporating proportion of female bidders, and employing number of bidders as the competition proxy

This table presents the results of equation 5 estimated using ordinary least squares. In the HAPM regressions the reference price is the price generated from the HAPM regression reported in Table 2. In the case of the "Mean price of self-similar properties" regressions, the reference price is the mean price of similar properties that were successfully auctioned in the same time period as our sample of 87 auctions using a number of the characteristics from the HAPM model (table 2). These characteristics were identified by Dublin based senior real estate professionals. Specifically: the time period of the auction, location, house type, square feet, number of bedrooms and the condition of the property. The dependent variable in both sets of regressions is the deviation of the winning bid from a reference price. In both cases the actual winning bid is divided by the reference price and the natural log is calculated. The competition variable is the number of bidders at the auction. The uncertainty variable is modelled using four methods: (1) adjusted co-efficient of variation (adj-CV), (2) coefficient of variation (CV), (3) mean absolute deviation (MAD) or (4) standard deviation (Stdev), in respect to self-similar property prices. The %G variable represents the proportion of bidders in each auction that are female bidders. The level of significance is denoted by *** p≤ 0.01, ** p≤ 0.05**, * p≤ 0.10.

Variable	Mean price of self- similar properties				HAPM			
	(2)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Constant	-0.15 (-1.98)*	-0.15 (-1.96)*	-0.19 (-2.65)***	-0.20 (-2.70)***	-0.23 (-4.69)***	-0.23 (-4.67)***	-0.22 (-4.84)***	-0.23 (-4.89)***
Comp (C)	0.06 (3.24)***	0.06 (3.25)***	0.06 (3.25)***	0.06 (3.21)***	0.06 (5.03)***	0.06 (5.03)***	0.06 (5.03)***	0.06 (5.03)***
Adj- CV	-0.20 (-1.02)	-	-	-	0.01 (0.04)	-	-	-
CV	-	-0.23 (-1.09)	-	-	-	0.01 (0.03)	-	-
MAD	-	-	0.01 (1.10)	-	-	-	0.01 (0.03)	-
Stdev	-	-	-	0.01 (1.24)	-	-	-	0.01 (0.01)
%Gender (%G)	0.12 (1.28)	0.12 (1.28)	0.11 (1.25)	0.10 (1.10)	- 0.01 (-0.06)	-0.01 (-0.06)	-0.01 (-0.03)	- 0.01 (-0.05)
R^2	10.4%	10.4%	10.4%	10.9%	20.6%	20.6%	20.7%	20.6%

Table 8 ■ Winning bid price relative regressions, incorporating the proportion of female bidders, and employing average number of bids per bidder as the competition proxy

This table presents the results from equation 5 estimated using ordinary least squares. In the HAPM regressions the reference price is the price generated from the HAPM regression reported in Table 2. In the case of the "Mean price of self-similar properties" regressions, the reference price is the mean price of similar properties that were successfully auctioned in the same time period as our sample of 87 auctions using a number of the characteristics from the HAPM model (table 2). These characteristics were identified by Dublin based senior real estate professionals. Specifically: the time period of the auction, location, house type, square feet ,number of bedrooms and the condition of the property. The dependent variable in both sets of regressions is the deviation of the winning bid from a reference price. In both cases the actual winning bid is divided by the reference price and the natural log is calculated. The competition variable is the average number of bids per bidder at the auction. The uncertainty variable is modelled using four methods: (1) adjusted co-efficient of variation (adj-CV), (2) coefficient of variation (CV), (3) mean absolute deviation (MAD) or (4) standard deviation (Stdev), in respect to self-similar property prices. The %G variable represents the proportion of bidders in each auction that are female bidders. The level of significance is denoted by *** p≤ 0.01, ** p≤ 0.05**, * p≤ 0.10.

Variable	Mean price of self- similar properties				HAPM			
	(2)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.06	-0.07	-0.12	-0.13	-0.14	-0.14	-0.15	- 0.15
	(-1.18)	(-1.16)	(-2.19)**	(-2.26)**	(-3.76)***	(-3.75)***	(-4.12)***	(-4.19)***
Comp (C)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.05
	(3.30)***	(3.31)***	(3.20)***	(3.22)***	(4.74)***	(4.74)***	(4.73)***	(4.74)***
Adj- CV	-0.27	-	-	-	-0.05	-	-	-
	(-1.32)				(-0.37)			
CV	-	- 0.30	-	-	-	- 0.05	-	-
		(-1.37)				(-0.40)		
MAD	-	-	0.01	-	-	-	0.01	-
			(1.16)				(0.02)	
Stdev	-	-	-	0.01	-	-	-	0.01
				(1.39)				(0.21)
%Gender (%G)	0.14	0.14	0.13	0.12	0.02	0.02	0.01	0.01
	(0.07)	(0.07)	(1.13)	(1.28)	(0.25)	(0.25)	(0.24)	(0.83)
R^2	10.8%	10.9%	10.4%	11.1%	18.5%	18.6%	18.4%	18.4%

Table 9 ■ Winning bid price relative regressions with gender interaction terms

This table presents the results of our hypothesis test with interaction terms included between gender and both uncertainty and competition (equation 6) using ordinary least squares. In the HAPM regressions the reference price is the price generated from the HAPM regression reported in Table 2. In the case of the "Mean price of self-similar properties" regressions, the reference price is the mean price of similar properties that were successfully auctioned in the same time period as our sample of 87 auctions using a number of the characteristics from the HAPM model (table 2). These characteristics were identified by Dublin based senior real estate professionals, specifically: the time period of the auction, location, house type, square feet and number of bedrooms and the condition of the property. The dependent variable in both regressions is the deviation of the winning bid from a reference price. In both cases the actual winning bid is divided by the reference price and the natural log is calculated. The competition variable (comp) in Panel A is the number of bidders and in Panel B is the average number of bids per bidder at the auction. The uncertainty variable (uncert) is modelled using four methods: (a) adjusted co-efficient of variation , columns 1 and 5, (b) coefficient of variation, columns 2 and 6, (c) mean absolute deviation, columns 3 and 7 and (d) standard deviation, columns 4 and 8. The gender variable (G) is a dummy variable (†) taking on a value of 1 if the winning bidder is a female bidder and 0 otherwise. The level of significance is denoted by *** p≤ 0.01, ** p≤ 0.05**, * p≤ 0.10.

Panel A: Employing number of bidders as the competition variable

Variable	Mean price of self-similar properties				HAPM			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.14	-0.14	-0.20	-0.20	-0.22	-0.22	-0.21	-0.22
	(-1.73)*	(-1.72)*	(-2.67)***	(-2.67)***	(-4.88)***	(-4.49)***	(-4.67)***	(-4.73)***
Comp (C)	0.07	0.07	0.07	0.07	0.06	0.06	0.06	0.06
	(3.37)***	(3.36)***	(3.39)***	(3.41)***	(4.72)***	(4.78)***	(4.68)***	(4.68)***
Uncert (U)	-0.22	- 0.24	0.01	0.01	-0.04	-0.03	-0.01	-0.01
	(-1.01)	(-1.05)	(1.36)	(1.16)	(-0.25)	(-0.25)	(-0.45)	(-0.23)
Gender (G)†	0.22	0.22	0.29	0.30	- 0.07	-0.08	- 0.09	- 0.09
	(0.88)	(0.78)	(1.26)	(1.29)	(-0.53)	(-0.53)	(-0.62)	(-0.60)
Gender*uncert	0.71	0.70	-0.01	-0.01	0.74	-0.75	0.01	0.01
	(0.88)	(0.78)	(-1.16)	(-0.92)	(1.36)	(1.36)	(0.57)	(0.49)
Gender*comp	-0.10	-0.10	-0.08	-0.07	-0.02	-0.02	0.01	0.01
	(-1.30)	(-1.24)	(-1.16)	(-1.16)	(-0.58)	(-0.58)	(0.24)	(0.23)
R^2	8.3%	8.3%	9.0%	9.9%	21.6%	21.6%	20.1%	20.0%

Panel B: Employing average number of bids per bidder as the competition variable

Variable	Mean price of self- similar properties				HAPM			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Constant	-0.04	-0.04	-0.10	-0.11	-0.15	-0.14	-0.15	-0.16
	(-0.64)	(-0.63)	(-1.95)*	(-2.09)*	(-4.23)***	(-4.23)***	(-4.69)***	(-4.68)***
Comp (C)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(3.75)***	(3.08)***	(3.08)***	(3.10)***	(5.00)***	(5.00)***	(4.86)***	(4.86)***
Uncert (U)	-0.27	-0.29	0.01	0.01	- 0.08	- 0.08	-0.01	- 0.01
	(-1.23)	(-1.27)	(1.47)	(1.26)	(-0.59)	(-0.62)	(-0.25)	(-0.96)
Gender (G)†	0.03	0.04	0.12	0.11	- 0.08	- 0.08	0.01	0.02
	(0.18)	(0.23)	(0.88)	(0.94)	(-0.91)	(-0.89)	(0.18)	(0.21)
Gender*uncert	0.28	0.24	- 0.01	-0.01	0.90	0.96	0.01	0.01
	(0.37)	(0.28)	(-0.75)	(-0.37)	(1.15)	(1.12)	(0.64)	(0.58)
Gender*comp	- 0.01	- 0.01	- 0.01	- 0.01	-0.01	- 0.01	-0.01	-0.01
	- (0.75)	(-0.72)	(-0.85)	(-0.39)	(-1.18)	(-1.15)	(-1.36)	(-1.40)
R^2	6.8%	6.9%	7.6%	8.6%	23.3%	23.3%	20.1%	20.1%