Measuring the Degree of Overpricing in a Sealed-Bid System:

with an Application of Multiple Fractional Polynomial Estimation to Hedonic Pricing

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Abstract

How do buyers judge whether a property is overpriced? Do they base their judgement simply on the difference between the asking price and the expected selling price or do they take into account the size of this differential relative to typical bid-offer spreads in the locality? Also, do they adjust their perceptions according to anticipated house price inflation? And when estimating the market value, how sophisticated is the procedure used to gauge the composite value of the location and attribute bundle? This paper considers these questions in the context of the Scottish sealed bid system. An adjusted measure is developed which controls for differences in local bidding conventions, price expectations and dwelling attributes. Comparison is made between a simple hedonic estimation of selling price and a complex Multiple Fractional Polynomial estimation. Measuring overpricing relative to the local average bid-offer spread is found to increase the significance of the overpricing variable in a log-normal survival model of marketing time. At the same time, the variance of local bid-offer spreads is found to mitigate the overpricing effect, confirming the proposition put forward in the paper that uncertainty about local bidding conventions will dampen the impact of overpricing on marketing time. Improvements to the hedonic method do not translate into corresponding improvements in the statistical significance of the overpricing variable, which may suggest that buyers and sellers base their estimation of the market value of a property on relatively simple calculations.

Introduction

The degree of overpricing has proved to be a crucial concept in both theoretical and empirical models of the housing transactions process. In particular, it has been found to be a significant determinant of time on the market (TOM). However, the literature on overpricing is predominantly American and almost exclusively in the context of list-price (or equivalent) selling systems. This paper considers the meaning of overpricing 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). Overpricing appears, at first, to have little meaning in such a setting. The paper offers a rationale for the concept in the sealed-bid context and considers the appropriate method of measurement.

The findings have implications not only for sealed-bid auctions but also for the modelling of overpricing in a list-price system. A crucial insight offered in the paper is that different submarkets will have different informal "conventions" with respect to 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 overpricing. It means that, for a property to be described as "overpriced", the difference between asking and selling price has to be measured relative to the *average bid-offer spread in the locality*. In the data considered (3,696 sales in the West End of Glasgow, Scotland) I find that on average the difference between asking and selling price rises (i.e. the "convention" changes) systematically 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 overpricing therefore give a biased estimate of the effect of overpricing because of the distorting effect of the incidental time-series correlation between the relative bid-offer spread and marketing time (see Figure 1 and Table 2). The true effect of overpricing can only be ascertained when this spurious time series correlation is controlled for (otherwise we have to assume that market agents take no account of the cyclical and secular movements in the average bid-offer spread when deciding whether a property is overpriced).

The paper also highlights the potential for further bias arising from the hedonic method used to predict the expected selling price of a property (crucial to the computation of most overpricing measures). Most hedonic regressions used in the computation of overpricing do not account for possible spatial or temporal variation in attribute prices. I I attempt to address this by employing a Fik et al (2003) type interactive hedonic regression. I extend the Fik et al approach by including a time interaction variable, along with lattitude and longitude interactions, and by applying Multiple Fractional Polynomial Estimation (MFP). MFP offers a new level of flexibility in functional form estimation, allowing for non-integer and non-positive power transformations of explanatory variables. The final section of the paper presents a log-normal survival model of time on the market used to compare the performance of different measures of overpricing.

Existing literature

Initial measures of overpricing were computed as the difference between asking and selling price as a proportion of selling price (Belkin, Hempel and McLeavey, 1976; Kang and Gardner, 1989;). Simple mark-up measures of this kind, however, are susceptible to distortions from the idiosyncrasies of individual sales. They are also particularly vulnerable to the distorting effect of concurrent cyclical movements in the average bid-offer spread and time on the market noted in the introduction. A preferred measure, therefore, is one that compares the asking price with the expected market price. Yavas and Yang (1995), for example, use the log of the ratio of predicted sale price to the listing price:

standard 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 (2001) 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 2001, p. 450). There remain a number of problems with this approach, however. *First*, there is the question of whether there are informal "conventions" regarding the bid-offer 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 TOM. *Second*, there are specification issues surrounding the computation of predicted selling price – overpricing variables may simply be measuring misspecification error in the hedonic price equation (hedonic regressions in most of the studies of overpricing have not, for example, accounted for non-linearities or spatial/temporal shifts in slope parameters). *Third*, 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 2001), 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). *Fourth*, expected movements in headline house price levels need to be controlled for, otherwise apparent "overpricing" 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 overpricing, having emerged in a literature devoted almost entirely to the analysis of sealed-bid systems, is transferable to alternative institutional settings. This question is discussed in this paper with reference to the Scottish sealed bid system as I attempt to construct a measure of overpricing that incorporates the aforementioned caveats.

Definition of over pricing in a sealed-bid system

Does the concept of overpricing have any meaning in the context of a sealed-bid system where asking prices are usually set well below the selling price? The concept seems at first to have little meaning in this setting, but on further examination, its relevance becomes clear. The converse statement, that no property is more overpriced than another, cannot be true because this would preclude the possibility of one seller offering a higher asking price (for the same property in a similar location and time period) than another seller. The quandry is essentially an informational one: how can a property be perceived to be overpriced in a sealed bid setting when most bids will exceed the asking price? In the Scottish 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. 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. The bid-offer 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 advise 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 given the cost of bidding (the cost of bidding is the price of having a professional survey done which is a prerequisite to bidding given that bids are legally binding – if the seller approves a bid, the bidder must follow through with the purchase).

We can formalize this process as follows. Let γ_i be the difference between asking and selling price 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* entity 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[1] 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 idiosynchratic 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. So if v_i = 0, the seller's reservation price is £120K, and the local convention on the bid-offer spread is -20% (i.e. properties in the area tend to sell for twenty per cent over the asking price), the seller will set the asking price at £100K. A property is said to be overpriced, therefore, when the expected market price, P_{ik}^{S*} is less than the asking price plus the current local differential,

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

So, sellers seeking to effect a rapid sale may set the asking price 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.

The degree of overpricing, θ, is given by,

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

It follows that:

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

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

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

The impact of overpricing on the probability of sale

Assume that potential bidders perceive the asking price to be a signal of the sellers reservation price. If (1 - γ_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 - γ_k^*) Pi^A + e_i^R, where $e_i^R \sim$ *iid*,

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*,

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

where $\sigma_{\gamma_{ik}}$ is the standard deviation of γ_i in area k , θ is the degree of overpricing, 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 overpricing relative to the current convention, the lower the number of bids. The second inequaility states that the inpact of overpricing on the number of bids is ameliorated by the standard deviation of the relative bid-offer 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 overpriced.

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,

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

,

where *b = 1, 2, ...*λ 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 overpricing (measured with respect to the current market convention on the bid-offer spread in area *k*) rises, the probability of sale falls in the current period (cf Green and Vandall who show that overpricing slows the rate of offers).

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". When asked, their 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. This explanation raises the question of why the bid-offer spread seems to rise systematically during a boom. During a slump one would think that there would be equally good, if not greater, reason to maximise 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. Two complementary explanations are worth considering. First, estate agents attempt to talk up the market and there is greater scope for doing this during an upswing. Reports of growing bid-offer spreads is a commonly perceived sign of a bouyant market and so 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 maximise 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, agents seek to maximise the variance of spreads not just the average spread. To illustrate, suppose we increase the variance if bids in such a way that for every increased bid there is an equivalent decrease in another bid. As a result, the mean bid stays the same in a symmetrical distribution, but will rises in a lower truncated normal distribution. Such a truncation of bids is likely because few will bid below the asking price given that the asking price is at least as large as the seller's reservation price. Either way, it is usually the maximum bid which the seller selects all sealed bids are finally revealed, so as the variance increases so does the likely maximum bid. Agents are keen to inform bidders of recent rises in local spreads because this helps to raise the average bid. This has limited effect, however, as bidders base their perception of the mean of the likely distribution of bids on recent local averages which agents cannot affect after the event. As such, there is no difference in the rise in the average bid compared to a fixed spread regime. However, if uncertainty rises with divergence then the greater the mean bid-offer spread and the greater the variation in the bid-offer spread (as the mean bid moves away from the lower truncation the variance of the distribution rises). So agents have an incentive to maximise the spread.

During downturns, the lower truncation (i.e. the asking price) cannot be reduced very much because the sellers reservation price will have a floor even in the severest slumps due to negative equity (see Stein, 1995). So the reservation price acts as a lower bound to the asking price and during a slump in the housing market, the asking price will converge towards this lower bound.

Possibility of Positive Herding in a sealed bid system?

Taylor (1999, p.556) argues 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." He contrasts this with the finding in the strategic pricing and consumer experimentation literature that shows that firms will "set low introductory prices so as to promote the flow of information among consumers, ie so as to encourage herding". 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 in a sealed bid system where the *number of viewers can act as a signal of quality/demand*. If there are many viewers, then interested buyers will be more likely to view the house as a desirable residence and will anticipate a larger number of bids. Because 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 maximising their chances of offering the highest bid. Note that the final number of bids is often not known to any party until after the bidding has closed since many bidders do not put in a bid until 30 minutes or less before the final deadline for bids.

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 a bargaining system (such as the list price systems in England and North America). Note that this cyclical asymmetry will result in an apparent correlation between overpricing and TOM, but this correlation is not causal.

Application to the List Price System

The qualifications introduced above to the definition and measurement of overpricing can be applied to other selling systems. It is perfectly feasible, for example, that buyers and sellers in a list price system will also be influenced by local bidding conventions when forming their beliefs about whether a property is overpriced. For example, if in a list price system the buyer knows that selling prices tend to go for around 20% below list price, he will bargain accordingly, unless he thinks the seller has set the asking price at odds with local bidding conventions, in which case the bidder may view the property as being overpriced and either offer less than 80% of the asking price, or if there is a cost to bidding, consider alternative properties.

The property will therefore be perceived as under or over priced relative to the current *convention*. This distinction only has any notable implications for the measurement of overpricing if the convention for γ varies significantly across submarkets and over time. That certainly seems to be the case in the Scottish sealed bid system (see Figure 1, Figure 2, and Figure 3) though it has yet to be verified whether similar discrepancies occur in list price systems. The other concerns listed in the literature review (and again below) about existing definitions of overpricing apply directly to list price systems.

Econometric Strategy

Problems with existing measures of DOP

Compare equation (3) with the following unadjusted measure of overpricing (denoted by $\theta^{\#}$),

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

where $P_i^{H\#}$ is the predicted value from a hedonic price regression for dwelling i. There are a number of sources of potential error associated with θ. First, the ommission of γ_{kt}^* will result in the degree of overpricing 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. A second potential source of bias arises from the specificaiton of $P_i^{H\#}$. 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.

Third, $P_i^{H\#}$ 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. Fourth, the rate of house price inflation has 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.

Explanation of Multiple Fractional Polynomial Estimation

The first step in achieving a measure of overpricing 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 agents use sophisticated valuation procedures in their perception of overpricing,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 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 Applied Statistics) argued that one of the weaknesses of conventional "integer" polynomial models (such as that of Fik et al) is that quadratic functions are "severely limited in their range of curve shaps", whereas "cubic and higher order curves often produce undesirable artifacts, such as "edge effects" and "waves"" (Stata manual, p.400). 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,

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

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,

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

(see Stata manual, p. 402). 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 peculiliar 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. Royston and Altman (1994, *Applied Statistics*) suggested a possible algorithm for joint estimation of fractional polynomials of several continuous variables, an approach later refined by Sauebrei and Royston (1999) and made available in Stata programming format. This is the algorithm applied here. It involves ordering the continuous explanatory variables eligible for fractional polynomial transformation into order of increaseing *p*-values with a view to modelling relatively significant variables before relatively insignificant ones. This approach, Sauebrei and Royston (1999) argue will "help reduce the potential model-fitting difficulties causes by collinearity or more generally, "concurvity", among the explanatory variables" (Stat manual, p. 401). It was found that MFP estimation works best if it starts with a reasonably well specified model. Therefore, prior to MFP estimation, an OLS stepwise procedure was run. This was akin to Fik et al 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.

Data

Table 1 presents summary statistics on the data which were provided 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. $\mathrm{d}Q_{ik}^{om}/Q_{ik}^{om}$ 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 seling 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 bid-offer 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 I define area k 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.

Table 1 Descriptives

	n	mean	sd
askingpr	3,445	76897.100	41522.980
sellingp	3,305	97169.970	57503.850
tom	3,352	41.408	41.682
dQ_{ik}^{om}/Q_{ik}^{om}	3,377	0.147	0.365
γ_i	3,377	0.159	0.034
hous_all	3,445	0.185	
bedrooms	3,425	1.989	
views	3,445	0.056	
driveway	3,445	0.025	
mature	3,445	0.015	
garden_d	3,445	0.506	
GCH	3,445	0.554	
alarm	3,445	0.054	
bay	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_I

	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%	

Figure 1

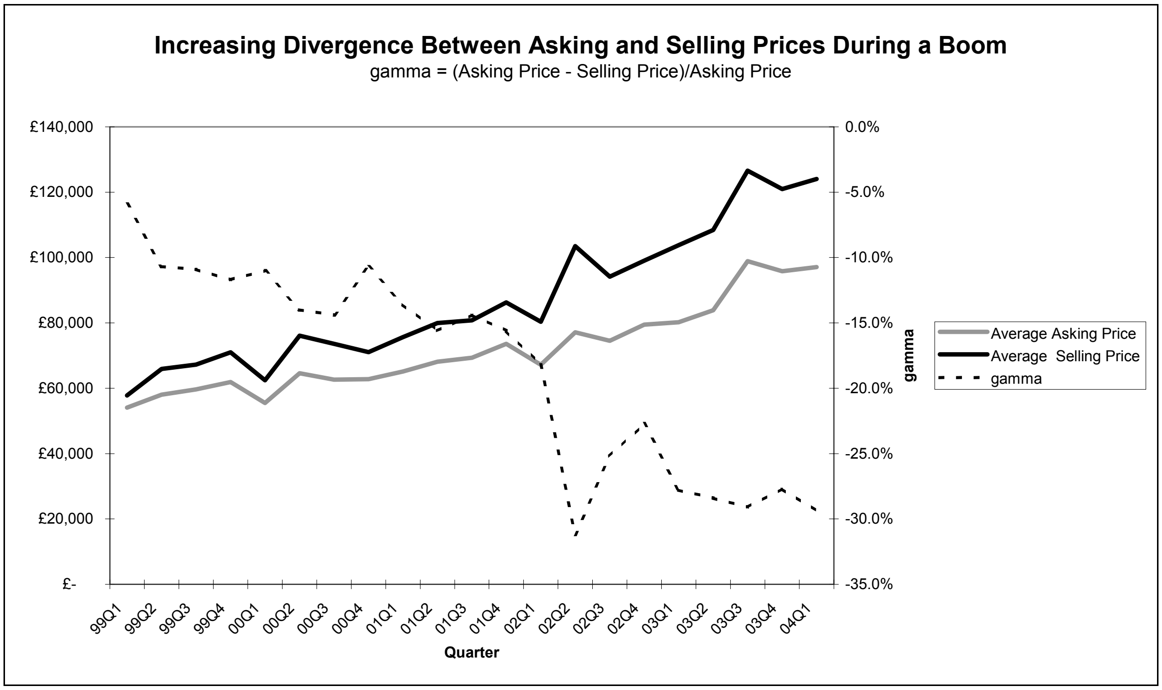


Figure 2

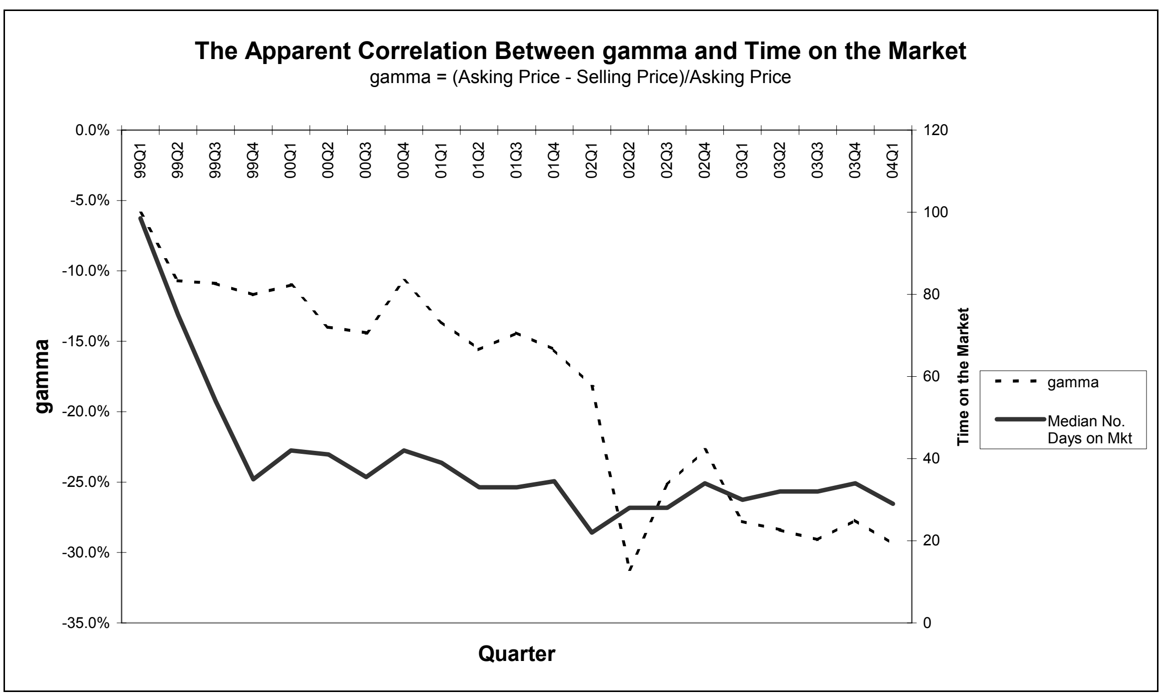
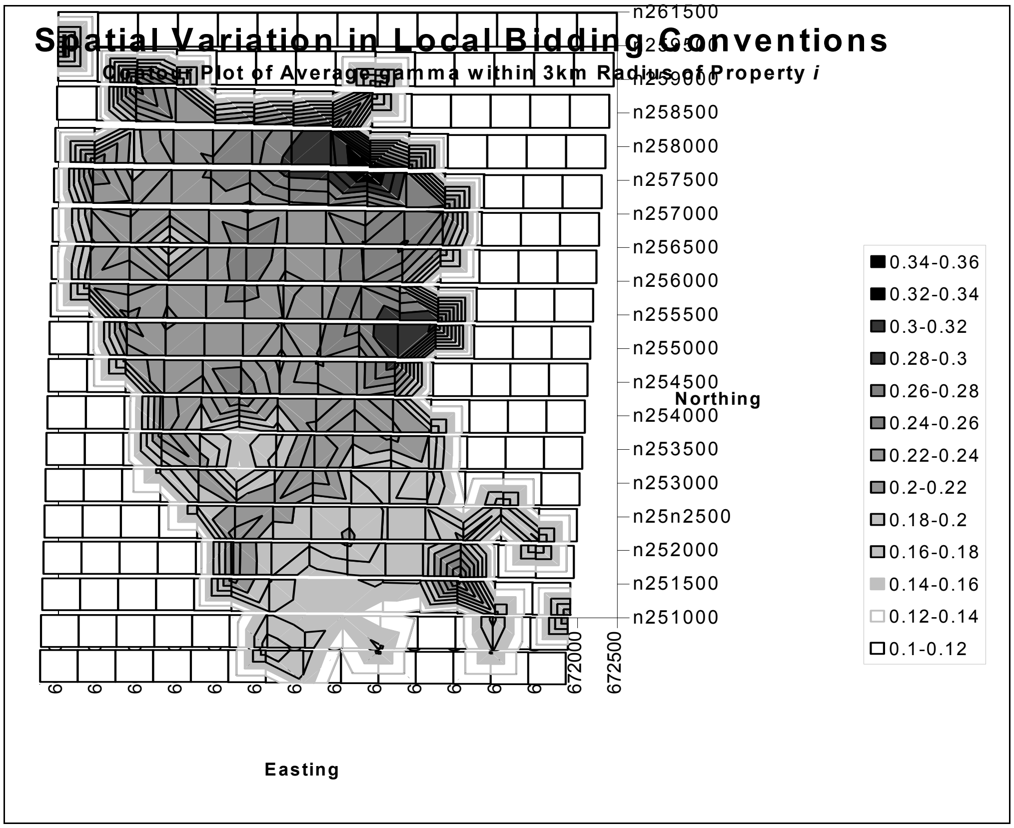


Table 3 Variation in γ Across Post Code Sectors

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**

Figure 3



Hedonics

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.

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	
$\text{bedrooms}^{0.4}$	-0.6875	-6.97	0.000	-0.8809	-0.4941
$\text{bedrooms}^{3.5}$	-1.1657	-5.03	0.000	-1.6198	-0.7117
$\text{publicrooms}^{-0.6}$	-0.1987	-3.87	0.000	-0.2994	-0.0980
$\text{CBD}^{0.2}$	19.8890	16.61	0.000	17.5416	22.2364
$\text{CBD}^{0.2}.\ln(\text{CBD})$	-3.3073	-17.04	0.000	-3.6878	-2.9268
x.rooms	2.8067	4.24	0.000	1.5100	4.1035
$(\text{x.y.rooms})^{-2}$	0.0737	7.2	0.000	0.0536	0.0937
x.y.rooms	-41.2626	-4.17	0.000	-60.6702	-21.8549
$(\text{t.x.rooms})^{0.6}$	-93.0295	-3.96	0.000	-139.1218	-46.9373
t.x.rooms	130.2189	4.81	0.000	77.1646	183.2732
$(\text{t.x.y.rooms})^{0.8}$	10.5065	2.97	0.003	3.5632	17.4497
$(\text{t.x.y.rooms})^{0.8}.\ln(\text{t.x.y.rooms})$	-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
$\text{x.y.house}^{4}.\ln(\text{x.y.house})$	-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
$(\text{x.bay})^{2.5}$	-185.1750	-10.74	0.000	-218.9919	-151.3581
$(\text{x.bay})^{4}$	28.4327	10.77	0.000	23.2551	33.6103
$(\text{x.y.bay})^{4}$	267.6344	10.71	0.000	218.6298	316.6391
$(\text{x.y.bay})^{4}\ln(\text{x.y.bay})$	-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

Impact of Overpricing on Marketing Time

In this section I construct a series of survival models of time on the market to compare the effects of different definitions of overpricing. Note that improvements in definition and measurement will not necessarily translate into higher t-values or larger coefficients. While the effects of uncorrected measures are blunted by the distortions inherent in their computation, they may also contain a spurious time-series correlation between contemporaneous momvents in time on the market and the bid-offer spread (see Figure 2). Note that if the data include submarkets that are at different phases of the housing cycle, the specious 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^*. Evidence has been found for a positive correlation between overpricing and time on the market. Measuring overpricing relative to the local average bid-offer spread increased the significance of the overpricing variable in a log-normal survival model of TOM. The improvement was surprisingly large given that the paper has argued that stripping out the spurious time-series correlation between TOM and average bid-offer spreads would ameliorate any gains from improvements in measurement precision. The variance of local bid-offer spreads also proved to be highly statistically significant in all the regressions and continued the proposition that the effect of overpricing would be mitigated by the degree of uncertainty regarding whether a property was in fact overpriced. The lower the variance of bid offer-spreads in an area, the easier it is to spot excessively high asking prices. Interestingly, improvements to the hedonic regression did not translate into corresponding improvements in the t-ratios of the overpricing variable. This suggests that market agents base their calculation of overpricing on relatively simple calculations. Attempts to capture the inflation expectations did not prove successful. Future versions of the paper will attempt to construct more robust measures of expectations with a view to rectifying this.

I also seek to use the survival models to test the proposition presented in the theoretical section 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 overpriced, and this will dampen the impact of overpricing on marketing time. In the regressions that follow, the standard deviation of γ_{ik} is used to measure the degree of uncertainty, where k is taken to be the area within a 3km radius of property i (if a radius smaller than 3km is used, there are sample size problems).

The variety of definitions of overpricing are compared log-normal survival model which controls for dwelling attribute differences between variables, and variations (between areas and over time) in market buoyancy at the time property i comes onto the market (Pryce and Gibb 2003 argue that failure to control for variation in market buoyancy across space and over time distorts the estimation of the survival function). The measure used to control for market buoyancy is dQ_{ik}^{om}/Q_{ik}^{om}, the change in the quantity of properties on the market 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 dQ_{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.

Results: Control Variables

First consider the results for the control variables reported in the various models (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 coefficient on the "house" and "garden" variables indicates 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 overpricing 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).

Comparing Overpricing Measures

Consider first survival regression (1). This has the unadjusted measure of overpricing 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 bid-offer 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]).

Regression (3) includes the same measure of overpricing as regression (2) but also includes, $\theta.\sigma_{\gamma_{ik}}$, the interaction the variance of proportional bid-offer spreads in area k. This variable is highly significant and negative in all three of the regressions which include it (3, 5, and 7), suggesting that the impact of overpricing is mitigated by uncertainty about the current local bidding convention.

Regressions (4) to (9) use the MFP estimation procedure to calculate the expected sale price. Although the size of the overpricing effect tends to be larger when this approach is used, the standard error rises also, 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 overpricing 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 their respective 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 overpricing. Put another way, overpricing will only affect time on the market if buyers and sellers realize that the property is overpriced because it is perceived *ex ante* to be over priced, rather than because of actual *ex post* discrepancies between asking and sale prices.

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), introduce a house price inflation expectations correction, π_k^*, to the definition of overpricing. 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 overpricing, is estimated as the predicted value from the hedonic regression multiplied by $(1+ \pi_k^*)$:

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

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 overpricing measures. It has also substantially reduced the t values on the market buoyancy measure 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.

Conclusion

In this paper I have argued that the interpretation of existing measures of overpricing is ambiguous because of a number of conceptual and measurement deficiencies inherent in these measures. This paper has attempted to reason through what the appropriate definition should be in a sealed-bid context. Evidence has been found for a positive correlation between overpricing and time on the market. Measuring overpricing relative to the local average bid-offer spread increased by a considerable margin the significance of the overpricing variable in a log-normal survival model of TOM. The improvement was surprisingly large given that the paper has argued that stripping out the spurious time-series correlation between TOM and the average bid-offer spread would ameliorate any gains due to advances in measurement precision. The variance of local bid-offer spreads also proved to be highly statistically significant in all the survival regressions and this confirmed the proposition that the effect of overpricing would be mitigated by the degree of uncertainty regarding whether a property was truly overpriced.

Interestingly, improvements to the hedonic method used to compute the expected market price did not translate into corresponding improvements in the statistical significance of the overpricing variable. This perhaps suggests that market agents base their estimation of the market value of a property on relatively simple calculations. Attempts to capture house price inflation expectation effects did not prove successful. Future versions of the paper will attempt to construct more robust measures of expected house price inflation (based on constant quality price change, for example).

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 the local bid-offer 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 house price inflation expectations measure, computed as the proportionate increase in average sale prices in area k in the previous 60 days.

References:

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 (2001) 'The Trade-off between the Selling Price of Residential Properties and Time-on-the-Market: The Impact of Price Setting', paper presented at European Real Estate Society meeting, Alicante, June.

Brown, M.B. and A.B. Forsythe (1974) Robust test for the equality of variances, Journal of the American Statistical Association, 69:364-367.

Chinloy, P (1980) 'An Empirical Model of the Market for Resale Homes', Journal of Urban Economics, Vol. 7, pp.279-92.

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

Conover, W.J., Johnson, M.E. and Johnson, M.M. (1981) A comparative study of tests for homogeneity of variances, with applications to the outer continental shelf bidding data, Technometrics, 23: 351-361.

Forgey, F, Rutherford, R and Springer, T (1996) 'Search and Liquidity in Single-Family Housing', Real Estate Economics, Vol. 24, pp. 273-92.

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

Grambsch, P.M. and T.M. Therneau (1994) 'Proportional hazards tests and diagnostics based on weighted residuals' Biometrika 81:515-526

Haurin, D (1988) 'The Duration of Marketing Time of Residential Housing', AREUEA Journal, Vol. 16, pp. 396-410.

Horovitz, J (1986)

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

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

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

Klein and Moeschberger (1997)

Kluger, B and Miller, N (1990) 'Measuring Real Estate Liquidity', AREUEA Journal, Vol. 18, pp. 145-59.

Knight, J (2000) 'Listing Price, Time on the Market and Ultimate Selling Price: Causes and Effect of Hidden Listing Price Changes'. Working Paper, University of the Pacific, Stockton, CA.

Knight, J, Sirmans, CF and Turnbull, G (1998) 'List Price Information in Residential Appraisal and Underwriting', Journal of Real Estate Research, Vol. 15, pp.59-76.

Krainer, J (2001) 'A Theory of Liquidity in Residential Real Estate Markets', Journal of Urban Economics, Vol. 49, pp. 32-53.

McAfee, R and McMillan, J (1987) 'Auctions and Bidding', Journal of Economic Literature, Vol. 25, pp. 699-738.

Michaels, R. G. and Smith, V. K. (1990) "Market Segmentation and Valuing Amenities with Hedonic Models: The Case of Hazardous Waste Sites", Journal of Urban Economics, 28, 223-242.

Palm, R. (1978) "Spatial Segmentation of the Urban Housing Market", Economic Geography, 54, pp.210-221.

Royston, P. and D. G. Altman (1994) Regression using fractional polynomials of continuous covariates: parsimonious parametric modelling, *Applied Statistics* 43(3): 429-467.

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

Sauerbrie, W. and P. Royston, (2002) Corrigendum: Building multivariable prognostic and diagnostic models: transformation of the predictors by using fractional polynomials, *Journal of the Royal Statistical Society*, (Series A) 165: 299-300.

Schoenfeld, D. (1982) 'Partial Residuals for the Proportional Hazards Regression Model', Biometrika 69:239-241

Turnbull, G and Sirmans, CF (1993) 'Information, Search and House Prices', Regional Science and Urban Economics, Vol. 23, pp. 545-57.

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