Spatial Variation in Bidding Conventions and the Degree of Over-pricing:

An Analysis of the Housing Market in the West End of Glasgow

Gwilym Pryce
Department of Urban Studies
25 Bute Gardens
University of Glasgow
Glasgow G12 8RS
Email: g.pryce@lbss.gla.ac.uk
Personal webpage: www.gpryce.com

Working Paper as at 20th November 2009

Discussion Paper No. 23

Abstract

How do buyers decide whether a property is over-priced? Do they base their judgement simply on the difference between the asking price and the expected selling price? Or do they take into account local bidding conventions—the typical asking-selling price spread in the neighbourhood? This paper explores the implications of bidding conventions for the definition and measurement of the degree of over-pricing (DOP) and the effect this has on a survival model of time on the market. The paper also considers the impact of uncertainty and employs fractional polynomial regression to explore whether spatio-temporal variations in attribute prices affect market perceptions of over-pricing.

1. Introduction

When a seller places her house on the market she usually has a choice with regard to the "*asking price*"—the price at which the property is advertised. She may set the asking price well below the "*expected market price*"—the average selling price of houses of the same type and location—in the hope of making a quick sale or attracting many potential buyers, or because she has underestimated the expected price. Or she may decide to set the asking price well above the expected market price in the hope, for example, of signaling higher value, or because she has overestimated the expected market price.

The "degree of over-pricing" (DOP)—the amount by which the asking price exceeds the expected market price (where DOP is negative if the seller has underpriced)—is clearly an important factor in the selling process, potentially affecting the number of bids submitted, the length of time a house will remain on the market and the final sale price (Jud *et al.* 1996; Levin and Pryce 2007). Unsurprisingly, therefore, DOP has proved to be an important concept in both theoretical and empirical models of the housing transactions process (Kang and Gardner 1989; Asabere *et al.* 1993; Yavas and Yang 1995; Anglin et al 2003). However, the literature on over-pricing is predominantly American and almost exclusively in the context of list-price (or equivalent) selling systems. This paper considers the meaning of over-pricing in the context of a *sealed-bid system* where asking prices are usually set well below the final selling price (the opposite tends to be true in list-price systems). Over-pricing appears, at first, to have little meaning in a sealed-bid setting, but this paper attempts to show that DOP not only has meaning in a sealed-bid context, but that this context reveals a deeper set of issues about DOP generally.

The first and most important hypothesis of the paper is that, in the same way that different submarkets may have different informal "conventions" with respect to the language used to advertise the property (Pryce and Oates, 2008), they may also have different “conventions” regarding the expected difference between asking and selling price. These "conventions" are neither static nor uniform across submarkets, but they are nonetheless an essential qualification to the meaning and measurement of over-pricing. It means that, for a property to be described as "over-priced", the difference between asking and selling price has to be measured relative to the *average difference between asking and selling price in the locality*. If the results support this proposition, then the findings will add weight to the reconceptualisation of the house transaction process as one that is complex, highly subjective, and locally dependent, wedded to, and driven by, the perceptions of local market norms (see Smith et al., 2006).

The paper also challenges standard methodological approaches to DOP analysis. In the data considered (over three thousand sales in the West End of Glasgow, Scotland) the paper finds that, on average, the difference between asking and selling price rises (i.e. the local bidding "convention" changes) as the market booms. Time on the market tends to fall during booms, but it would be erroneous to assert that this decline in time on the market was due to the fall in over-pricing. In a dynamic market, standard measures of over-pricing, therefore, give a biased estimate of the effect of over-pricing because of the distorting effect of the time-series correlation between the relative asking-selling price spread and marketing time. The true effect of over-pricing can only be ascertained when this time series correlation is controlled for (otherwise we have to assume that market participants take no account of the cyclical and secular movements in the average asking-selling price spread when deciding whether a property is over-priced).

The second hypothesis explored in the paper concerns the impact of uncertainty. One would anticipate that, the greater the uncertainty about the local bidding convention, the greater the ambiguity about whether a property is to be regarded as over-priced, and the less impact over-pricing will have on selling times.

The paper also highlights the potential for further bias arising from the hedonic method used to predict the expected market price of a property (crucial to the computation of most over-pricing measures). Hedonic methods are needed to approximate the expected market price of each dwelling in the data for each time period of interest.[1] Most hedonic regressions used in the computation of over-pricing do not account for possible spatial or temporal variation in attribute prices when making this calculation. The attribute variation

[1] Regression analysis is employed because it allows the researcher to estimate how selling price is determined by dwelling attributes, location and time period. One can then use the estimated coefficients from this regression to predict the expected market value of any house that comes on the market in a given time period provided one has information on the dwelling's characteristics and location that match the variables used in the estimated regression. See Malpezzi (2003) for an accessible overview of hedonic methods.

problem is addressed here using the Fik *et al.* (2003) approach which involves including in the hedonic regression model interactions between the geographical coordinates of dwellings and their structural characteristics. The approach is extended by including a time interaction variable (along with latitude and longitude interactions), and by applying Multiple Fractional Polynomial Estimation (MFP). MFP (not to be confused with Fractional Logit Regression[2]) offers a new level of flexibility in functional form estimation, allowing for non-integer and non-positive power transformations of explanatory variables. Of interest is whether market participants take into account these subtle movements in attribute prices when deciphering the extent to which a property is over-priced. Thus, the third hypothesis considered in the paper is that selling times will be more sensitive to overpricing measures that take into account spatio-temporal variation in attribute prices.

All three hypotheses are tested using a log-normal survival model of time on the market in order to compare the performance of different measures of over-pricing in terms of their ability to explain selling time. Survival analysis has become the accepted way to analyze time-to-event data (such as time on the market). Such data tend to lead to models that have a bounded/censored dependent variable, non-normal distribution of errors, and the existence of duration dependence—the tendency for the probability of sale to itself be

[2] Fractional Logit Regression (FLR) is a variant on standard logit analysis. It allows one to model dependent variables that are bounded between zero and one (see Hendershott and Pryce, 2006, for an application to housing). FLR is, therefore, a very different estimation method (based on logit regression) for a very different sort of econometric problem (FLR is relevant when one has fractional dependent variables, whereas MFP regression allows one to estimate fractional power transformations of explanatory variables).

affected by how long a property has been on the market (see Cleves et al 2002, p.2 and Pryce and Gibb 2006, p.378-379). These properties violate various assumptions of ordinary least squares and have led to the development a variety of modeling techniques which fall under the banner of survival analysis. The paper concludes with a discussion of the implications the paper's findings and suggestions for future research.

2. Existing literature

Horowitz (1992) argued that the price that a property is advertised at—the "list price" or "asking price" —"conveys information to buyers in the form of an upper bound on the seller's reservation price. An infinite list price conveys no such information and, therefore, is equivalent to no list price at all." (Horowitz, 1992, p.118). If asking prices convey information to buyers, then they are potentially important in determining the length of time it takes for the seller to receive an offer that exceeds her reservation price. And for a given seller with a given property, there will be an optimal list price. Given that sellers have different trade-offs for selling time against final sale price, there will be some variation in this optimal list price even for properties of the same type and location. There is the possibility of pricing errors—sellers setting the asking price above or below the optimal given their preferences. From a buyer's point of view, properties may be seen as over-priced if the list price is set above that typically associated with a property of that type and location, so over-ambitious list prices can slow the rate at which bids are received: “A high initial list price relative to ultimate selling price may be representative of a seller with unrealistic expectations or low motivation for a quick sale” (Knight 2002, p.220; for the signaling role of list prices see also Springer 1996 and Glower et al. 1998).

Early measures of over-pricing were computed as simply the difference between asking and selling price as a proportion of observed selling price (e.g. Kang and Gardner, 1989). Simple mark-up measures of this kind are problematic, however, because they do not compare the asking price with the “expected market price” (the average selling price of houses of the same type and location). Instead, the asking price is compared with the actual sale price of the particular property in question. Such measures are susceptible to distortions that arise from the idiosyncrasies of individual sales. For example, if the final sale price is well below the asking price, this may not be evidence of over-pricing – rather it may indicate that the seller accepted an unusually low sale price for that type and location of property. In other words, one has to have some idea of the current expected market price of the property—the average selling price of dwellings of a similar type and location—before one can decipher whether it has been over-priced. This simple mark-up approach is also particularly vulnerable to the distorting effect of concurrent cyclical movements in the average asking-selling price spread and time on the market noted in the introduction (if the expected market price falls significantly during the period a property is on the market, a low sale price relative to asking price may give the impression of over-pricing, when, in fact, one is simply observing a change in market conditions).

A preferred measure, therefore, is one that compares the asking price with the *expected market price in a given period*. Yavas and Yang (1995), for example, use the log of the ratio of expected sale price, P_i^{S*} of each dwelling (estimated using hedonic regression analysis based on many house sales), to the asking price, P_i^A:

$$\text{Overpricing measure for dwelling } i = \ln\left(\frac{P_i^{S*}}{P_i^A}\right)$$

$$= \ln P_i^{S*} - \ln P_i^A$$

Similarly, Jud *et al.* (1996) compute "the difference between the natural logarithm of the list-price and the natural logarithm of the predicted price form a hedonic price equation" (Jud *et al.* 1996, p. 450), and *Anglin et al.* (2003, p.99) compute the percentage deviation between the list price and the expected list price, where expected list price is estimated using a hedonic regression with list price as the dependent variable.

There remain a number of problems with this approach, however. Firstly, there is the question of whether there are informal "conventions" regarding the asking-selling price spread, and whether these conventions vary across submarkets or over the course of the housing cycle. If so, it is the deviation from this convention, rather than the actual difference between asking and (predicted) selling price, that will be important in determining time on the market

(TOM). To illustrate, consider a neighborhood where it is conventional to set the asking price 20% below the final sale price. Buyers come to market anticipating that a property with an asking price of £80,000 will sell for £100,000. If £100,000 is within budget, they will consider viewing and bidding for this property if they feel the property is worth £100,000. If the same property is placed on the market for £90,000, however, given the local convention, buyers will assume that the owners are expecting to achieve a price of £112,500, screening-out potential buyers (such as those who are only willing/able to pay £100,000). So buyers use local bidding conventions to place a mark-up on the advertised price. It is this value—the asking price plus mark-up—that buyers use as a guide to whether they can afford the property in question.

Secondly, the effect of bidding conventions may not be fully accounted for if the analysis presumes that market participants are perfectly informed about local asking-selling price spreads. There may be considerable variation in these spreads even at a local level and so an econometric model of selling times needs to include an interaction effect between DOP and the uncertainty surrounding the local bidding convention.

Thirdly, there are specification issues surrounding the computation of predicted selling price. Over-pricing variables may simply be measuring misspecification error in the hedonic price equation (hedonic regressions in most of the studies of over-pricing have not, for example, accounted for non-linearities or spatial/temporal shifts in slope parameters).

Fourthly, there is a simultaneity issue with regard to the hedonic price computation. If final selling price can be affected by time on the market (such as the seller's decision to hold out for a higher offer or by negative herding/stigma effects – see Taylor 1999; Jud *et al.* 1996), then there is a case for the predicted sale price being standardized for time on the market (for example, sale price could be predicted for each dwelling for a common marketing time of, say, 40 days).

Fifthly, expected movements in house price levels need to be controlled for, otherwise apparent "over-pricing" may in fact reflect movements in market expectations (a seller might set an apparently high asking price, for example, but this may simply reflect an anticipated house price boom).

Finally, there is the question of whether the concept of over-pricing, having emerged in a literature devoted almost entirely to the analysis of list-price systems, is transferable to alternative institutional settings. This question is discussed in this paper with reference to the Scottish sealed-bid system. An attempt is made to construct a measure of over-pricing in this context that addresses the aforementioned shortcomings and which can be applied more generally.

3. Over-pricing in a sealed-bid system

Many selling systems (such as those in England and North America) typically involve the seller advertising the property for sale with an asking price set above what is normally secured in the final transaction. Once the property is advertised, buyers make arrangements to view and are free to make offers at any point. In a sealed-bid system, such as the one in Scotland, properties are advertised at an asking price (sometimes described as the “Offers Over” price) set well below the final transaction price. Interested buyers do not typically submit a bid until a closing date for the auction is agreed (which is only established when the seller believes there are enough interested bidders to make the auction worthwhile), at which point, all bids are revealed simultaneously. While these are accepted norms that prevail during normal market conditions, they are subject to flux. For example, and there is nothing preventing a buyer offering below the asking price in a sealed-bid system (in the same way that there is nothing preventing a buyer in a list-price system submitting a bid that exceeds the asking price). Moreover, when the market is flat, many sellers in the Scottish system will advertise the property as a Fixed Price sale, i.e. the first offer that meets the asking price is accepted. However, there is nothing preventing bidders offering below the Fixed Price, and nothing preventing sellers revising their asking price. Thus, during a slump, the Scottish process is not dissimilar to the English and American selling systems. Further details on the Scottish selling system are given in Gibb (1992), Pryce and Gibb (2006) and Smith et al (2006).

The question of interest here is whether concept of over-pricing has any meaning in the context of a selling system where asking prices are usually set well below the selling price (such as in the Scottish sealed-bid system), particularly during boom periods? If our answer is "no", we are saying that no property is more over-priced than another, which is implausible because this would preclude the possibility of one seller offering a higher asking price (for a similar property, in a similar location, in a given time period) than another seller. The quandary is essentially an informational one: how can a property be perceived to be over-priced in a sealed-bid setting when most bids will exceed the asking price?

One possibility is that, in a sealed-bid system, bidders will ask estate agents and surveyors to guide them on the typical difference between asking and selling price on recent sales in that area. Estate agents will advise buyers on what the typical difference between asking and selling price in locality k as a proportion of the asking price at that given moment. This proportion becomes the *convention* by which bidders and sellers judge whether a property is over-priced. If we include surveyors in this process (Smith et al. 2006 p.87) then we assume that buyers pay for professional guidance from a qualified surveyor before bidding, in which case the surveyor will advise on expected market price and the current local asking-selling price spreads. Ultimately, though, it is the buyer that has to decide whether and how much to bid, and she is free to accept or reject the advice of the surveyor.

The asking-selling price spread might typically be 20% of the asking price in one area and 10% in another. Both buyers and sellers can confirm the accuracy of this advice by checking the recent sales prices of properties in the locality (through web sites such as www.whathouseprice.co.uk) against the original asking prices (which are published on the web and in local newspapers, past editions of which are available from public libraries). Bidders judge the likely reservation price of the seller and the likely sale price and decide whether it is worth their while making a bid.

Expressing the above arguments more formally, let γ_i be the difference between asking and selling price, expressed as a proportion of the asking price for dwelling i:

$$\gamma_i = \frac{(P_i^A - P_i^S)}{P_i^A}.$$

γ_i is an *ex post* measure, since it can only be computed after the event. Let P_{ik}^{S*} be the average selling price (i.e. "market price") of properties of type[3] i in area k, and let γ_k^* be the expected differential (as a proportion of asking price) between asking and selling prices in area k, computed as follows,

$$\gamma_k^* = \int \gamma_i \, f(\gamma_i) d\gamma_{i \in k}.$$

We assume that (in the absence of strategic pricing – see Taylor 1999) sellers set the asking price on a property according to the following ratio,

$$P_i^A = \frac{P_i^R}{(1-\gamma_k^*)} + v_i, \qquad (1)$$

where P_i^R is the seller's reservation price plus an idiosyncratic mark-up, v_i (v_i captures, for example, the seller's beliefs regarding optimal price setting). Note that γ_k^* can vary over time – the t subscript is omitted for sake of parsimony.

To illustrate, suppose that v_i = 0, that the seller's reservation price is £120K, and that the local convention on the asking-selling price spread is -20% (i.e. properties in the area tend to sell for twenty per cent over the asking price). Equation (1) tells us that the seller will set the asking price at £100K. A property is said to be over-priced, therefore, when the expected market price, P_{ik}^{S*} is less than the asking price plus the current local differential,

$$P_i^{S*} < (1-\gamma_k^*)P_i^A \tag{2}$$

So, sellers seeking to effect a rapid sale may set the asking price well below what might be expected (i.e. below what would be anticipated given the current proportionate price differential, γ), and those willing to hold out for a higher price might set the asking price higher than similar properties in an area. While the asking price is not usually equivalent to the reservation price (the seller will typically expect the sale price to be above the asking price and has the right to refuse any or all offers) it remains a signal of seller reservation prices.

We can now write the degree of over-pricing, θ, as,

$$\theta_{ikt} = \frac{(1-\gamma_{ik}^*)P_i^A - P_{ik}^{S*}}{(1-\gamma_{ik}^*)P_i^A}, \tag{3}$$

---

[3] defined in terms of structural and location attributes.

It follows that:

$\frac{\partial \theta_{ikt}}{\partial P_i^A} > 0,$ over-pricing rises as the asking price rises, cet par;

$\frac{\partial \theta_{ikt}}{\partial P_{ik}^{S*}} < 0,$ over-pricing falls as the expected sales price falls, cet par.

The impact of over-pricing on the probability of sale

Assume that potential bidders perceive the asking price to be a signal of the sellers reservation price. If $(1 - \gamma_k^*)\ P_i^A$ is perceived to be a signal of the reservation price, P_i^R, then the bidders estimate of the reservation price is given by,

$$P_i^R = (1 - \gamma_k^*)\ Pi^A + e_i^R \quad , \quad \text{where } e_i^R \sim \textit{iid} \text{ normal.}$$

If bidders face a budget constraint, then the greater the value of P_i^A, the less likely the potential buyer will be to submit a bid. The smaller the difference between a bidders' maximum possible bid (given her budget constraint) and P^R, the greater the perceived probability that her bid will be superceded by other bids. Therefore, if there is a non-trivial cost to bidding, the risk of making a failed bid will deter bidders who cannot bid significantly above the asking price. So raising the asking price *cet par* has a screening effect and this will be exacerbated if there are close substitutes currently for sale in the area. For a given house type, therefore, the higher the asking price the more bidders will be screened out and the lower the number of bids, λ_t, in period t,

$$\lambda_t \quad = \lambda_t(\theta, \sigma_{\gamma_{ik}})$$

where $\sigma_{\gamma_{ik}}$ is the standard deviation of γ_i in area k , θ is the degree of over-pricing, and,

$$\frac{\partial \lambda_t}{\partial \theta_t} < 0 \,,$$

$$\frac{\partial^2 \lambda_t}{\partial \theta_t \partial \sigma_{\gamma_{ik}}} > 0 \,.$$

The first inequality says that the greater the degree of over-pricing relative to the current convention, the lower the number of bids. The second inequality states that the impact of over-pricing on the number of bids is ameliorated by the standard deviation of the relative asking-selling price spread in area k. The greater the standard deviation of spreads, the greater the uncertainty about the current convention and the greater the ambiguity about whether a property is to be regarded as over-priced.

If the distribution of bids is normal, the probability of the seller receiving a bid greater than his reservation price in period t will be given by,

$$\psi = \Pr(\max_b [P_{ib}^B] \geq P_i^R) = \lambda_t(\theta, \sigma_{\gamma_{ik}}) \int \phi(z) dz \quad ,$$

where $b = 1, 2, \ldots \lambda$ denotes bids received in time period t and where, $z = (P_i^R - \mu)/\sigma$. It can be seen that, $\frac{\partial \psi_{it}}{\partial \theta_t} < 0$. In other words, as θ, the degree of over-pricing (measured with respect to the current market convention on the asking-selling price spread in area *k*) rises, the probability of sale falls in the current period.

Why do asking and selling prices diverge during a housing boom?

Estate agents in the Scottish system often advise sellers to set the asking price well below the expected selling price and as such brokers have an important role in shaping the “current convention”. A possible justification for this strategy is that by setting asking price as low as possible they will attract more viewers, and hence more surveys and bids. The more bids, the greater the probability of receiving an extremely large bid (Levin and Pryce 2007).

This explanation does not, however, account for the rise in asking-selling price spreads during a boom (see Figure 1). During a slump one would think that there would be equally good, if not greater, reasons to maximize the number of bidders. Also, one would anticipate that even imperfectly informed potential bidders will accommodate the diverging spread by adjusting their expectations regarding the likely selling price based on the average spread on the locality in the last time period, so no more bidders will be attracted. There are four complementary explanations. First, estate agents attempt to talk up the market and there is greater scope for doing this during an upswing. Reports of growing asking-selling price spreads is a commonly perceived sign of a buoyant market and so estate agents are keen to reinforce this view by restraining the growth in asking prices during an upswing to be less than the growth in sale price.

Second, estate agents have an incentive to maximize bidder uncertainty as a means of extracting the maximum surplus. They benefit from achieving greater sales price because their commission is based on a proportion of sales prices. As such, estate agents seek to maximize the variance of spreads, not just the average spread. Estate agents are keen to inform bidders of recent rises in local spreads because this helps to give the impression of a rising market and encourage higher bids. For similar reasons, estate agents have an incentive to maximize the spread by encouraging sellers to set a low asking price. During downturns, such a tactic will not work because buyers and sellers know that prices are falling and bids are so few that sellers will accept the first bid that exceeds their reservation price. So the reservation price acts as a lower bound to the asking price during a slump in the housing market, and the asking price will converge towards this lower bound during a downswing.

Third, the cost to the buyer of not bidding on a viewed property may increase during a boom, which means that the marginal benefit of getting an extra buyer to view also tends to rise with the market. This is similar to the argument employed by Pryce and Oates (2008) to explain the apparent increase in emotive language by estate agents as the market boomed. Suppose that: (a) a buyer has a limited time frame to buy a house (e.g. needs to move in to get children in local schools before a given cut-off date), (b) viewing a property takes time and effort, and (c) viewed properties do not stay on the market indefinitely. Together, these imply an opportunity cost to viewing, and this rises as the probability of viewed properties leaving the market increases.

For example, suppose, during a housing boom, a buyer views 10 properties over the course of a fortnight. By the time he has viewed the 10th property, the first two properties have already been sold. There is an incentive to terminate the search process and submit a bid because, if he delays bidding on any of the remaining 8 properties he has viewed, and decides to survey an 11th property instead, he is gambling that this additional property is going to be better than the 8 properties already viewed. He is gambling because there is some probability that one or more out of the 8 remaining might leave the market before he has had chance to view the 11th property, and that the 11th property may not be as good as any of those foregone. That is, he fears regretting not submitting a bid on one of the earlier properties. This risk rises as the market booms because selling times shorten and so the probability that properties already viewed will leave the market also increases.

Assuming that buyers will not purchase before viewing, the seller knows that by getting a buyer to view (buy setting a very low asking price, for example), she has increased the probability from zero to some positive value that a buyer will bid. She knows that, even if the buyer is thoroughly disappointed when viewing the property, or realizes that the asking price has been set very low relative to the likely maximum bid, he will have an incentive to submit a bid due to the risk of not finding a better alternative within his search period. As the market booms, the probability of properties leaving the market increases, the opportunity cost of viewing another property rises, and the incentive for sellers to set low asking prices to entice viewers also rises. This may help explain the apparent correlation between asking-selling price spreads (gamma) and time on the market (Figure 2).

A fourth complementary explanation arises from the possibility of positive herding during boom periods. In the strategic pricing and consumer experimentation literature, firms "set low introductory prices so as to promote the flow of information among consumers, i.e. so as to encourage herding" (Taylor 1999, p.556). However, this phenomenon has been ruled-out in the context of the housing market. Taylor (1999), for example, has argued that, "if an individual has only a single house to sell, then positive herding can never occur because the first consumer who likes the house enough to buy it ends the game" (Taylor 1999, p.556). Taylor argues that this kind of positive herding can only occur when the seller has a future stream of output to market, whereas house sellers typically have a single property they want to sell.

Perhaps positive herding can, however, occur during boom periods when many buyers show interest in a single property. At such times, the *number of interested buyers can act as a signal of quality*. If there are many viewers, then other potential buyers will be more likely to perceive the house as being a desirable residence and will anticipate a larger number of bids. When there is a cost to bidding, bidders want to avoid unsuccessful bids and so if they anticipate stiff competition for the property they will be more likely to offer a higher bid in the hope of maximizing their chances of offering the highest bid. Note that the final number of bids in sealed-bid systems is often not known to any party until after the bidding has closed (either because of convention or regulation, or because bidders deliberately delay submitting a bid until the eleventh hour).

During a slump, there is less scope for positive herding because in many cases there will be only one or two bids received within the seller's optimal/maximum time frame for moving. As housing market slows, the total number of bids declines, converging to zero in a completely stagnant market. Sellers will be forced to either accept or reject the first offer given and so the sealed-bid system during a slump becomes analogous to the no-herding game described by Taylor (1999).

Together, these explanations provide a theoretical rationale for expecting bidding conventions to change over the market cycle, and reinforce the need to control for the correlation between DOP and TOM when constructing the survival model.

Application to List-Price Systems

The qualifications implied by bidding conventions to the definition and measurement of over-pricing in a sealed-bid system may be applicable to other selling systems. It seems implausible, for example, that buyers and sellers in a *list-price* system will not be influenced in a similar way by local bidding conventions when forming their beliefs about whether a property is over-priced. For example, if, in a list-price system, the buyer knows that selling prices tend to go for around 20% below the asking price, he will bid accordingly. If he thinks the seller has set the asking price too high, taking into account local bidding conventions, the bidder may view the property as being over-priced and consider alternative properties. Thus, the perception of whether a property is under- or over-priced, will be affected by the current local bidding convention in a similar way as in a sealed-bid system. Other concerns listed in the literature review about existing definitions of over-pricing also apply.

4. Hypotheses

The key elements of the preceding discussion are summarized in the following three hypotheses:

Hypothesis 1: Local conventions in asking-selling price spreads will be important in determining buyers' interpretation of asking prices.

> *Empirical Implication of Hypothesis 1:* Selling times will be more sensitive to measures of DOP that take into account local market conventions with respect to asking-selling price spreads than to measures that do not.

Hypothesis 2: The greater the uncertainty about local bidding conventions with respect to asking-selling price spreads, the greater the ambiguity about whether a property is to be regarded as over-priced, and the less impact over-pricing will have on selling times.

> *Empirical Implication of Hypothesis 2:* The greater the standard deviation of asking-selling price spreads in a locality, the less sensitive selling times will be to DOP.

Hypothesis 3: The search process is relatively efficient. As such, buyers will be sensitive to changes over time and space in the value of dwellings, despite the complexities associated with the heterogeneity of properties and locations. When deciding whether a property is over-priced, buyers will therefore take into account spatio-temporal variations in expected price.

> *Empirical Implication of Hypothesis 3:* Selling time will be more

sensitive to measures of DOP that take into account spatio-temporal shifts in attribute prices than to measures that do not.

The next section will consider how these hypotheses can be tested using the data available and the factors that need to be controlled for if the impact on selling time is to be isolated (such as the time series correlation between gamma and TOM).

5. Econometric Strategy

Comparing adjusted and unadjusted measures of DOP

The primary goal of the econometric analysis is to test the three main hypotheses listed above by comparing the impact on selling time of different measures of DOP. The underlying presupposition is that the more a given approximation for overpricing differs from that used by market participants actually, the less effective it will be in explaining selling times. The plan is to compare equation (3) with unadjusted measures of over-pricing (denoted by $\theta^{\#}$), such as,

$$\theta^{\#} = \frac{P_i^A - P_i^{H\#}}{P_i^A}, \qquad (3)^{\#}$$

where $P_i^{H\#}$ is the predicted market price from a simple hedonic price regression for dwelling i. There are a number of sources of potential error associated with

$\theta^{\#}$. First and foremost, the omission of γ_{kt}^{*} will result in the degree of over-pricing being over (under) estimated in areas where γ_{kt}^{*} is below (above) the mean value of γ across all areas in a given period, and similar bias will arise from changes in γ_{kt}^{*} over time.

The proposition that the less certain bidders are about the current "convention" in the market they seek to bid in, the less obvious it will be that a property is over-priced (and the smaller the impact of over-pricing on marketing time), suggests that survival analysis of selling times will suffer from further omitted variable bias if there is no attempt to control for uncertainty. This is addressed in the regressions that follow by including the standard deviation of γ_{ik} as a measure the degree of uncertainty, where k is taken to be the area within a 3km radius of property i.[4]

Also, as discussed, spatial and temporal shifts in the market valuation of attributes may give rise to further misleading estimates of over-pricing if $P_i^{H\#}$ is not estimated in such a way as to account for structural breaks of this kind, though there is a question over the degree of rationality and perfect foresight on which bids are based. Perhaps buyer/seller beliefs about a property's value are based on simple rules of thumb that are best approximated by a fairly rudimentary hedonic model. This may be true even when the bidder is assisted by the advice of a Chartered Surveyor, as valuers' "professional judgement" may in fact boil down to a fairly simple set of intuitive rules.

[4] If a radius smaller than 3km is used, then sample size problems can arise.

Also, $P_i^{H\#}$ is only meaningful if it is estimated for a specific time on the market in a given area, as differences in observed sale prices may be partly due to different holding periods between sales that have nothing to do with the attributes of the dwelling. The rate of house price inflation may also have to be taken into account since both buyers and sellers are likely to adjust their valuation of the property according to expected price rises in the area.

Multiple Fractional Polynomial Estimation

The first step in achieving a measure of over-pricing is to decide on the hedonic method to be used for estimating the "market value" of a property on the market. To investigate whether market participants use sophisticated valuation procedures in their perception of over-pricing, two contrasting hedonic models are used. The first is a very simple hedonic price regression that includes neither spatial interactions nor non-linear transformations. The second procedure is a relatively sophisticated hedonic regression which uses Multiple Fractional Polynomial (MFP) regression estimation to arrive at a unique Time Location Value Signature (TVLS) for each property. This is draws on the intuition and methodology of Fik *et al.* (2003) and extends it in two important ways. First, the Fik *et al.* model is static in that it takes no account of changes to the Location Value Signature over time. We augment the Fik *et al.* model to include continuous time interactives (interacted with both attributes and latitude and longitude to account for movements and twists in the price surface over time) complemented by year and season dummies to capture step shifts in attribute values.

Second, rather than a simple OLS interaction model, we adopt a “multiple fractional polynomial” estimation procedure. Royston and Altman (1994) argue that one of the weaknesses of conventional “integer” polynomial models (such as that employed by Fik *et al*) is that quadratic functions offer limited flexibility and can lead to unhelpful distortions: "low order polynomials offer a limited family of shapes, and high order polynomials may fit poorly at the extreme values of the covariates" (Royston and Altman 1994, p.429).

For example, an integer polynomial (in a single variable) of degree m can be written as,

$$\beta_0 + \beta_1 x + \beta_2 x^2 + \ldots \beta_m x^m.$$

A fractional polynomial on the other hand, of the same degree, has *m* integer and/or fractional powers, $p_1 < \ldots < p_m$,

$$\beta_0 + \beta_1 x^{(p1)} + \beta_2 x^{(p2)} + \ldots \beta_m x^{(pm)}.$$

where,

$$x(p) \quad x(p) = \begin{cases} x^p & \text{if } p \neq 0 \\ \log x & \text{if } p = 0 \end{cases}, \qquad \textit{where } x > 0.$$

This can be extended to include *repeated powers* of the form,

$$\beta_0 + \beta_1 x^{(p)} + \beta_2 x^{(p)} \log x + \ldots + \beta_m x^{(p)} (\log x)^{m-1}$$

A fractional polynomial of degree *m* = 2 with repeated powers of 0.5 is,

$$\beta_0 + \beta_1 x^{0.5} + \beta_2 x^{0.5} \log x + \beta_2 x^{0.5} \log x$$

Royston and Altman illustrate that although the deviance of such models does not improve greatly on integer polynomial estimation, the estimated curves avoid some of the peculiar shapes produced by integer polynomial estimation. A fractional polynomial can include a combination of unique and repeated powers. If the powers are listed as (-1, 1, 3, 3) the model estimated would be,

$$\beta_0 + \beta_1 x^{-1} + \beta_2 x + \beta_3 x^3 + \beta_4 x^3 \log x$$

As appealing as this method may be, the estimation of a regression with fractional polynomials in one variable is of limited value in the current context because there many possible determinants of a dwelling's market value (note that, in the example above, there is only one explanatory variable, denoted x, which is then transformed accordingly). Royston and Altman (1994) suggested a possible algorithm for joint estimation of fractional polynomials of several continuous variables, an approach later refined by Sauebrei and Royston (1999) and Ambler and Royston (2001), and subsequently made available in Stata programming format.

This was the algorithm applied here. It involved ordering the continuous explanatory variables eligible for fractional polynomial transformation in order of increasing p-values with a view to modeling relatively significant variables before relatively insignificant ones. It was found that the MFP estimation worked best if it starts with a reasonably well specified model. Therefore, prior to MFP estimation, an OLS stepwise procedure was used to derive a basic model akin to the Fik *et al.* model but without non-linear transformations of the explanatory variables. Having dropped out the least significant interactions and variables, the MFP model was estimated with the following set of possible power transformations: -4, -3.5, -3, -2.5, -2, -1.5, -1, -0.8, -0.6, -0.4, -0.2, 0, 0.2, 0.4, 0.6, 0.8, 1, 1.5, 2, 2.5, 3, 3.5, and 4.

Controlling for Market Buoyancy, and Expected Inflation

Pryce and Gibb (2006) argue that failure to control for variation in market buoyancy across space and over time could distort the estimation of the survival function. Consequently, variations between areas and over time in market buoyancy at the time property i comes onto the market needs to be controlled for if the effect of over-pricing on selling time is to be isolated. The measure proposed here to control for market buoyancy is $\mathrm{d}Q_{ik}^{om}/Q_{ik}^{om}$, the change in the quantity of properties on the market in area k, as a proportion of the number of properties on the market before the change (where k is again defined as those properties within a 3km radius of the property i). The period used to compute $\mathrm{d}Q_{ik}^{om}/Q_{ik}^{om}$ is the 60 day period prior to property i coming onto the market – any shorter period of time results in sample size problems. Note that the computation of the k based variables is not truncated by the boundaries of our data (i.e. the “West End”) since data on contiguous areas were also available.

In an attempt to control for the possible effect of inflation expectations, the final two survival regressions include a house price inflation expectations correction, π_k^*, to the definition of over-pricing. π_k^* is computed as the proportionate increase in average sale prices in area k in 60 days prior to the property coming on the market. It is a simple raw average of all sales in the area and does not control for attribute variation. The expected selling price, P_{ik}^{S*}, used in the computation of over-pricing, is estimated as the predicted value from the hedonic regression multiplied by $(1+ \pi_k^*)$:

$$P_{ik}^{S*} = (1+\pi_k^*)\, P_i^{H\#}$$

Having derived appropriate measures for the degree of over-pricing, the uncertainty surrounding local bidding conventions, local market buoyancy, and price expectations, the plan is to include these along with property characteristics into a survival time regression of time on the market, estimated using maximum likelihood assuming a log-normal survival time distribution. A positive (negative) coefficient will indicate that, the larger the value of the variable, the longer (shorter) the time on the market.

6. Data

Table 1 presents summary statistics on the data, supplied by Glasgow Solicitors Property Centre (GSPC), a consortium of estate agents with market shares across the city of Glasgow and surrounding areas. The data are for the period 1999 quarter 1 to 2004 quarter 1 for the West End of Glasgow. As the table shows, the area has relatively few houses (18.5%) and is largely made up of tenement flats. The typical sale is of a two bedroom flat with no driveway. dQ_{ik}^{om}/Q_{ik}^{om} and γ_I are defined below. Table 2, Figure 1 and Figure 2 show the dynamic nature of the market over the period under consideration. Asking prices rose by a total of 79.6% over the five year period, and selling prices rose by an even more impressive 114.6%. The divergence between asking and selling is highlighted further by the spectacular increase in γ (asking price less selling price all over asking price) from 5.9% to 29.4%. While γ and TOM appear to decline over time (see Figure 2) it seems highly unlikely that the fall in γ is the cause of the fall in TOM.

Table 3 demonstrates the variation of γ across space by computing the average for each post code sector in the West End of Glasgow. Ignoring the sectors with less than 100 sales it can be seen that the average asking-selling price spread relative to the asking price varies considerably between post code sectors from –33.5% in sector G11 5 to –15.7% in sector G14 0. Post code sectors are administrative constructs and do not necessarily correspond to submarket boundaries, however. In an attempt to rectify this problem, area k is defined not in terms of post code sectors or local authority areas but in terms of the 3km radius around each dwelling. The contour plot of γ_i^*, the average value of in the 3km radius of each property sale in the West End of Glasgow, is presented in Figure 3. Significant variation in contours again suggest significant spatial differentials in bidding conventions.

7. Results

Table 4 presents the results of the simple hedonic model developed for comparative purposes. Table 5 presents the results of the Multiple Fractional Polynomial procedure described above. Many of the interactions between attributes, time (*t*) and space (*x*, *y* coordinates) were found to be highly significant, as were many of the non-linear fractional polynomial transformations. Crucially, the fractional polynomial model has an Adjusted R^2 of 0.70 (Table 5), compared with 0.44 in the simple linear model (Table 4). This suggests that the relationship between dwelling attributes, location and the value of a house is highly complex and certainly not a simple linear sum.

Survival models of time on the market (see Cleves *et al.,* 2002; Kalbfleisch and Prentice, 2002) were constructed to compare the effects of different definitions of over-pricing, the results of which are presented in Table 6. Note that, while the effects of uncorrected measures of DOP are blunted by the distortions inherent in their computation, they may also contain a time-series correlation between contemporaneous movements in time on the market and the asking-selling price spread (see Figure 2). If the data include submarkets that are at different phases of the housing cycle, the time series correlation will have a spatial/cross-sectional manifestation. Different areas will have different conventions regarding gamma and so even studies of short time periods may be affected. Spatial differentials may also arise from long-term structural differences between areas that produce secular differences in γ_k^*.

Results presented in Table 6 confirm the anticipated positive correlation between over-pricing and time on the market. (This is the standard finding of the literature and is confirmed for all measures of DOP—the coefficient on theta had a positive sign in all 9 regressions, though it was not statistically significant in regression (1)). The results also confirm Hypothesis 1. DOP in regression (1) is an unadjusted measure of over-pricing computed as asking price less expected selling price all over asking price, where expected sale price is derived from a simple hedonic without spatial or temporal interactive terms. This measure has the least significant coefficient of all the measures (t value = 0.664; 95% CI = [-.036, .064]). When this same measure is calculated *relative to* γ_k^* (the average asking-selling price spread in area k, where k is again defined as those properties within a 3km radius of property i) it can be seen from regression (2) that its t value rises to 2.385 (95% CI =[.002, .012]). Measuring over-pricing relative to the local average asking-selling price spread (regressions (2) through (9)) rather than as an entity independent of local bidding conventions (regression (1)), therefore, increased the significance of the over-pricing variable in a log-normal survival model of TOM. The improvement is evident even when the time-series correlation between TOM and average asking-selling price spreads (regressions (6) through (9)) and expected inflation (regressions (8) and (9)) are controlled for.

With regard to Hypothesis 2, the interaction of the standard deviation of local asking-selling price spreads also proved to be highly statistically significant.

Regression (3) includes the same measure of over-pricing as regression (2) but also includes, $\theta.\sigma_{\gamma_{ik}}$, the interaction with the *standard deviation* of proportional asking-selling price spreads in area k. This variable is highly significant and has a negative sign in all three of the regressions which include it ((3), (5), and (7)), confirming the proposition that the impact of over-pricing is mitigated by uncertainty about the current local bidding convention (conversely, the lower the standard deviation of asking-selling price spreads in an area, the easier it is to spot excessively high asking prices, and the bigger the impact DOP has on selling time).

Hypothesis 3 was tested by comparing measures of DOP based on simple hedonic prediction of expected market price (regressions (1), (2) and (3)) with measures of DOP that employed Fractional Polynomial methods to capture non-linear spatio-temporal variation in attribute prices (regressions (4) through (9)). Although the size of the over-pricing effect tends to be larger when the more sophisticated estimates of expected sale price is used, the standard error rises also, with the net result being slightly lower t-values compared with the simple hedonic formulation used in regressions (2) and (3). This finding suggests that the hedonic method used to compute the expected selling price used in the computation of over-pricing should perhaps have a fairly simple formulation reflecting the bounded rationality of buyers and sellers. Using a sophisticated estimation procedure effectively assumes that buyers and sellers are able to make similarly sophisticated estimates of the property's market value. If complex hedonics are used when, in fact, valuers, buyers, sellers and estate agents tend to use relatively simple rules of thumb regarding the expected sale price, then such an approach, while producing more accurate hedonic estimates, will actually lead to less precise measures of over-pricing. Put another way, over-pricing will only affect time on the market if buyers and sellers *realize* that the property is over-priced before the transaction is complete, rather than because of actual *ex post* discrepancies between asking and sale prices.

Results: Control Variables

Consider, now, the results for the control variables reported in the various models of Table 6. The progressively negative values on the time dummies (compared with the baseline period, which is the first in the dataset – the quarter one of 1999) show that the market as a whole is experiencing an upswing until quarter 3 of 2003, after which the coefficients on the time dummies become less negative (there is also a dip in the second half of 2002). Attribute coefficients remain relatively stable across the different model specifications. The significant negative coefficients on the "house" and "garden" variables indicate that houses tend to sell faster than flats and that dwellings with gardens sell more rapidly than those without. Similarly, houses with notable views tend to sell more quickly than those without, as do dwellings with a driveway, those in a mature area, those with gas central heating, or those a bay window (though the effect of these attributes is less statistically significant). The most statistically significant attribute effect comes from the size of dwellings, as measured by number of rooms where larger dwellings are found to take significantly longer to sell.

The market buoyancy measure, $\mathrm{d}Q_{ik}^{om}/Q_{ik}^{om}$, seems to work well in that it is one of the most statistically significant variables in the model. The estimated coefficient and standard error tend to vary with the various specifications of the over-pricing measure, suggesting a degree of multicolinearity. In particular, the t-value falls substantially when the over-pricing measure is corrected for expected house price inflation. This is not surprising since the two will obviously be related (houses will sell more quickly if prices are expected to rise).

Regressions (6) to (9) control for time on the market when predicting the market value of the property by including TOM in the hedonic regression (see Table 5 – note that the MFP regression without TOM used to compute θ in regressions (4) and (5) is not presented). When computing the predicted values, the value for TOM is set equal to 46 days – the average marketing time in the West End. This results in a slight improvement in the t ratios of (6) and (7) compared with (4) and (5) and a small rise in the size of the θ coefficient.

The final two survival regressions, (8) and (9), include the house price inflation expectations correction, π_k^*, in the definition of over-pricing. Comparing (8) and (9) with (6) and (7) it can be seen that the expectations adjustment has slightly reduced the *t*-values and coefficients for the over-pricing measures. It has also substantially reduced the *t*-values on the market buoyancy variable suggesting a degree of multicolinearity. This is not surprising since the change in properties on the market will be correlated with price changes. As such the buoyancy variable may already be capturing house price inflation expectations.

8. Conclusion

What do we mean when we say that a property is “over-priced”? It is intuitive to say that asking too much for a property will deter buyers. However, when we ask what we mean by “too much”, we begin to discover how subjective and relativistic price determination is. Hypothesis 1 of the paper contended that a sound notion of over-pricing has to incorporate the effect of local bidding conventions. The question of over-pricing is inseparable from the issue of how the market interprets the asking price. If the local “convention” is to set the asking price 20% above the expected selling price, then potential buyers will view a property as being “over-priced”, and be discouraged from bidding if the asking price is set higher than this (e.g. at 30% or 40% above the expected price for a property of a given type and location). The same logic applies if one is considering a sealed-bid system where asking prices are typically set below the expected market price. Survival regressions of selling time appeared to confirm Hypothesis 1 – the impact of DOP on TOM only became significantly greater than zero when local bidding conventions were incorporated into the definition of DOP.

More unraveling ensues when we consider the possibility that the bidding convention may not be known with certainty by either buyers or sellers (Hypothesis 2). Indeed, the uncertainty measure included in the time on the market proved highly significant, mitigating profoundly the deleterious effect of over-pricing on speed of sale. In other words, the results of the analysis appear to suggest that the greater the uncertainty about local bidding conventions, the more one can overprice without fear of prolonging time on the market. This in turn raises epistemological questions about whether and how buyers know their levels of uncertainty, and how uncertainty is determined and responded to.

The paper did not, however, find conclusive evidence in support of the hypothesis that market participants take into account spatio-temporal variations in attribute prices when computing DOP (Hypothesis 3). Although the survival regression coefficients were slightly higher when fractional polynomial estimates of DOP were used, the standard errors were also higher, to the extent that t-ratios fell.

There are a number of ways the analysis could be extended. For example, little has been said here about the intersection of behavioral explanations of market outcomes with probabilistic processes inherent in the bidding system. Suppose increased market buoyancy causes an increase in the number of bids for a property. Since the propensity of extreme bids is likely to rise with the number of bids due to the sampling properties of the maximum (see Levin and Pryce 2007), the corollary of market buoyancy is that one will observe increased variation of (and hence inflated buyer uncertainty with regard to) the final sale price for a given type of property, other things being equal. If over-pricing is less deleterious to liquidity the more uncertain the expected market price, then one might ask whether sellers have greater incentive to overprice during periods of frenetic market activity when uncertainty may expand due to the 'fog of war'. Yet, this is the opposite of what appears to happen in the Glasgow housing market, where there is evidence of a strategy to *under*-price as the market rises, possibly as a means to attract more bidders (perhaps due to the rising opportunity cost of viewing during boom periods, or the greater potential for estate agents to talk-up the market when market prices are rapidly changing and uncertainty is more prevalent). If all sellers in an area adopt a strategy of over-pricing or under-pricing when market conditions change, one is essentially observing a shift in the local bidding convention, and preconceptions of what it means for a property to be over-priced are then recalibrated. One has entered a new DOP regime.

While this strand of reasoning may offer some clues as to how conventions change, it is far from a general theory, and raises further questions about the circularity of market knowledge and how information is disseminated in the market system. A possible avenue to explore here is the potential for using information cascade theory (Bikhchandani *et al.* 1992, 1998) to explain the dynamics of bidding conventions. For example, an information cascade framework could be constructed to explore how information about pricing conventions are disseminated throughout the market system. Estate agents and spatially-specific barriers (such as social networks) shape the flow of information and the pattern of bidding conventions. Estate agents may act as gatekeepers at key nodes in the information system, with local networks of social interaction modulating the density and direction of information flow within and between neighborhoods.

There is more work to be done also in understanding the role of time on the market. Taylor (1999) explores TOM as a signal of quality, but selling times potentially have a central role to play in the determination of equilibrium prices in the wider market. For example, it is possible to extend an inventory adjustment model (Glosten and Harris 1988, Hasbrouk 1991, Levin and Wright 2002) to the housing market (Levin and Pryce 2009). Because sellers of houses usually only have one dwelling to sell, the classic inventory adjustment model does not directly apply. However, rising (falling) TOM might act as a signal to buyers and sellers that there is a growing (diminishing) stockpile of unsold properties on the market (Levin and Pryce 2009), and hence indicate the need to adjust prices downwards (upwards). Similarly, TOM may have a crucial role to play as a signaling device in the process of shifting from one regime of bidding conventions to another. Where there appear to be fundamental differences across space in the relationship between TOM and the dynamics of bidding conventions, we might interpret this in terms of submarkets, where information flows have persistent territorial constraints and idiosyncrasies.

Another implication of uncertainty surrounding the expected market price of a dwelling is that it may affect the extent to which price perceptions are subject to manipulation. Uncertainty opens the door to persuasion. Perceptions then become malleable and exploitable, presenting opportunities for estate agents to become rather more than neutral disseminators of information. There is ample evidence to suggest that estate agents are not slow to make the most of such opportunities, as the rich idiom of estate agency bears testimony (Oates and Pryce 2008). Interestingly, the language of property selling may itself be subject to local idiosyncrasy, cyclical variation and seasonal fluctuation (Oates and Pryce 2008); each of which add further layers of complexity to the determination of local perceptions of value. It also highlights another possible direction for exploration – the extent to which conventions in the local idiom of house selling are related to local conventions in asking-selling price spreads, and the extent to which these also correspond to local submarkets.

References:

Asabere, P. K., Huffman, F.E. and Mehdian, S. (1993) Mispricing and Optimal Time on the Market, Journal of Real Estate Research, 8, 149-156.

Ambler, G. and P.Royston (2001) Fractional polynomial model selection procedures: investigation of Type I error rate, *Journal of Statistical Simulation and Computation* 69, 89-108.

Anglin, P, Rutherford, R and Springer, T (2003) 'The Trade-off between the Selling Price of Residential Properties and Time-on-the-Market: The Impact of Price Setting', *Journal of Real Estate Finance and Economics*, 26, 95-111.

Bikhchandani, S., Hirshleifer, D. and Welch, I. 1992. A theory of fads, fashion, custom and cultural change as informational cascades. Journal of Political Economy 100, 992–1026.

Bikhchandani, S., Hirshleifer, D. and Welch, I. 1998. Learning from the behavior of others: conformity, fads, and informational cascades. Journal of Economic Perspectives 12, 151–70.

Cleves, M. A., Gould, W.W. and R.G. Gutierrez (2002) "An introduction to Survival Analysis Using Stata", Stata Press, Texas.

Fik, T.J., Ling, D.C., Mulligan, G.F. (2003) Modeling spatial variation in housing prices, *Real Estate Economics*, 31, 623-646

Gibb, K. (1992) 'Bidding, Auctions and House Purchase', *Environment and Planning A*, 24, 853-69.

Glosten, L. and Harris, L. (1988), 'Estimating the Components of the Bid-ask Spread.' Journal of Financial Economics, 21, 123-142.

Glower, M., Haurin, D. and Hendershott, P. (1998) Selling Time and Selling Price: The Influence of Seller Motivation. *Real Estate Economics*, 26, 719-740.

Hasbrouck, J. (1991), 'Measuring the Information Content of Stock Trades.' Journal of Finance, 46, 179-207.

Horowitz, J. (1992) 'The Role of the List Price on Housing Markets: Theory and an Econometric Model', *Journal of Applied Econometrics*, 7, 115-29.

Jud, G., Seeks, T. and Winkler, D. (1996) 'Time on the Market: The Impact of Residential Brokerage', *Journal of Real Estate Research*, 12, 447-458.

Kang, H. and Gardner, M. (1989) 'Selling Price and Marketing Time in the Residential Real Estate Market', *Journal of Real Estate Research*, 4, 21-35.

Kalbfleisch, J.D. and R.L. Prentice (2002) *The Statistical Analysis of Failure Time Data*. 2nd ed. New York: Wiley

Knight, J.R. (2002) Listing Price, Time on Market, and Ultimate Selling Price: Causes and Effects of Listing Price Changes, *Real Estate Economics*, 30, 213-237.

Levin, E. J. and Wright, R. E. (2002) 'Estimating the Price Elasticity of Demand in the London Stock Market', European Journal of Finance, 8, 222-237

Levin, E. and Pryce, G. (2007) 'A Statistical Explanation for Extreme Bids in the House Market', Urban Studies, 44, 2339-2355.

Levin, E. and Pryce, G. (2009) A regional house price model of excess demand for housing, RICS Research Report, London: RICS.

Malpezzi, S. (2003) "*Hedonic Pricing Models: a Selective and Applied Review*", in O'Sullivan, A. and Gibb, K. Ed. Housing Economics and Public Policy, Blackwell: Oxford.

Pryce, G and Gibb, K. (2006) 'Submarket Dynamics of Time to Sale', Real Estate Economics, 34, 377-415.

Pryce, G. and Oates, S. (2008) 'Rhetoric in the Language of Real Estate Marketing', Housing Studies, 23, 319-348.

Royston, P. and D.G. Altman (1994) Regression using fractional polynomials of continuous covariates: parsimonious parametric modeling (with discussion), *Applied Statistics*, 43, 429-467.

Sauerbrie, W. and P. Royston, (1999) Building multivariable prognostic and diagnostic models: transformation of the predictors by using fractional polynomials, *Journal of the Royal Statistical Society* (*Series A*), 162, 71-94.

Smith, SJ., Munro, M., and Christie, H. (2006) "Performing (housing) markets", Urban Studies, 43, 81-98.

Springer, T. M. (1996) Single-Family Housing Transactions: Seller Motivations, Price, and Marketing Time, *Journal of Real Estate Finance and Economics*, 13, 237-254.

Taylor, C.R. 1999. Time-on-the-Market as a Sign of Quality. Review of Economic Studies 66, 555–578.

Yavas, A and Yang, S (1995) 'The Strategic Role of Listing Price in Marketing Real Estate: Theory and Evidence', *AREUEA Journal*, 23, 347-68.

Table 1 Descriptive Statistics on Key Variables

Variable	Description	n	mean	sd
askingpr	Asking price	3,445	76897.100	41522.980
sellingp	Selling price	3,305	97169.970	57503.850
tom	Time on the market	3,352	41.408	41.682
dQ_{ik}^{om}/Q_{ik}^{om}	Measure of market activity	3,377	0.147	0.365
γ_i	Measure of asking-selling price spread	3,377	0.159	0.034
house_all	Dwelling is a house rather than a flat	3,445	0.185	
bedrooms	Number of bedrooms	3,425	1.989	
views	Dwelling has notable views	3,445	0.056	
driveway	Dwelling has its own driveway	3,445	0.025	
mature	Area is described as mature	3,445	0.015	
garden_d	Dwelling has a garden	3,445	0.506	
GCH	Gas Central Heating	3,445	0.554	
alarm	Burglar alarm	3,445	0.054	
Bay window	Dwelling has bay window(s)	3,445	0.397	

CBD = distance to central business district; GCH = gas central heating; TOM = time on the market

Table 2 West End: Quarterly Change in γ

	Average Asking Price	Annual % change in Asking Price	Quarterly % change since 1999q1	Average Selling Price	Annual % change in Selling Price	Quarterly % change since 1999q1	Median No. Days on Mkt	Annual % change in Median DOM	Quarterly % change since 1999q1	γ_i	Annual % change in g*i*	Quarterly % change since 1999q1
99Q1	£ 54,047		0.0%	£ 57,806		0.0%	98.5		0.0%	-5.9%		0.0%
99Q2	£ 58,012		7.3%	£ 65,916		14.0%	75		-23.9%	-10.7%		80.5%
99Q3	£ 59,680		10.4%	£ 67,246		16.3%	54		-45.2%	-10.9%		84.1%
99Q4	£ 61,883		14.5%	£ 71,008		22.8%	35		-64.5%	-11.7%		98.3%
00Q1	£ 55,493	**2.7%**	2.7%	£ 62,467	8.1%	8.1%	42	-57.4%	-57.4%	-11.0%	**86.9%**	86.9%
00Q2	£ 64,592	**11.3%**	19.5%	£ 76,056	15.4%	31.6%	41	-45.3%	-58.4%	-14.0%	**31.9%**	138.0%
00Q3	£ 62,620	**4.9%**	15.9%	£ 73,623	9.5%	27.4%	35.5	-34.3%	-64.0%	-14.4%	**32.2%**	143.4%
00Q4	£ 62,780	**1.4%**	16.2%	£ 71,026	0.0%	22.9%	42	20.0%	-57.4%	-10.7%	**-8.4%**	81.7%
01Q1	£ 65,169	**17.4%**	20.6%	£ 75,640	21.1%	30.9%	39	-7.1%	-60.4%	-13.6%	**23.7%**	131.2%
01Q2	£ 68,141	**5.5%**	26.1%	£ 79,947	5.1%	38.3%	33	-19.5%	-66.5%	-15.6%	**11.3%**	164.8%
01Q3	£ 69,370	**10.8%**	28.3%	£ 80,806	9.8%	39.8%	33	-7.0%	-66.5%	-14.4%	**0.0%**	143.3%
01Q4	£ 73,596	**17.2%**	36.2%	£ 86,288	21.5%	49.3%	34.5	-17.9%	-65.0%	-15.6%	**45.2%**	163.8%
02Q1	£ 67,145	**3.0%**	24.2%	£ 80,340	6.2%	39.0%	22	-43.6%	-77.7%	-18.2%	**33.5%**	208.6%
02Q2	£ 77,117	**13.2%**	42.7%	£103,505	29.5%	79.1%	28	-15.2%	-71.6%	-31.2%	**99.4%**	428.1%
02Q3	£ 74,535	**7.4%**	37.9%	£ 94,148	16.5%	62.9%	28	-15.2%	-71.6%	-25.2%	**75.4%**	326.8%
02Q4	£ 79,459	**8.0%**	47.0%	£ 99,025	14.8%	71.3%	34	-1.4%	-65.5%	-22.7%	**45.8%**	284.5%
03Q1	£ 80,166	**19.4%**	48.3%	£103,768	29.2%	79.5%	30	36.4%	-69.5%	-27.8%	**52.8%**	371.6%
03Q2	£ 83,881	**8.8%**	55.2%	£108,415	4.7%	87.6%	32	14.3%	-67.5%	-28.4%	**-8.8%**	381.9%
03Q3	£ 98,910	**32.7%**	83.0%	£126,608	34.5%	119.0%	32	14.3%	-67.5%	-29.1%	**15.7%**	393.7%
03Q4	£ 95,832	**20.6%**	77.3%	£120,957	22.1%	109.2%	34	0.0%	-65.5%	-27.7%	**21.9%**	368.8%
04Q1	£ 97,074	**21.1%**	79.6%	£124,034	19.5%	114.6%	29	-3.3%	-70.6%	-29.4%	**5.5%**	397.7%
99ave	£ 58,405			£ 65,494			66			-9.8%		
00 ave	£ 61,371	**5.1%**		£ 70,793	**8.2%**		40	**-29.2%**		-12.5%	**35.7%**	
01 ave	£ 69,069	**12.7%**		£ 80,670	**14.4%**		35	**-12.9%**		-14.8%	**20.1%**	
02 ave	£ 74,564	**7.9%**		£ 94,255	**16.7%**		28	**-18.8%**		-24.3%	**63.5%**	
03 ave	£ 89,697	**20.4%**		£114,937	**22.6%**		32	**16.2%**		-28.3%	**20.4%**	
Ave	£ 70,621	11.5%		£ 85,230	15.5%		40	-11.2%		-17.9%	34.9%	

Table 3 Variation in γ Across Postcode Sectors

Post Code Sector	Mean γ	Standard Deviation of γ	N
G11 5	-33.5%	17.1%	213
G12 9	-33.3%	18.1%	297
G61 1	-30.9%	9.5%	2
G12 8	-29.6%	18.1%	141
G4 9	-28.9%	16.9%	74
G20 6	-28.8%	16.6%	241
G11 7	-28.6%	17.2%	378
G3 7	-26.8%	18.1%	39
G11 6	-25.0%	12.9%	110
G3 8	-24.6%	13.7%	96
G12 0	-24.2%	16.6%	251
G14 9	-23.9%	17.4%	206
G20 8	-23.4%	16.3%	160
G3 6	-22.5%	14.8%	42
G20 9	-21.4%	21.0%	32
G13 3	-21.3%	14.3%	211
G20 7	-20.8%	13.2%	76
G13 1	-20.7%	14.8%	305
G13 2	-17.3%	14.7%	208
G15 6	-17.0%	13.3%	80
G20 0	-16.3%	15.5%	70
G13 4	-16.3%	12.1%	82
G14 0	-15.7%	15.2%	147
G23 5	-13.7%	17.8%	64
G1 5	-13.3%	0.0%	1
G15 8	-9.9%	7.3%	17
G15 7	-9.1%	10.5%	10
G22 6	-7.6%	0.0%	1
G64 2	-6.3%	0.0%	1
G31 1	-4.1%	0.0%	1
Total	**-24.5%**	**17.0%**	**3556**

Table 4 Simple OLS Hedonic Model

	β	t	sig.	95% Conf. Interval	
rooms	0.2207	37.06	0.000	0.2090	0.2324
traditional-Victorian	0.1984	12.63	0.000	0.1676	0.2291
lower flat	-0.0500	-2.89	0.004	-0.0839	-0.0161
upper flat	-0.0333	-1.89	0.059	-0.0678	0.0013
main door flat	0.1682	3.37	0.001	0.0703	0.2661
garage	0.1237	5.34	0.000	0.0783	0.1692
parking	0.0256	1.22	0.223	-0.0156	0.0669
needs-upgrading	-0.1886	-2.34	0.019	-0.3464	-0.0308
luxury	0.2169	5.69	0.000	0.1422	0.2917
Spring	0.0095	0.47	0.637	-0.0300	0.0491
Summer	0.0423	1.96	0.050	0.0000	0.0846
Autumn	0.0130	0.54	0.589	-0.0342	0.0603
D2002	-0.2973	-1.55	0.121	-0.6729	0.0783
D2003	-0.2321	-0.91	0.361	-0.7306	0.2663
D2004	0.5583	17.30	0.000	0.4950	0.6215
t.D2001	0.0599	6.60	0.000	0.0421	0.0777
t.D2002	0.1538	2.85	0.004	0.0480	0.2596
t.D2003	0.1487	2.63	0.009	0.0378	0.2595
constant	10.1041	300.88	0.000	10.0382	10.1699
Number of obs	3,530				
F(18, 3511)	152.04				
Prob > F	0.000				
R-squared	0.438				
Adj R-squared	0.4352				

Table 5 Multiple Fractional Polynomial Time-Space Interaction Model

	β	t	sig.	95% Conf. Interval	
$bedrooms^{0.4}$	-0.6875	-6.97	0.000	-0.8809	-0.4941
$bedrooms^{3.5}$	-1.1657	-5.03	0.000	-1.6198	-0.7117
$publicrooms^{-0.6}$	-0.1987	-3.87	0.000	-0.2994	-0.0980
$CBD^{0.2}$	19.8890	16.61	0.000	17.5416	22.2364
$CBD^{0.2}$.ln(CBD)	-3.3073	-17.04	0.000	-3.6878	-2.9268
x.rooms	2.8067	4.24	0.000	1.5100	4.1035
$(x.y.rooms)^{-2}$	0.0737	7.2	0.000	0.0536	0.0937
x.y.rooms	-41.2626	-4.17	0.000	-60.6702	-21.8549
$(t.x.rooms)^{0.6}$	-93.0295	-3.96	0.000	-139.1218	-46.9373
t.x.rooms	130.2189	4.81	0.000	77.1646	183.2732
$(t.x.y.rooms)^{0.8}$	10.5065	2.97	0.003	3.5632	17.4497
$(t.x.y.rooms)^{0.8}$.ln(t.x.y.rooms)	-9.7263	-4.52	0.000	-13.9441	-5.5085
y.spacious	0.0075	4.25	0.000	0.0040	0.0110
x.conservatory	0.0657	2.97	0.003	0.0223	0.1092
$x.house^{3}$	-120.6101	-7.03	0.000	-154.2352	-86.9850
$x.house^{4}$	35.5495	7.02	0.000	25.6276	45.4713
$x.y.house^{4}$	186.3960	7.1	0.000	134.8970	237.8949
$x.y.house^{4}$.ln(x.y.house)	-239.1487	-7.12	0.000	-305.0418	-173.2556
x.detached-bungalow	0.1960	6.47	0.000	0.1366	0.2554
y.semi-bungalow	0.0587	3.57	0.000	0.0264	0.0909
x.detached-villa	0.0387	1.72	0.085	-0.0054	0.0829
t.y.semi-villa	0.0039	3.77	0.000	0.0019	0.0059
x.house.Victorian	-0.0072	-0.52	0.602	-0.0344	0.0199
x.y.conversion	0.0222	13.69	0.000	0.0190	0.0253
t.x.garden	1.0133	1.32	0.188	-0.4959	2.5224
t.y.garden	0.1796	2.57	0.010	0.0424	0.3168
t.x.y.garden	-0.2217	-1.72	0.086	-0.4748	0.0314
x.y.views	0.0025	2.07	0.039	0.0001	0.0049
x.garage	1.7111	1.69	0.090	-0.2693	3.6915
t.y.parking	0.3374	3.77	0.000	0.1618	0.5129
t.x.y.parking	-0.1317	-3.76	0.000	-0.2004	-0.0631
y.luxury	-1.7461	-0.67	0.500	-6.8222	3.3301
$(x.bay)^{2.5}$	-185.1750	-10.74	0.000	-218.9919	-151.3581
$(x.bay)^{4}$	28.4327	10.77	0.000	23.2551	33.6103
$(x.y.bay)^{4}$	267.6344	10.71	0.000	218.6298	316.6391
$(x.y.bay)^{4}$ln(x.y.bay)	-341.7590	-10.72	0.000	-404.2703	-279.2478
t.x.bay	0.0035	1.32	0.186	-0.0017	0.0088
y.ensuite	0.0277	6.41	0.000	0.0192	0.0362
x.y.GCH	0.0078	5.83	0.000	0.0052	0.0105
t.x.GCH	-0.0032	-1.22	0.221	-0.0084	0.0019
$t.D_{2001}$	-0.0064	-0.03	0.975	-0.4131	0.4003
$t.D_{2002}$	0.1845	1.31	0.192	-0.0924	0.4614
$t.D_{2003}$	0.3895	2.54	0.011	0.0887	0.6903
TOM	-0.0004	-4.28	0.000	-0.0006	-0.0002
traditional-Victorian	0.0696	5.43	0.000	0.0444	0.0947
lower-flat	0.0206	1.51	0.131	-0.0061	0.0474
upper-flat	0.0246	1.77	0.077	-0.0027	0.0519

main-door-flat	0.1032	2.78	0.006	0.0303	0.1761
garage	-4.2435	-1.65	0.099	-9.2855	0.7986
parking	0.0435	1.27	0.206	-0.0239	0.1110
needs-upgrading	-0.1040	-1.76	0.079	-0.2200	0.0120
luxury	11.7956	0.68	0.495	-22.1156	45.7068
Spring	-0.0026	-0.15	0.885	-0.0379	0.0327
Summer	-0.0008	-0.03	0.972	-0.0444	0.0428
Autumn	-0.0256	-1.17	0.240	-0.0683	0.0171
D_{1999q2}	-0.1041	-2	0.046	-0.2064	-0.0018
D_{1999q3}	-0.2025	-3.3	0.001	-0.3230	-0.0820
D_{1999q4}	-0.2614	-3.81	0.000	-0.3958	-0.1270
D_{2000q1}	-0.4065	-5.33	0.000	-0.5561	-0.2569
D_{2000q2}	-0.3713	-4.69	0.000	-0.5266	-0.2160
D_{2000q3}	-0.4235	-4.89	0.000	-0.5935	-0.2535
D_{2000q4}	-0.4402	-4.79	0.000	-0.6204	-0.2599
D_{2001q1}	-0.5044	-1.13	0.259	-1.3801	0.3713
D_{2001q2}	-0.4854	-0.97	0.330	-1.4631	0.4923
D_{2001q3}	-0.5055	-0.93	0.354	-1.5746	0.5635
D_{2001q4}	-0.4768	-0.81	0.421	-1.6377	0.6841
D_{2002q1}	-1.0718	-2.39	0.017	-1.9527	-0.1909
D_{2002q2}	-0.9840	-2.03	0.042	-1.9332	-0.0349
D_{2002q3}	-1.0863	-2.11	0.035	-2.0960	-0.0765
D_{2002q4}	-1.1190	-2.05	0.040	-2.1895	-0.0485
D_{2003q1}	-1.9709	-3.08	0.002	-3.2268	-0.7149
D_{2003q2}	-2.0391	-3.04	0.002	-3.3537	-0.7244
D_{2003q3}	-2.0590	-2.9	0.004	-3.4504	-0.6675
D_{2003q4}	-2.1801	-2.93	0.003	-3.6393	-0.7210
D_{2004q1}	-0.2452	-2.07	0.039	-0.4780	-0.0124
Constant	-71.0876	-10.05	0.000	-84.9604	-57.2149
N	3,530				
F(75, 3,454)	112.630				
Prob > F	0.0000				
Adj R-squared	0.7035				

CBD = distance to central business district; GCH = gas central heating; TOM = time on the market

Table 6 Log-Normal Survival Models of Time on the Market

NB These regressions model the "survival on the market" of properties for sale, so positive coefficients indicate that a variable increases survival time (i.e. increases time on the market) whereas negative coefficients indicate that a variable reduces survival time (i.e. reduces time on the market).

	T3iA	T3iiA	T3iiB	T3iiiA	T3iiiB	T3ivA	T3ivB	T3vA	T3vB
	(1) Simple hedonic	(2) Simple hedonic	(3) Simple hedonic	(4) MFP hedonic	(5) MFP hedonic	(6) MFP hedonic with TOM control	(7) MFP hedonic with TOM control	(8) MFP hedonic with TOM control & π* adj.	(9) MFP hedonic with TOM control & π* adj.
	θ unadjusted	γ^*	γ^* var(γ_i)	γ^*	γ^* var(γ_i)	γ^*	γ^* var(γ_i)	γ^* π*	γ^* var(γ_i) π*
θ	0.017	0.007	0.045	0.010	0.099	0.013	0.101	0.009	0.092
	(0.664)	(2.385)	(4.975)	(1.510)	(4.212)	(1.897)	(4.410)	(1.447)	(4.264)
$\theta.\sigma_{\gamma_{ik}}$			-0.356		-0.608		-0.608		-0.572
			(-4.449)		(-3.946)		(-4.034)		(-4.017)
dQ_{ik}^{om}/Q_{ik}^{om}	0.098	0.095	0.091	0.116	0.115	0.116	0.115	0.103	0.101
	(2.703)	(2.639)	(2.533)	(3.188)	(3.168)	(3.198)	(3.176)	(2.857)	(2.815)
house	-0.168	-0.173	-0.174	-0.170	-0.183	-0.170	-0.185	-0.168	-0.180
	(-4.494)	(-4.625)	(-4.664)	(-4.526)	(-4.859)	(-4.536)	(-4.907)	(-4.500)	(-4.814)
bedrooms	0.103	0.102	0.102	0.102	0.102	0.101	0.102	0.102	0.102
	(6.783)	(6.750)	(6.773)	(6.690)	(6.702)	(6.660)	(6.703)	(6.706)	(6.731)
views	-0.106	-0.101	-0.102	-0.103	-0.103	-0.102	-0.102	-0.096	-0.096
	(-2.014)	(-1.932)	(-1.947)	(-1.953)	(-1.963)	(-1.945)	(-1.953)	(-1.833)	(-1.833)
driveway	-0.081	-0.082	-0.090	-0.076	-0.089	-0.076	-0.088	-0.077	-0.086
	(-1.052)	(-1.067)	(-1.166)	(-0.990)	(-1.154)	(-0.982)	(-1.147)	(-1.009)	(-1.122)
mature	-0.186	-0.182	-0.180	-0.182	-0.169	-0.181	-0.170	-0.180	-0.169
	(-1.849)	(-1.811)	(-1.794)	(-1.813)	(-1.692)	(-1.809)	(-1.696)	(-1.806)	(-1.694)
garden_d	-0.090	-0.095	-0.089	-0.090	-0.091	-0.089	-0.090	-0.088	-0.090
	(-3.270)	(-3.446)	(-3.262)	(-3.247)	(-3.296)	(-3.224)	(-3.261)	(-3.220)	(-3.279)
gch_d	-0.018	-0.014	-0.024	-0.017	-0.020	-0.018	-0.020	-0.012	-0.014
	(-0.689)	(-0.527)	(-0.929)	(-0.672)	(-0.764)	(-0.685)	(-0.790)	(-0.446)	(-0.543)
alarm	-0.121	-0.120	-0.126	-0.120	-0.120	-0.118	-0.120	-0.118	-0.119
	(-2.299)	(-2.270)	(-2.387)	(-2.261)	(-2.279)	(-2.233)	(-2.263)	(-2.242)	(-2.275)
bay	-0.046	-0.037	-0.045	-0.042	-0.039	-0.042	-0.038	-0.048	-0.044
	(-1.789)	(-1.467)	(-1.799)	(-1.646)	(-1.531)	(-1.661)	(-1.520)	(-1.885)	(-1.758)
y1999q4	-0.408	-0.411	-0.404	-0.401	-0.387	-0.399	-0.385	-0.354	-0.337
	(-5.727)	(-5.773)	(-5.698)	(-5.650)	(-5.451)	(-5.627)	(-5.423)	(-4.968)	(-4.734)
y2000q1	-0.205	-0.224	-0.242	-0.189	-0.188	-0.190	-0.193	-0.151	-0.160
	(-2.502)	(-2.723)	(-2.957)	(-2.293)	(-2.285)	(-2.308)	(-2.355)	(-1.840)	(-1.948)
y2000q2	-0.412	-0.402	-0.410	-0.416	-0.405	-0.415	-0.403	-0.370	-0.361

	(-5.377)	(-5.249)	(-5.374)	(-5.441)	(-5.296)	(-5.426)	(-5.280)	(-4.844)	(-4.735)
y2000q3	-0.481	-0.471	-0.484	-0.468	-0.446	-0.466	-0.444	-0.424	-0.405
	(-5.339)	(-5.231)	(-5.386)	(-5.185)	(-4.942)	(-5.160)	(-4.925)	(-4.704)	(-4.496)
y2000q4	-0.405	-0.391	-0.401	-0.424	-0.418	-0.423	-0.416	-0.385	-0.376
	(-4.051)	(-3.914)	(-4.028)	(-4.236)	(-4.183)	(-4.221)	(-4.159)	(-3.856)	(-3.776)
y2001q1	-0.436	-0.424	-0.440	-0.432	-0.426	-0.431	-0.424	-0.386	-0.371
	(-5.123)	(-4.989)	(-5.188)	(-5.092)	(-5.032)	(-5.081)	(-5.017)	(-4.558)	(-4.391)
y2001q2	-0.630	-0.621	-0.618	-0.636	-0.617	-0.634	-0.615	-0.590	-0.573
	(-7.818)	(-7.704)	(-7.693)	(-7.892)	(-7.663)	(-7.871)	(-7.642)	(-7.329)	(-7.129)
y2001q3	-0.646	-0.633	-0.634	-0.642	-0.636	-0.640	-0.633	-0.593	-0.585
	(-8.648)	(-8.465)	(-8.508)	(-8.547)	(-8.483)	(-8.518)	(-8.443)	(-7.899)	(-7.802)
y2001q4	-0.582	-0.565	-0.569	-0.579	-0.564	-0.577	-0.561	-0.534	-0.518
	(-6.507)	(-6.318)	(-6.383)	(-6.446)	(-6.281)	(-6.423)	(-6.250)	(-5.949)	(-5.786)
y2002q1	-0.739	-0.736	-0.721	-0.755	-0.730	-0.753	-0.727	-0.704	-0.673
	(-10.949)	(-10.901)	(-10.704)	(-10.725)	(-10.352)	(-10.695)	(-10.313)	(-9.980)	(-9.518)
y2002q2	-0.726	-0.713	-0.700	-0.725	-0.673	-0.722	-0.671	-0.674	-0.623
	(-10.928)	(-10.707)	(-10.540)	(-10.936)	(-9.984)	(-10.898)	(-9.965)	(-10.149)	(-9.238)
y2002q3	-0.765	-0.759	-0.736	-0.765	-0.729	-0.762	-0.727	-0.717	-0.682
	(-12.040)	(-11.967)	(-11.594)	(-12.075)	(-11.431)	(-12.026)	(-11.390)	(-11.283)	(-10.658)
y2002q4	-0.592	-0.582	-0.570	-0.591	-0.567	-0.589	-0.564	-0.543	-0.518
	(-9.490)	(-9.308)	(-9.136)	(-9.490)	(-9.071)	(-9.443)	(-9.020)	(-8.695)	(-8.265)
y2003q1	-0.592	-0.587	-0.567	-0.592	-0.561	-0.589	-0.559	-0.545	-0.515
	(-9.012)	(-8.941)	(-8.642)	(-9.042)	(-8.538)	(-9.002)	(-8.498)	(-8.302)	(-7.813)
y2003q2	-0.723	-0.715	-0.696	-0.725	-0.693	-0.722	-0.690	-0.676	-0.642
	(-10.993)	(-10.857)	(-10.589)	(-11.033)	(-10.490)	(-10.982)	(-10.445)	(-10.269)	(-9.704)
y2003q3	-0.653	-0.644	-0.626	-0.651	-0.608	-0.649	-0.605	-0.604	-0.563
	(-10.349)	(-10.185)	(-9.927)	(-10.347)	(-9.530)	(-10.303)	(-9.491)	(-9.567)	(-8.816)
y2003q4	-0.588	-0.582	-0.558	-0.586	-0.540	-0.584	-0.538	-0.542	-0.492
	(-8.726)	(-8.636)	(-8.286)	(-8.727)	(-7.945)	(-8.689)	(-7.908)	(-8.065)	(-7.226)
y2004q1	-0.371	-0.363	-0.345	-0.366	-0.316	-0.363	-0.313	-0.375	-0.332
	(-4.963)	(-4.855)	(-4.612)	(-4.903)	(-4.175)	(-4.866)	(-4.136)	(-4.893)	(-4.311)
Constant	3.909	3.884	3.901	3.887	3.871	3.882	3.866	3.841	3.825
	(66.978)	(66.674)	(67.023)	(66.639)	(66.375)	(66.463)	(66.205)	(65.440)	(65.175)
/ln(σ)	-0.378	-0.379	-0.382	-0.381	-0.383	-0.381	-0.384	-0.387	-0.389
	(-30.603)	(-30.668)	(-30.912)	(-30.603)	(-30.796)	(-30.619)	(-30.821)	(-30.994)	(-31.195)
N	3,275	3,275	3,275	3,228	3,228	3,228	3,228	3,212	3,212
	-	-	-	-	-	-	-	-	-
log-likelihood	3408.64	3406.02	3396.16	3350.87	3343.10	3350.21	3342.09	3315.55	3307.50
χ^2	332.30	337.54	357.27	336.96	352.49	338.28	354.51	310.18	326.28
AIC	6879.29	6874.04	6856.31	6763.74	6750.20	6762.42	6748.19	6693.10	6679.00
σ	0.69	0.69	0.68	0.68	0.68	0.68	0.68	0.68	0.68

Figures in brackets are t-ratios. Area k is defined as those properties within a 3km radius of property i.

θ is the degree of overpricing; $\theta.\sigma_{\gamma_{ik}}$ is the interaction of the overpricing variable with the standard deviation of local asking-selling price spreads. dQ_{ik}^{om}/Q_{ik}^{om} is a measure of market buoyancy, computed as the change in the quantity of properties on the market in area k, as a proportion of the number of properties on the market before the change. The period used to compute dQ_{ik}^{om}/Q_{ik}^{om} is the 60 day period prior to property i coming onto the market. π^* is the local backwards-looking house price inflation expectations measure, computed as the proportionate increase in average sale prices in area k in the previous 60 days.

Figure 1

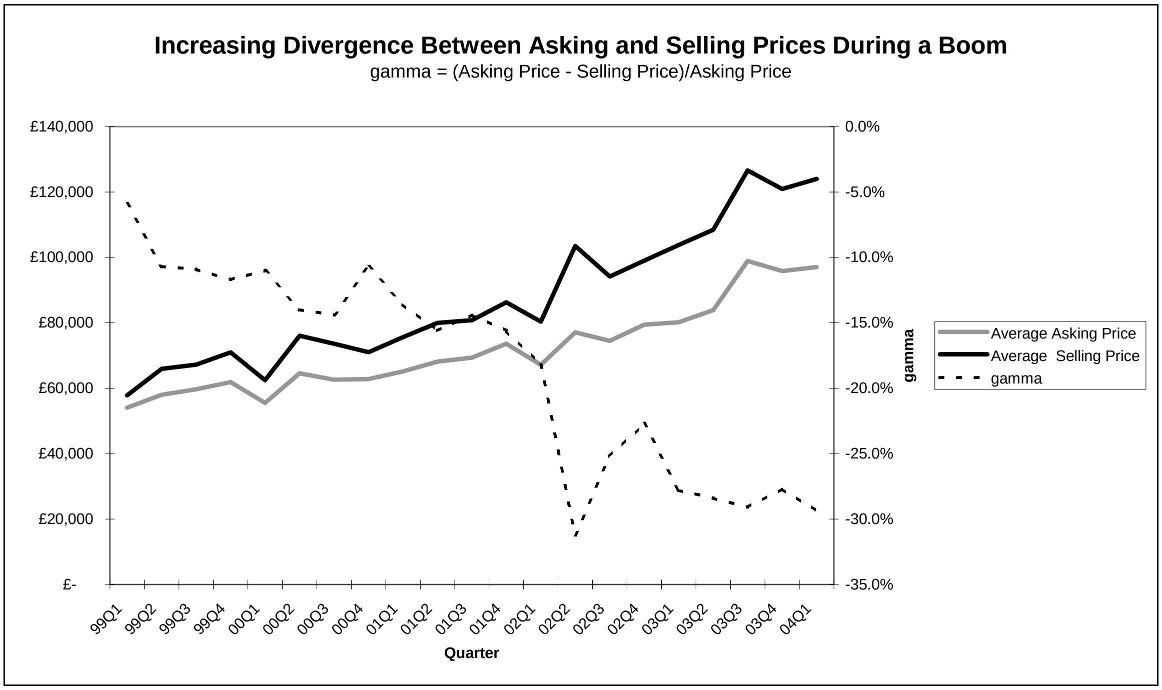


Figure 2

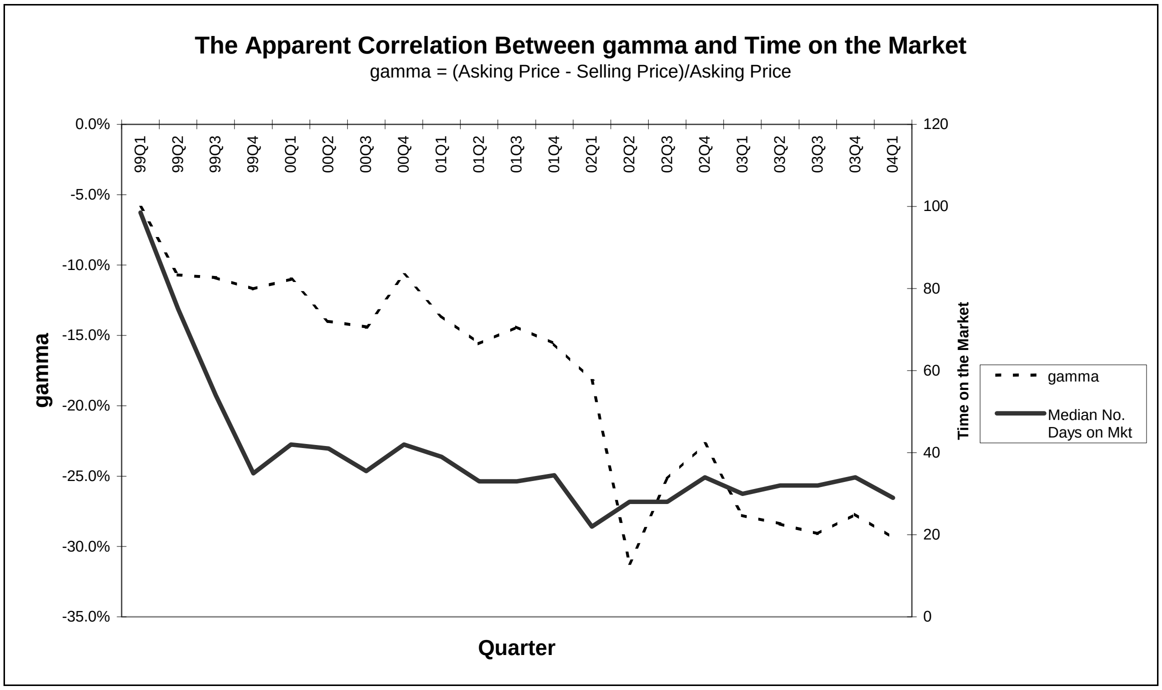
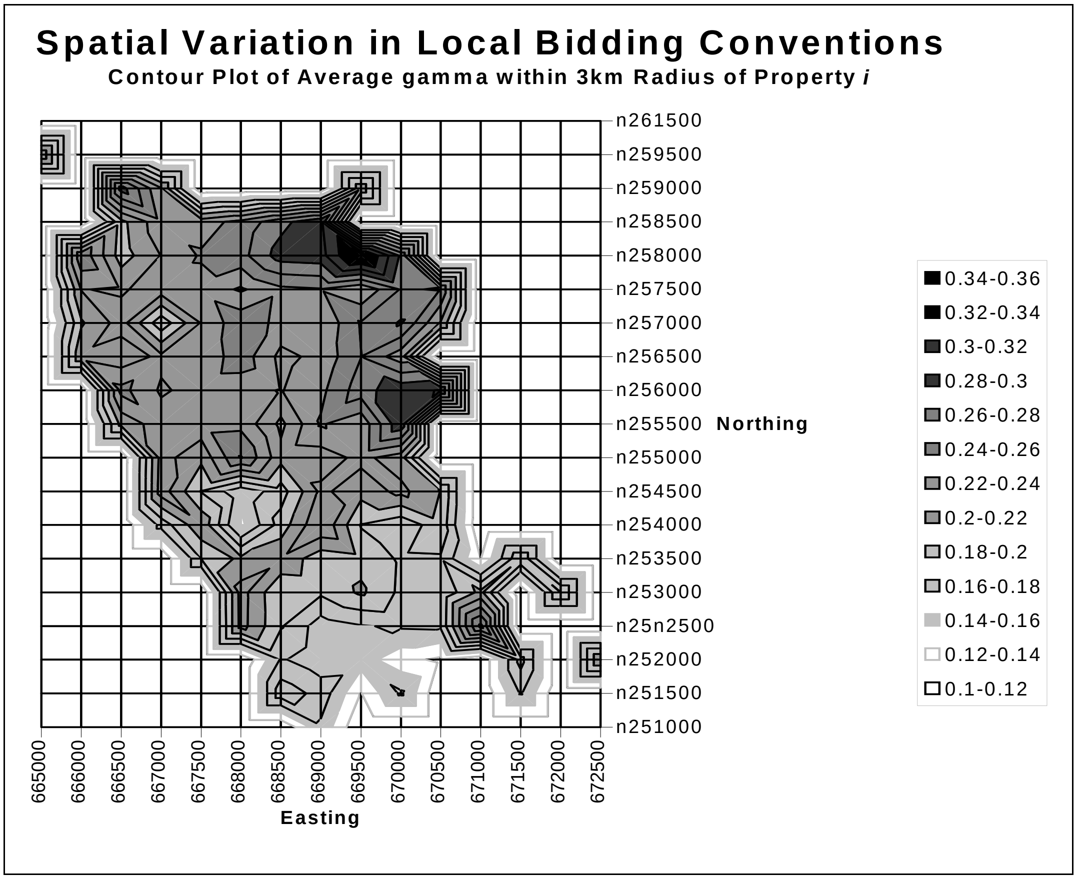


Figure 3


Spatial Variation in Local Bidding Conventions
Contour Plot of Average gamma within 3km Radius of Property i
n261500
n259500
n259000
n258500
n258000
n257500
n257000
n256500
n256000
n255500
n255000
n254500
n254000
n253500
n253000
n25n2500
n252000
n251500
n251000
Northing
665000
666000
666500
667000
667500
668000
668500
669000
669500
670000
670500
671000
671500
672000
672500
Easting
0.34-0.36
0.32-0.34
0.3-0.32
0.28-0.3
0.26-0.28
0.24-0.26
0.22-0.24
0.2-0.22
0.18-0.2
0.16-0.18
0.14-0.16
0.12-0.14
0.1-0.12