2006 V34 3: pp. 377–415
REAL ESTATE
ECONOMICS

Submarket Dynamics of Time to Sale

Gwilym Pryce* and Kenneth Gibb**

We argue that the rush to apply multiple regression estimation to time on the market (TOM) durations may have led to important details and idiosyncrasies in local housing market dynamics being overlooked. What is needed is a more careful examination of the fundamental properties of time to sale data. The approach promoted and presented here, therefore, is to provide an examination of housing sale dynamics using a "step-by-step" approach. We present three hypotheses about TOM: (i) there is nonmonotonic duration dependence in the hazard of sale; (ii) the hazard curve will vary both over time and across intra-urban areas providing evidence of the existence of submarkets and (iii) institutional idiosyncrasies can have a profound effect on the shape and position of the hazard curve. We apply life tables, kernel-smoothed hazard functions and likelihood ratio tests for homogeneity to a large Scottish data set to investigate these hypotheses. Our findings have important implications for TOM analysis.

In the past 30 years, there have been over 20 published studies of time on the market (TOM) for residential properties. The number of papers doubled in the 1980s,[1] compared with the 1970s.[2] The number doubled again in the 1990s,[3] and there is a good chance that the number of papers will double again by the end of the current decade.[4] This bourgeoning of the literature is partly driven by the increasing popularity of survival analysis techniques per se (assisted by their incorporation into popular statistical software packages) and partly because of the emerging availability of suitable housing data. With

*Department of Urban Studies, University of Glasgow, Glasgow G12 8RS or g.pryce@socsci.gla.ac.uk.
**Department of Urban Studies, University of Glasgow, Glasgow G12 8RS or k.gibb@socsci.gla.ac.uk.

[1] For example, see Zuehlke (1987), Haurin (1988), Kang and Gardner (1989) and Larsen and Park (1989).

[2] For example, see Cubbins (1974) and Miller (1978).

[3] For example, see Kluger and Miller (1990), Asabere, Huffman and Mehdian (1993), Kalra and Chan (1994), Jud, Seaks and Winkler (1996), Sirmans, Turnbull and Dombrow (1995), Yang and Yavas (1995), Yavas and Yang (1995), Forgey, Rutherford and Springer (1996), Springer (1996) and Glower, Haurin and Hendershott (1998).

[4] For example, see Genesove and Mayer (2001), Huang and Palmquist (2001), Munneke and Yavas (2001) and Anglin, Rutherford and Springer (2003).

respect to the second cause, the present study is a case in point: this is the first large-sample published analysis of residential time to sale in the United Kingdom. The only previous United Kingdom–based paper was the very first in the literature (Cubbins (1974), based on 83 sales in Coventry, England). To our knowledge, all other published studies have used U.S. data.

We argue that the rush to apply multiple regression estimation to TOM may have led to important details and idiosyncrasies in local market dynamics being overlooked. What is needed is a more careful examination of the fundamental properties of time to sale data. The approach promoted and presented here, therefore, is to provide an examination of housing sale dynamics using a step-by-step approach. Kernel-smoothed nonparametric estimates of the aggregate hazard function (complemented by life table analysis and likelihood ratio tests) are applied to different subgroups of housing sales over different time periods. This anatomy of the selling process reveals insights and caveats previously unexamined in the housing literature—results that can inform future analysis of time to sale and related topics.

The starting point for our article is that time to sale cannot be analyzed in the same way as other continuous variables. This is because it is a "duration" variable and hence subject to two crucial characteristics: time-dependency and censoring. The first of these relates to the fact that the probability of sale in any given period may itself be contingent on the length of time a property has already been on the market. As each day goes by, the probability of sale for a property on the market may change. Traditional approaches to estimating probability, such as logit and probit regression, assume that the probability of sale is independent of duration and so are unlikely to be applicable (note that this includes the application of Heckman correction of liquidity bias in hedonic regression, which relies on simple probit estimates of the probability of sale). The second effect arises because some properties will be withdrawn from the market before sale or remain unsold at the time of analysis. Ordinary least squares (OLS) and two-stage least squares (2SLS) techniques do not account for the effect of censoring, neither do they allow for the possibility of duration dependence (though both have been widely used in the housing literature; see, for example, Miller (1978), Kang and Gardner (1989), Asabere, Huffman and Mehdian (1993) and Forgey, Rutherford and Springer (1996)).

Techniques (developed largely in the medical statistics literature), which explicitly account for both these phenomena have become known as duration (or "survival" or "time to event") models. Most of these techniques use the log of the relative hazard as the dependent variable. The meaning of "hazard" is similar to that of "probability," except that a hazard may vary between zero and infinity whereas probabilities vary between zero and one. So the "hazard of sale" can be thought of as simply a monotonic transformation of the probability of sale. The "relative" hazard accounts for the duration the property has already been on the market. In this article, we are particularly interested in how the (relative) hazard behaves over the duration of selling time (duration is also called "analysis time" = the number of days a property has been on the market). That is, we want to know whether the hazard remains constant, rises or falls with TOM. We shall therefore be examining the "hazard function"—the hazard of sale as a function of analysis time. We also want to know whether (and how) the hazard function changes over time, across space and by marketing method.

The shape and stability of the hazard function is important because it will determine which empirical technique is most applicable. If the hazard function is flat (*i.e.*, completely horizontal over the entire length of time a property is on the market), then we know that the hazard of sale is not duration-dependent. This means that even the most basic duration technique—one that assumes exponentially distributed errors—could be applied, as could the more sophisticated approaches—those that assume Weibull, Log-logistic, Log-normal or Gompertz distributions, or those which adopt a semi-parametric approach. If, however, the hazard function is not horizontal, but either continually rising or falling, then the Exponential approach is inappropriate because it assumes duration independence in the hazard of sale. The choice of modeling technique is further limited if the hazard function is nonmonotonic because both the Weibull and the Gompertz duration models assume a monotonic hazard function. Further problems arise if the hazard function is not stable over time or across areas or institutional arrangements. Because nearly all existing studies are based on data aggregated for a particular city over a maximum of two years (Cubbins 1974, Miller 1978, Zuehlke 1987, Haurin 1988, Larsen and Park 1989, Kluger and Miller 1990, Yang and Yavas 1995, Yavas and Yang 1995), it is not clear whether their results are peculiar to the particular phase of the housing cycle considered. The literature has yet to reveal whether or how the hazard curve changes over time or across submarkets. Note also that when there is only one year of data, and where this data only include properties put on the market in that year, then the right tail of the hazard function cannot be reliably estimated because some properties take much longer than a year to sell, and such properties are not always withdrawn from the market (*i.e.*, there will be a large degree of censoring). Ideally, analysis should therefore be based on several years of data, employing statistical analysis that allows the hazard function to vary over both time and space. In permitting the hazard curve to vary across space, one has to make the prior assumption that submarkets exist and have some means of identifying where their boundaries are likely to lie.

The remainder of the article is structured as follows. First, we provide background information on the Scottish house-selling system and summarize the relevant literature. A description of our methodology and a summary of three intuitive hypotheses about the time to sale follow. We then briefly describe the data and consider each of the stated hypotheses in turn. The article concludes with a brief summary and discussion of the implications of our analysis for future research.

Background to the Scottish Selling System

Three in five Scots now own their homes and periodically confront the stresses of attempting to both sell and purchase potentially illiquid, expensive properties. To achieve this, households employ housing market professionals to wade through legal and other transactions procedures. In Scotland, the buyer and seller agree on a price through a *sealed bid auction* where a potential purchaser works up a bid on the basis of both a professional valuation and an "Offers Over" price set by the seller. The uncertainties and opportunities created by a system that can allow the seller to capture economic rent in this way (see Gibb 1992) and in which housing market professionals such as estate agents, lawyers and valuation surveyors prosper, means that house purchase and the housing market are always topical and contentious economic phenomena.

In the Scottish sealed bid system, the chances that a property will still be on the market at a given point in time can be thought of as being determined by the cumulative probability, up to that point, of the seller having received a suitable offer, where "suitable" is defined as an offer at least equal to the seller's reservation price. Sellers may hold out for a higher bid by asking for a second closing date, but this is extremely rare; the Offers Over price is typically set so that the auction will produce a successful outcome. This does not mean that the Offers Over price will necessarily equal the seller's reservation price—the seller will be advised by the estate agent as to the Offers Over price, which would attract the most interest, and so the advertised price may actually be below the seller's reservation price; however, potential buyers who express an interest in bidding are often given clues to the minimum price the seller would accept as well as some indication of the typical bid-offer spread of recent auctions in the area. Because there is a significant cost to bidding—the price of obtaining a survey—spuriously low bids are rare, and the auction nearly always results in a sale. Thus, the probability of selling will depend not only on how long the property has been on the market, but also on the range of offers and the seller's reservation price (Zuehlke 1987, Haurin 1988, Yavas and Yang 1995.).

What determines the seller's reservation price? It is likely that the seller will at least want to cover the outstanding mortgage and transactions costs to avoid negative equity but may also have some other minimum driven by external constraints, such as the equity required by the seller to purchase a desired destination dwelling (Stein 1995, Genesove and Mayer 1997). To some extent, however, one might argue that there is a degree of endogeneity about the reservation price that may cause it to change during the period of time the dwelling is on the market. For example, if there is little interest from buyers and negative news about the general state of the market, then the seller may revise his or her reservation price downward.

Current Scottish legislation aims both to reduce the transactions costs facing potential purchasers of private housing and to make "objective" property valuation information publicly available at zero cost. While increasing efficiency in the system, these reforms do nothing to alter the basic vendor benefits (in terms of economic rent maximization) associated with the sealed bid system.

In our study, the dynamics of the selling process are complicated further by a particular idiosyncrasy of the Scottish system. Most dwellings are sold on an Offers Over basis, where bids are not revealed to the seller until the "closing date" (the day of the auction). A closing date is set as soon as one or more buyers commission a survey and/or sufficient notes of interest are lodged with the selling agent. The seller usually takes the highest offer (though the move-in date set by the bidder may also be a deciding factor). As we have noted, it is unusual for the seller to reject all offers revealed on the closing date, though this is an option (typically discouraged by the estate agent or solicitor who is usually keen not to delay the sale). A seller can, however, switch the terms of sale to "Fixed Price" at any point in the marketing process. This alternative selling mechanism entails the seller revealing his or her true reservation price and marketing the property on a first come, first served basis (this precludes bargaining or bidding). It therefore bypasses the auction process and is used as a means of achieving a speedy sale. It is always within the gift of the seller to negotiate a price directly with the first interested party and thereby bypass the sealed bid system. In practice, this is the exception rather than the rule, and in our data, such transactions would still be recorded as Offers Over sales.

Differences Between the Scottish Sealed Bid Auction and Traditional Property Auctions

Note that the auction used in the Scottish selling system is different than those commonly used in Australia and elsewhere in a number of important respects. Crucially, the closing date for the Scottish auction is dependent on the seller receiving notification of an intention to bid from a second prospective buyer. Because an auction cannot occur with a single bidder, and because the number of bidders usually consists only of those who have viewed and commissioned a survey of the property, the auction date is entirely dependent on the emergence of buyers willing and able to purchase. As such, the auction date is fully endogenous. The consequence of this is to make TOM contingent on market demand and supply conditions in very much the same way as it is in the English and American list price selling systems.

This contrasts with the more typical format of a property auction, such as those commonly conducted in Australia or in the sale of repossessed properties (see Eklof and Lunander (2003) for an example from Sweden), where the date of the auction is predetermined, and potential buyers are invited to bid on that date. In Sweden, for example, forced sales of properties following debt default occur through the Enforcement Administrator's office in Stockholm, which holds open outcry auctions every second week of the month: "Several apartments of various types, located everywhere in the Stockholm metropolitan area, were usually auctioned out at the same occasion" (Eklof and Lunander 2003, p. 248). It is also possible that no bids will be placed for a particular property. This is not the case in the Scottish system where the auction only comes into existence if there are at least two bids "on the table." As a result, the auction is usually successful in that it nearly always results in a sale.

Another major difference from traditional property auctions is that the seller has the option at any stage, prior to an auction date being agreed, of switching to a first come, first served sale (the Fixed Price sale option noted earlier). This option only arises because of the endogenous nature of the auction date in the Scottish selling system. If an auction date has still not been achieved after a prolonged period (or if the maximum bid is less than the seller's reservation price), then the seller will typically market the property as Fixed Price. This is a scenario that would not occur in other auction systems where the auction date is exogenous. Also, as noted earlier, the seller has the option under the Scottish system to market the property as Fixed Price from the outset, the propensity of which is contingent on the seller's expectations about the likelihood of finding two buyers in the desired time period. Because time to sale will be dependent on local market conditions, we would also expect the propensity to sell properties as Fixed Price to also be contingent on market conditions (in Table 2, it can be seen that the incidence of Fixed Price sales is generally lower in areas where TOM is short[5]).

[5] Note also that we have found time series evidence of this relationship: in a simple time series regression over 24 quarters of the incidence of 'Fixed Price' sales in Strathclyde, time-on-the-market explains 74% of the variation in the dependent variable and has a t ratio of 8.00; the positive relationship between TOM and the incidence of 'Fixed Price' is similarly confirmed by a simple cross sectional regression across 171 Post Code regions [t ratio $= 5.95$; $R^2 = 0.17$]

Literature Review

There are two literatures relevant to the current article: the submarket literature and the TOM literature. By and large, the two streams of writing have remained separate. The submarket literature is the older of the two, its theoretical frameworks being developed in the 1950s and 1960s (see Rapkin, Winnickand and Blank 1953 and Grigsby 1963). A large number of studies have since attempted to provide empirical verification of the existence of submarkets. Schnare and Struyk (1976) coauthored one of the earliest empirical studies, and they found that attribute prices varied significantly between market segments, where segmentation is by inner/outer city, income and number of rooms. A study by Goodman (1981) followed a similar logic but used local government areas to delineate submarkets and also found instability in attribute prices, as have a steady stream of subsequent papers (see Watkins (2001) for a recent review).

The weakness of adopting administrative boundaries to segment the market is that they may bear little relation to the true market boundaries. Consequently, some authors have argued that real estate board jurisdictions would provide a more appropriate spatial framework given that these jurisdictions reflect the flow of information between estate agents and determine how households in different areas obtain information about vacancies. (In practice, however, estate agent boundaries are often related to administrative boundaries, partly because of data-recording convenience, and partly because of tax and service bundle discontinuities across administrative areas). Palm (1978), for example, finds stronger spatial segmentation by real estate jurisdictions than by racial–ethnic and economic divisions. Similarly, Michaels and Smith (1990) asked real estate agents to define housing submarkets in Boston and found that coefficients vary between the designated submarkets. This is akin to the approach adopted in the current article in that we utilize the submarket boundaries designated by the Glasgow Solicitors Property Centre (GSPC) (structural break tests on hedonic functions categorically reject the null hypothesis of no segmentation—see Appendix).

The results presented here suggest that submarkets can be distinguished in terms of their time to sale dynamics, not just their hedonic structure. This is something of a departure from the mainstream submarket literature, which has tended to focus on static and/or price equation analysis. There are exceptions, such as the recent U.K. study by Jones, Leishman and Watkins (2003), which tests whether house price indices for separate Glasgow submarkets are cointegrated. These studies have tended, however, to overlook the differences in short-run dynamics across submarkets, particularly with respect to TOM and the possibility of nonproportional shifts in the hazard function across market segments. This is an important omission because liquidity is a crucial ingredient in the asset investment decision. Forgey, Rutherford and Springer (1996, p. 273) define liquidity as “the optimal expected time to transform the asset into money,” noting that, “Under any circumstances, . . . an asset’s value is enhanced when it is more easily sold.” In addition to the usual factors that give a property value (such as structural attributes and location quality), the liquidity premium is a separable component of the market price of a house. Both buyers and sellers are aware of the value of liquidity, and this will be factored into the expected selling price. Forgey, Rutherford and Springer (1996) attempt to estimate the value of liquidity (they find that a house that takes one standard deviation longer than the average TOM to sell will be worth 2% less, *ceteris paribus*). Because liquidity can vary substantially over the market cycle, there have also been attempts to develop ways of correcting house price indices for this variation, such as Fisher *et al*. (2003) constant-liquidity price indices (developed in the context of commercial real estate).

The estimation procedures used in these two types of study (one, estimating the value of liquidity in individual sales, and, two, constructing constant liquidity price indices) have, however, tended to overlook the duration dependence inherent in TOM. Forgey, Rutherford and Springer (1996), for example, employ a 2SLS methodology where ln(TOM) and ln(selling price) are modeled using OLS. Fisher*et al*. (2003) use a Heckman two-stage procedure, where the probability of a property leaving the market is modeled in the first stage using a probit regression. Both approaches assume zero duration dependence. That is, they assume that the probability of a property selling in the next time period is not contingent on how long the property has already been on the market. This is highly unlikely to reflect the true probability structure of selling time because most properties have very little chance of selling the first day they come onto the market. The likelihood of sale will rise as more people become aware that the property is available, and it will possibly decline again as the extended TOM is viewed as a signal of poor quality (see Taylor (1999), Jud, Seaks and Winkler (1996) and also our analysis below which finds both a high degree of nonmonotonicity in real estate duration dependence and also shifts in the degree of duration dependence across submarkets and over time). Whether this oversight makes much difference in practice to the precision of either type of two-step estimation procedures has yet to be established.

Other aspects of TOM have been explored in the literature (though almost exclusively in the context of the U.S. selling system). Knight, Sirmans and Turnbull (1998) ask whether list prices lead market values and can act as housing market predictors. They find that once account is taken of market segments and of dynamics over time, there is a need to model market activity with due care to these aggregation and temporal questions. Early studies viewed housing transactions as straightforward; Chinloy (1980) and Yavas and Yang (1995) assume that the list price is a perfect signal of seller intent. Other authors (*e.g.*, Horovitz 1992) incorporate imperfect vendor signals through the list price and buyer search behavior. The latter study is also important because it found that predicted sales price depends on property attributes in addition to the list price.

Anglin, Rutherford and Springer (2003) start from the premise that there is a trade-off between final selling price and TOM (also associated with work by Kang and Gardner (1989), Turnbull and Sirmans (1993) and Yavas and Yang (1995)). They develop the concept of "overpricing" where the list price is higher than expected and may lead to fewer visits and hence a longer TOM. Interestingly, their data do incorporate withdrawals from the market capturing unsold properties, and thus they overcome the downward bias associated with censored data in other studies. They found that overpricing does increase the TOM, and that more generally, spatial location and market conditions have a larger impact on selling duration than do property attributes.

Haurin (1988) focuses on asset atypicality and thin markets caused by heterogeneity as important sources of extended TOM, where atypicality measures the differences between a given house and a "typical" property within a market. Jud, Seaks and Winkler (1996) confirm these results. Kluger and Miller (1990) develop a hazard model to test whether liquidity is important (*i.e.*, the benefits derived to vendors from properties likely to achieve a quick sale). Forgey, Rutherford and Springer (1996) indicate that TOM is explained by property characteristics such as house age and size as well as market variables. Krainer (2001) finds that both selling price and the probability of sale are positively associated with the flow of buyers. Glower, Haurin and Hendershott (1998) looked at seller motivations regarding TOM, and, using a hazard model, found that job starts and specified-moving dates had the biggest influence on TOM. Knight (2002) examined the dynamics of list price changes (*i.e.*, the list price quoted is not independent of TOM). His study also indicated that empirical effects are sensitive to how TOM is defined and in terms of which list price is used. Note, however, that Knight (2002) also employs a standard 2SLS methodology which assumes that marketing time is characterized by zero duration dependence.

Taking this field of work together, a number of conclusions emerge. First, the institutional design of the housing transaction matters. Second, the types of imperfections created by these processes may help to explain market inefficiency in housing markets. Third, studies thus far have been primarily in North American or non-European institutional contexts, and they have tended to be aspatial. These conclusions form the backdrop for our empirical analysis of the Greater Glasgow housing market.

Before proceeding to outline our three hypotheses, it is worth pointing out the relevance of research that attempts to correct for sample selection bias in transactions data (Gatzlaff and Haurin 1994, 1997, 1998). There are two important connections we need to highlight. The first, and most obvious, is that the data we use here (as in all preceding studies of TOM) are drawn from the population of transactions and not from the population of all dwellings. This literature has demonstrated that the probability of a dwelling coming onto the market is not independent of its price and type, and so it is unlikely that our sample is an unbiased random selection of all properties. Because we do not have attribute data on the entire stock of dwellings (surprisingly, such information does not currently exist for the Strathclyde region of Scotland), we cannot easily control for this bias. We did, however, attempt to test for a link between the length of time a property had remained *off* the market (ToffM) with TOM.[6] However, our results proved inconclusive because we could only do this for a subset of our data, and this subsample was itself not a random subsample.

A second connection follows from the point made earlier about the problems associated with attempting to control for liquidity bias. Like the liquidity studies, the transactions bias papers have tended to use Heckman-type correction procedures. However, like TOM, time *off* the market (equal to duration of stay less TOM) is likely to be duration-dependent, and so the simple probit or logit procedures usually employed in Heckman-type analysis will not give a true reflection of the probability of sale. Pryce (2004), for example, finds that the probability of a property coming onto the market starts off very low (few people put their house on the market the day after they have moved in), initially rises, reaches a zenith and then gradually falls. A corollary is that the questions asked in the analysis below, regarding the hazard curves for TOM, may also be found to have counterparts for time *off* the market (albeit over a much longer time

[6] To see whether our data were typical of all transactions we merged 1,514 of the GSPC sales with land registry records of all sales (56,938 in total) in 1999 and 2000. We found that non-GSPC sales tend to have a higher average selling price (£53,777) than GSPC sales (£49,866), with a difference of around 8% on average. We found though, that replication of these tests at submarket level (subject to sample size) revealed considerable variation in the difference (for example, in the East End the price difference is 27% compared with 0% in the West End). It was also possible to determine from the merged GSPC/land registry data how long a property has been off the market prior to entering the market. A property that tends to sell frequently may be more likely to have a short time off the market (ToffM), so we test for variations in TOM for given categories of ToffM. A simple one-way analysis of variance test is highly significant (sig. < 0.0001) indicating that TOM does indeed vary across the ToffM categories. Overall the relationship between time on and off the market appears negative but there is evidence of non-linearity. These results should be treated with a degree of caution, however, since there appears to be a higher than expected proportion of properties in the merged sample that have been off the market for less than a year (it is possible, therefore, that the GSPC-land registry merge has itself introduced a new source of sample selection bias).

scale). For example, both the extent of nonmonotonicity in the hazard function as well as the existence of shifts in that function over time and across submarkets are questions worth investigating with regard to time *off* the market (particularly if it will help us derive more reliable estimates of the probability that a property will come onto the market, and hence, make more precise corrections for transactions data bias in house price indices).

Hypotheses

Our goal in this article is to test the following hypotheses:

Hypothesis 1: There is both duration dependence and nonmonotonicity in the hazard of sale, and these combine to preclude OLS, 2SLS, Probit/Heckman, Exponential and Weibull estimation of the probability of sale.

If a property has been on the market for a prolonged period, the evident difficulty the owner is experiencing in selling the property will be a signal of poor quality and will deter bidders. This rationale has been suggested by Jud, Seaks and Winkler (1996, p. 452), who have found that the likelihood of sale rises rapidly at first, "reaches a plateau and then declines at a decreasing rate." This is interpreted as indicating that "homesellers initially enjoy increasing prospects for a home sale. However, after some period of TOM, unsold homes become more difficult to sell. One might interpret these results as increasing visibility and recognition for new home listings, followed by a gradual "stigma" attached to unsold homes" (Jud, Seaks and Winkler 1996, p. 452); see also Zuehlke (1987), who finds that TOM exhibits positive (zero) duration dependence for vacant (occupied) dwellings but who does not, however, consider the possibility of nonmonotonicity in the hazard function. This stigma effect is identified by Taylor (1999) as being a form of herding behavior of the kind analyzed in the informational cascades literature (see Banerjee 1992 and Bikhchandani, Hirshleifer and Welch 1992). Taylor notes that "consumers who discover the house on the market late in the selling season use TOM to update their assessments of quality." (p. 555). Our anticipation, therefore, is that the hazard function will initially rise, reach a peak and fall.

Note that the existence of duration dependence will rule out the application of OLS and probit to TOM, because these techniques assume that the probability of sale at any given point is not affected by how long a property has already been on the market. By extension, both the standard application of 2SLS (where one of the structural equations is a time to sale function) and the application of Heckman correction procedures (where the probit is used to correct for the probability of sale) will also be inappropriate. Furthermore, duration dependence of the kind that causes the hazard curve not only to rise but also to eventually fall will preclude the application of Weibull and Gompertz duration models because both assume a monotonic hazard function. The large number of papers that have applied the Weibull model to TOM (Haurin 1988, Zuehlke 1987, Yang and Yavas 1995, Jud, Seaks and Winkler 1996, Anglin, Rutherford and Springer 2003) have therefore implicitly assumed that the stigma effect does not exist, or that it has only limited effect on the hazard of sale. We argue that this is likely to be an invalid assumption.

Hypothesis 2: Movements in the hazard curve (i) over the housing cycle and (ii) across space preclude unstratified proportional hazard regression; movements across space are also evidence of the existence of submarkets.

How does the hazard function vary across space, and to what extent, does the shape of the hazard function change over the course of the housing cycle? To our knowledge, neither the dynamics of the house-selling hazard function nor spatial variation have been explored in any great depth in the literature. Such movements may constitute nonproportional shifts in the hazard curve, and these will preclude the use of *unstratified Cox regression*, which is the only form of semi-parametric hazard regression to be applied in the housing TOM literature (Larsen and Park 1989, Kluger and Miller 1990). For movements in the hazard function to be nonproportional (shifts that are not parallel) the hazard function has to change shape, not just position. Our rationale for why the hazard function will vary nonproportionately in this way is that the shape of the hazard function is determined by the nature of duration dependence. Positive duration dependence (the initial rise in the hazard of sale immediately following the property's entrance to the market) depends crucially on the buoyancy of the local market. This is because the greater the number of bidders per property on the market, the more likely a property is to sell, *ceteris paribus*. So, we would expect the first phase of the hazard function to be steeper (more positively duration-dependent) for markets experiencing a boom.

An interesting question is whether the stigma effect (which is the cause of the negative duration dependence indicated by the anticipated downturn in the hazard function noted in Hypothesis 1) is exacerbated or ameliorated during a boom. We argue that the stigma effect will actually become more acute during an upswing because the implication of an extended period on the market becomes an increasingly unambiguous signal of quality as the market booms. If, for example, a property has been on the market for over a year, how that property is perceived by potential bidders depends crucially on how this duration compares with the TOM of other properties in the area. If the market is generally depressed, then it is quite possible that the property has not sold because of general market conditions, and so the length of time the property has been on the market cannot be taken as a reliable signal of poor quality. During a boom, however, a property that has been on the market for over a year will be perceived (with a degree of certainty) to have some defect. So, the scope for herding (Taylor 1999), and hence, the shape of the hazard function, will depend crucially on the state of the market. In short, we argue that nonproportionality is likely to be the norm when considering shifts in the hazard function over the course of the business cycle and across markets that are at different phases of the cycle or that have different long-term levels of buoyancy.

The corollary to this line of reasoning is that the existence of nonproportional shifts in the hazard curve across different spatial segments of an urban housing market constitutes evidence of the existence of housing submarkets. Proof is by contradiction. If there exists a single urban housing market, how can the hazard function vary significantly in shape across space at a given point in time? In a single unified housing market, properties in one area of that market will be subject to the same workings of the stigma effect as properties in any other area. This is because there is no reason for TOM to be perceived as a different signal of quality if the market dynamics are contemporaneously homogenous across the urban landscape. As such, all areas of the city should have hazard functions with turning points that occur at the same point in analysis time and have similar slopes of ascent and descent. Evidence to the contrary can be taken as evidence of submarkets.

This discussion leads us to the very heart of the nature and measurement of submarkets. The early literature (Rapkin, Winnickand and Blank 1953, Grigsby 1963) framed their discussion of submarkets in terms of substitutability. If two goods can be considered as close substitutes, then they can be thought of as being part of the same market. The converse is also true: poor substitutes will necessarily entail separate markets because consumers do not consider them as competing alternatives for the satisfaction of a particular need or function. A practical difficulty, however, is that substitutability has to be held distinct from issues of quantity, which is no easy task in the context of housing where a single dwelling unit is typically made up of different quantities of many attributes. The estimation of attribute marginal prices is, therefore, a useful exercise in identifying submarkets because (in principle) it offers a way of controlling for quantity variation. A large dwelling may still be considered part of the same submarket as a much smaller dwelling if the attribute prices are similar: the heterogeneity in this instance is just a matter of scale. Differences in attribute prices can persist: “Due to either supply- or demand-related factors, the normal arbitrage that would be expected to equalize prices both within and across metropolitan areas may work either slowly or not at all” (Goodman and Thibodeau 2003, p. 183). Significant differences in attribute prices can in particular reflect fundamental differences in value of a particular location, which arise owing to differences in school performance, access to amenities or in any factor that shapes the quality or perception of a neighborhood (Goodman and Thibodeau 1998).

However, while similarity of attribute prices may be a *necessary* condition for the existence of a submarket, it is not a *sufficient* condition. For two properties to be considered part of the same market, they also have to be considered elements of the choice set for a typical purchaser in both localities, holding quantity differences constant, in order for the notion of submarkets to have any meaning. They have to be *considered* as substitutes in the housing decisions associated with actual transactions. Apartments in the outskirts of Paris may, coincidentally, have a similar set of attribute prices to flats in the West End of Glasgow. Few would contend, however, that they are part of the same submarket. Typical house purchasers in the West End of Glasgow are unlikely to have weighed their choice against a similar apartment in Paris. Changes to the Paris housing market are unlikely therefore to have much influence on the purchase of dwellings in Glasgow. (Similarly, dwellings of a contrasting style or type may coincidentally have similar attribute prices at a given point in time even though they belong to separate submarkets—they may be bought and sold by distinctly different sets of buyers and sellers, and hence have independent market dynamics).

Consideration of other aspects of submarkets, such as the short-run dynamics of time to sale, may provide useful additional evidence as to whether or not submarkets exist. Independence of housing markets arises because buyers and sellers in area *A* do not consider properties in area *B* to belong to the same market, and so market signals in area *B* do not affect the behavior of buyers and sellers in area *A* in the same way that similar signals in area *B* would. One market signal is TOM, and how buyers view TOM drives the shape of the hazard curve. This is because the shape of the hazard function is closely related to the stigma effect (a corollary of Taylor (1999)), which in turn is contingent on the short-run dynamics of a submarket. It would be reasonable, therefore, to expect the shape of the hazard function to vary across submarkets. This is a necessary but not a sufficient condition because there is likely to be some lower bound to the average TOM in an area. Even if the electronic dissemination of property details is instantaneous, processing of marketing information by potential buyers will take time. There is also the time it takes buyers to arrange viewing, organize surveys, obtain provisional mortgage approval, *etc*. The implication is that each submarket will converge to some common minimum[7] time to sale

[7] It is possible that the minimum feasible average time-on-the-market could vary between areas due to variations in information efficiency which arise from differences in estate agent productivity and the spatial pattern of estate agent market shares. Also, even during boom periods, the market for atypical dwellings may remain relatively thin, and

as all submarkets boom. Nevertheless, one is likely to be able to detect different rates of convergence of the hazard curve across submarkets, and these differences can be interpreted as evidence of the existence of submarkets.[8]

Although differences in duration dependency will not provide a sufficient condition for the existence of submarkets, it is still worth comparing hazard curves because, while it is possible for two submarkets to coincidentally have similar attribute prices, or coincidentally have similar hazard functions, they are far less likely to coincidentally have both. Therefore, examination of duration dependency can potentially provide useful corroborative evidence to the usual tests employed to identify submarket boundaries. This is reinforced by the fact that measures of duration dependency are not handicapped by some of the complications that frustrate tests for homogenous attribute price (most notably, the difficulty of finding the true functional form for the hedonic regression and the measurement problems associated with incorporating all relevant dwelling attributes).

To summarize, we believe that there are good economic reasons (following Taylor 1999) to expect differences to arise in the shape of the hazard curves of different submarkets. This means both that differences are likely to exist, and that observed differences are unlikely to be due to random sampling variation alone. As such, analysis of the variation in the hazard function across space is likely to offer a complementary tool in identifying submarkets. It also has important implications for the construction of duration models because only particular types of estimation techniques (those allowing for nonproportional shifts in the hazard curve within the sample) may be applicable.

Hypothesis 3: Institutional Idiosyncrasies can have a profound effect on the shape and position of the hazard curve.

One of the peculiarities of the Scottish house-selling system is that the seller has the choice to sell the property via a sealed bid auction (an Offers Over sale) or

---

so differences in average TOM may persist even during the peak of a boom. The point still remains, however, that average TOM is likely to converge during citywide booms and so hazard functions are less likely to be useful ways of distinguishing between submarkets during those periods.

[8] A related point is made by Jones, Leishman and Watkins 2003 who argue that for localities to be considered as separate submarkets, not only must their attribute prices be different at a particular point in time, but also the dynamics of house prices must be independent: “We consider whether price differences between submarkets have been eroded by a process of arbitrage operating through supply-side responses and/or migration flows” (p. 1315). They employ cointegration tests as a practical method of investigation and find that “a stable system of housing submarkets persists throughout the study period” (p. 1315).

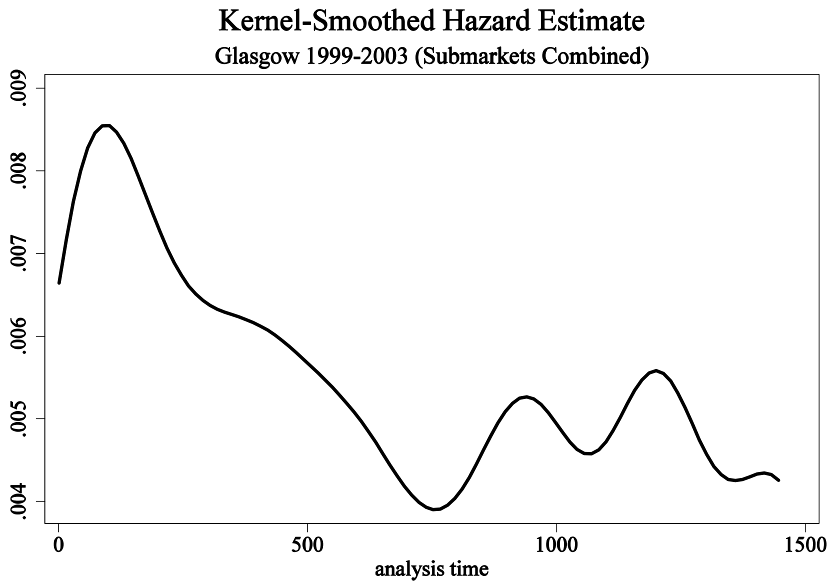
as a first come, first served sale (a Fixed Price sale). A seller will usually place a property on the market as Fixed Price for one of three reasons: (i) they need to sell the property quickly and need to avoid the delays associated with the sealed bid system; (ii) they anticipate that the property will be difficult to sell (because of poor quality, or because of a depressed or thin local market) and (iii) the property has been initially marketed as Offers Over but has failed to sell for a prolonged period (or if the maximum bid is less than the seller's reservation price). Reasons (ii) and (iii) constitute sources of *adverse selection* for the total selling time of all Fixed Price sales in that they imply a disproportionate number of difficult to sell properties will eventually be marketed as Fixed Price. (Note, however, that one would expect properties that have been advertised as Fixed Price *from the outset* will, all other things being equal, sell more quickly than identical properties marketed as Offers Over).

Note that the proportion of sales marketed as Fixed Price is likely to vary over the course of the housing cycle. During a boom, properties tend to sell more quickly, and so there is less recourse to Fixed Price marketing. As such, it is important to consider how the Fixed Price option affects the results from Hypotheses 1 and 2. Given that there is no reason to believe that the stigma effect will disappear if one were to consider Fixed Price (or Offers Over) sales in isolation, one would expect the hazard curve to remain nonmonotonic (so, Hypothesis 1 is likely to remain intact). However, the possible change in the proportion of Fixed Price sales during an upswing might affect the shapes of the separate Fixed Price and Offers Over hazard functions when considered separately. This is because Offers Over properties with very long TOM will tend to switch to Fixed Price, leaving a favorable selection of properties in the sample used to derive the Offers Over hazard curve. The effect will be to reduce the variation in the hazard of sale over the course of the housing cycle because some of the variation during an upswing or downswing will be absorbed into the propensity to switch to Fixed Price. Variation in the hazard curve *across submarkets* might also be less pronounced if one considers only Offers Over sales (for similar reasons).

Methods

To test our hypotheses, we estimate the shape of the hazard function using kernel-smoothed nonparametric estimates of the hazard function for different subgroups of housing sales. In estimating these functions, we follow the procedure in Klein and Moeschberger (1997, p. 153) in which hazards are estimated nonparametrically and smoothed using a kernel function. More specifically, the hazard curves plotted in Figures 1–5 are based on the following computation of the hazard of sale:

Figure 1 ■ The nonmonotonic duration-dependent hazard function for Glasgow. This figure uses kernel-smoothed density estimation techniques to plot the hazard of sale for each day a property is on the market ("analysis time"). The serpentine undulations suggest that there is not only a high degree of duration dependence (the hazard of sale varies the longer a property has been on the market) but also nonmonotonicity (the hazard rate goes down as well as up).

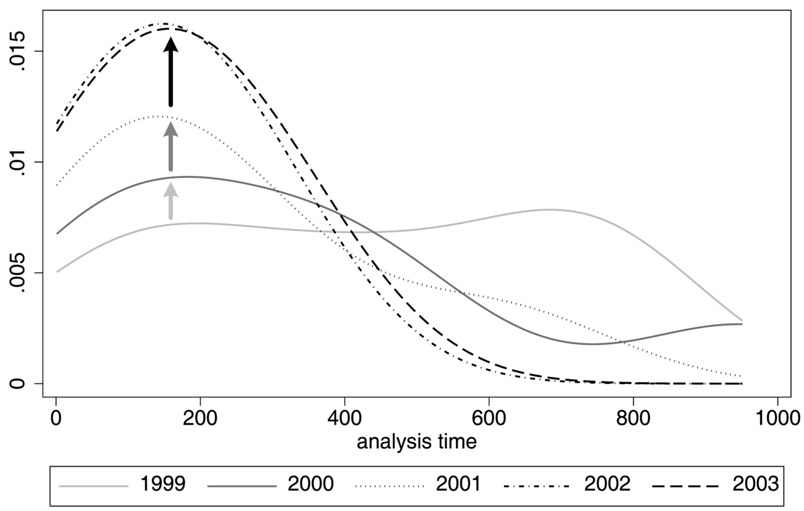


$\hat{h}(t) = b^{-1} \sum_{j=1}^{D} K(\frac{t-t_j}{b})\Delta\hat{H}(t_j)$, where $\Delta\hat{H}$ is the estimated change in the cumulative hazard, $K()$ is the kernel function, $t-t_j$ are analysis–time intervals, b is the bandwidth (typically set at 150)[9] and the summation is over the D times at which failure occurs. The nonparametric approach does not constrain the hazard function to follow a particular analytical shape, so we can gain a genuine picture of how the hazard function shifts over time and across submarkets and institutional arrangements.

We complement the Klein and Moeschberger graphical approach with "life tables" and likelihood ratio tests of changes to the hazard function. Life tables (Kalbfleisch and Prentice (2002, p. 10, 15) and for an intuitive introduction to life tables and related techniques, see Lee (1992)) are derived by grouping

[9] A lower bandwidth of 100 was used in Figure 1 to reduce the complexity of the curve. Note, however, that the key findings of the paper (duration dependence, non-monotonicity, non-proportional shifts over time and across submarkets) were not sensitive to the selected bandwidth; when alternative bandwidths were applied to the graphs the results still supported our hypotheses.

Figure 2 ■ Metamorphosis of the hazard function during a boom in the West End of Glasgow for each year 1999–2003. This figure plots separate time to sale hazard functions for each year of data. As the market booms, the hazard function becomes more peaked. Of particular interest is the fact that the post-zenith decline becomes steeper as the upswing progresses, confirming our hypothesis that the stigma effect becomes more potent as average time on the market falls.



data into analysis–time intervals given by t_j, where $j = 1, \ldots, J$. Each interval contains the frequency of sale or censoring for the group of properties under consideration. That is, the number of properties where $t_j < = T < t_j+1$, where t_i is the analysis time of failure or censoring for property i. The maximum likelihood estimate of the within-interval hazard reported in the life tables is given by

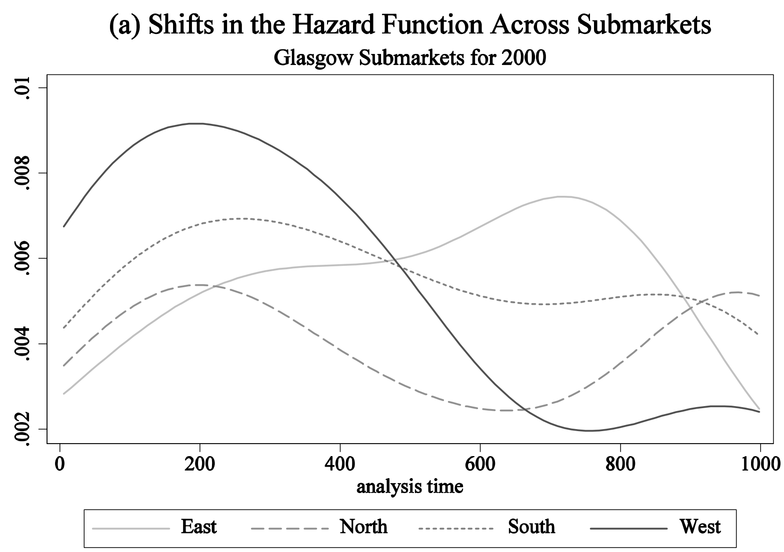
$$h_j = \frac{f_j}{(1 - f_j/2)(t_{j+1} - t_j)},$$

where $f_i = d_j/n_j$, d_j is the number of failures during the interval, $n_j = N_j - m_j/2$, N_j is the number of properties still "alive" at the start of the interval, and m_j is the number of censored observations during the interval. Confidence intervals for the estimated hazards are based on the following standard error:

$$s_{h_j} = h_j \sqrt{\frac{1 - \{(t_{j+1} - t_j)h_j/2\}^2}{d_j}}$$

(see Kalbfleisch and Prentice 2002, p. 10, 15). The likelihood ratio test for homogeneity of the hazard function between groups is based on the method

Figure 3 ■ Convergence of hazard functions across submarkets during an upswing. Hazard functions are plotted here for each of our four submarkets, first for a slump year (2000, panel (a)) and then for a boom year (2003, panel (b)). Comparison of the two panels reveals how the hazards across all submarkets converge during a boom. The graphs also show how the hazard curve for time to sale varies nonproportionately both across submarkets and over time.



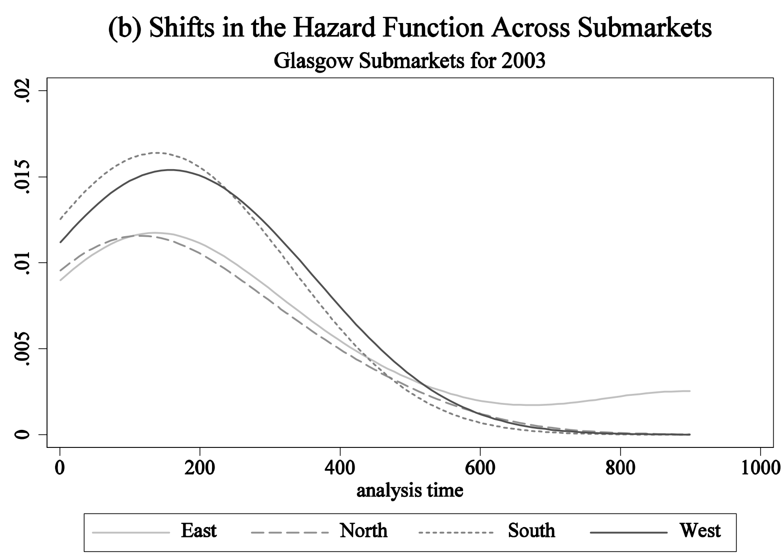
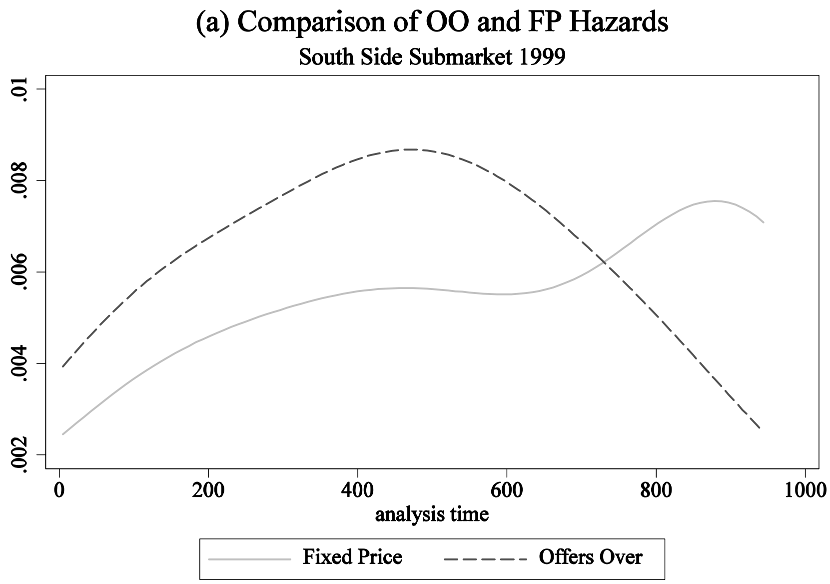


Figure 4 ■ Comparing the hazard functions of "Fixed Price" and "Offers Over" sales. Panel (a) plots the kernel-density estimated hazard functions for Fixed Price (FP) and Offers Over (OO) sales in 1999. Panel (b) re-plots the hazard functions for sales in 2001. The graphs demonstrate that Fixed Price and Offers Over hazard curves are not proportional and that they shift nonproportionately over time.



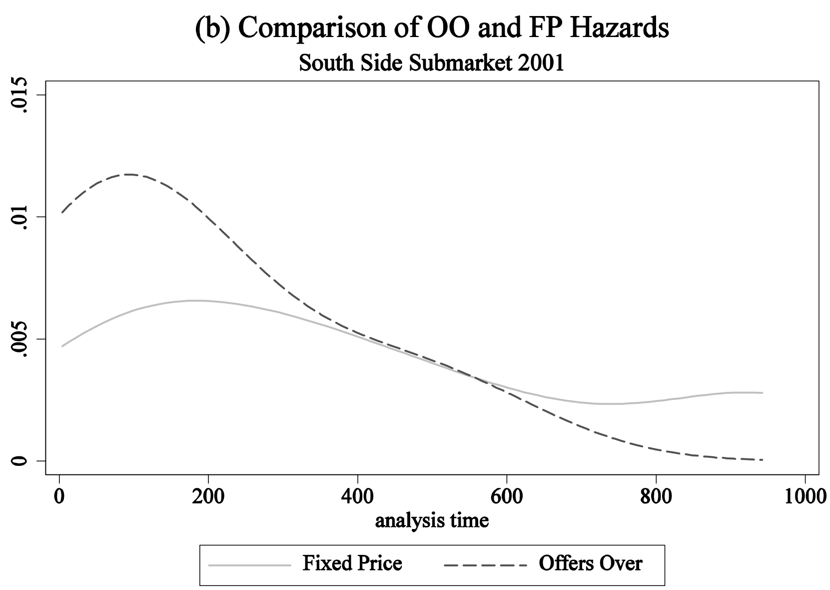
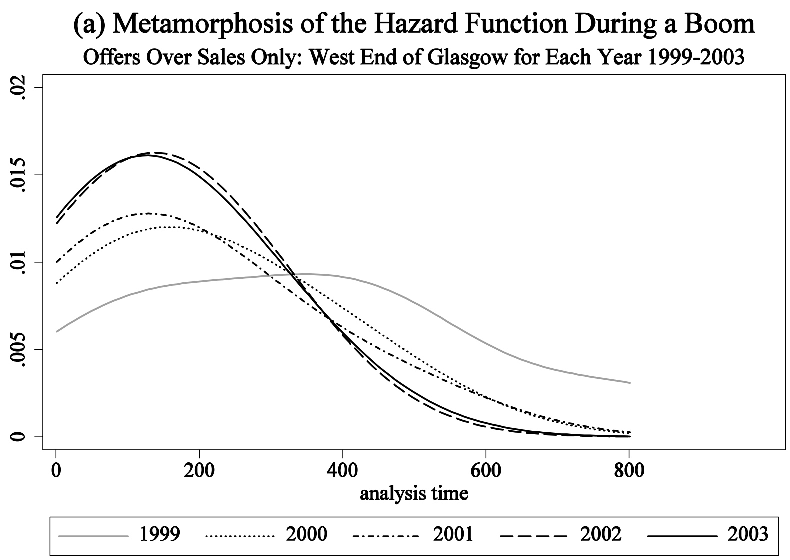
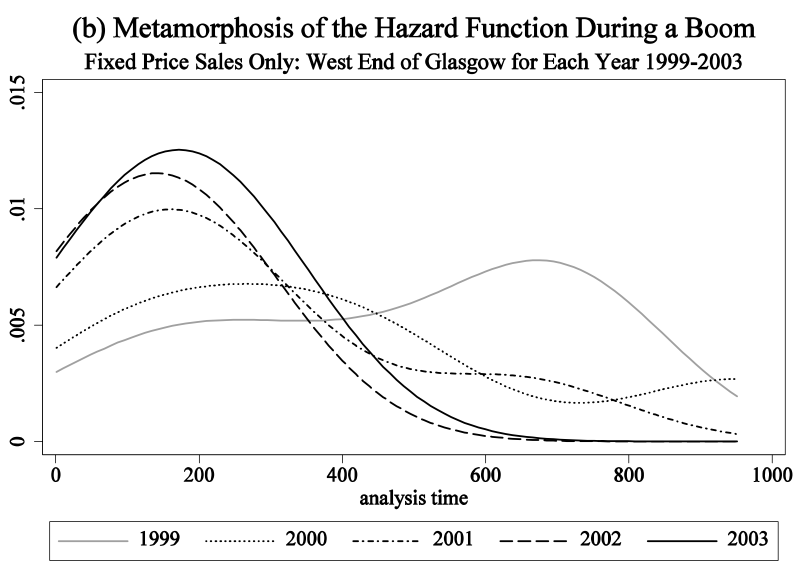


Figure 5 ■ Metamorphosis of the hazard function: Offers Over vs. Fixed Price. Panel (a) illustrates the metamorphosis of the hazard function over time for Offers Over sales by plotting the function separately for each year. The results are similar to the hazard curves derived from all transactions (Figure 2) but without the initial right-hand humps. This is because properties with very long TOM will have tended to switch to Fixed Price. Conversely, the right-hand humps persist when we plot the hazard curves for Fixed Price sales (panel (b)).





explained by Lawless (1982, p. 113), which employs the following χ^2 statistic with G-1 degrees of freedom (G is the total number of groups):

$$\chi^2 = 2\left\{\left(\sum d_g\right)\log\left(\frac{\sum T_g}{\sum d_g}\right) - \sum d_g \log\left(\frac{T_g}{d_g}\right)\right\},$$

where d_g is the total number of failures in the gth group, $T_g = \sum_{i\in g}\tau_i$ and i is the index of the individual failure and censoring times.

Note that the results of the likelihood ratio tests were confirmed by both log-rank tests for homogenous hazards and stratified Wilcoxon (Breslow) tests for equality of survivor functions (not reported).

Description of the Data

Data were supplied by GSPC, a consortium of estate agents in the Strathclyde region of Scotland (comprising Greater Glasgow and West of Scotland areas) for the period 1999–2003. The total number of transactions in the data is 28,777, the largest database used so far in cross-sectional analysis of TOM. Of these, 1,140 observations were censored. The period considered is one of a rising market, characterized by falling time to sale and rising house prices (see data Columns one and four of Table 1) across a range of heterogeneous submarkets. The data set has a comparatively dense spatial distribution of observations: 80% of the submarket data lie within 6 kilometers of the center of Glasgow, and all submarket data are located no further than 10 kilometers from the center of Glasgow. It therefore provides us with an excellent opportunity to analyze the dynamics of time to sale across submarkets of relative proximity within the city of Glasgow. These submarkets are as delineated by the estate agents who supplied the data and labeled by GSPC as *West End*, *East End*, *South Side* and *North Side* (tests for attribute price shifts are presented in the Appendix—we find that the probability of falsely rejecting the null hypothesis of homogenous attribute prices is less than one in a thousand). The bulk of the article is based on the 12,344 observations that fall within these four submarkets, which we examine either as individual submarkets (labeled accordingly) or collectively (labeled as “Glasgow”).

That the jurisdictions used by the GSPC real estate agents reflect real underlying differences between areas is demonstrated in Table 2, which presents basic descriptive statistics for each of the four Glasgow submarkets over the period 1999–2003. It can be seen that there is considerable variation between the four areas in terms of price, attribute, location and marketing characteristics. Average selling prices in the West End (£89,835) are almost double those in the East End (£48,327) and are significantly above those in both the South Side

Table 1 ■ Summary statistics for key variables.

	Strathclyde			Glasgow		
N	28,777			12,344		
Uncensored	27,637			12,040		
Censored	1,140			304		
	Mean	Std. Dev.	*n*	Mean	Std. Dev.	*n*
TOM (days, all years)	88.5	137.18	27,637	78.0	125.9	11,285
TOM (days, 1999)	168.3	188.8	5,599	155.7	182.4	2,457
TOM (days, 2000)	130.9	173.0	4,011	118.3	167.1	1,395
TOM (days, 2001)	86.0	131.6	3,857	62.1	89.4	1,272
TOM (days, 2002)	50.2	81.0	6,865	43.3	76.0	2,908
TOM (days, 2003)	41.2	51.5	7,305	39.3	40.79	3,253
Selling Price (all years)	£69,134	£49,657	27,289	£69,225	£47,369	11,164
Selling Price (1999)	£53,848	£33,547	5,580	£51,055	£31,268	2,451
Selling Price (2000)	£52,770	£35,307	3,907	£52,353	£35,471	1,362
Selling Price (2001)	£58,796	£39,419	3,684	£62,192	£40,314	1,235
Selling Price (2002)	£73,625	£50,394	6,813	£73,500	£48,264	2,863
Selling Price (2003)	£90,586	£60,659	7,305	£88,887	£54,614	3,253

Note: This table presents summary statistics for the key variables used in the analysis. Time on the market (TOM) is measured in days. Figures are presented for Glasgow and the wider conurbation of Strathclyde.

(£62,498) and North Side (£50,703). We do not have data on the floor area of properties, but it is unlikely that these price differentials can be explained in terms of dwelling size alone. For example, price per room for flats (houses) ranges from £13,224 (£17,965) in the North Side to £30,181 (£25,115) in the West End.

These price variations reflect a complex set of attribute and amenity differences between the areas. In the West End, for example, almost 80% of sales are of flats (as opposed to houses), compared with only 58.6% in the North Side, 63.56% in the East End and 75.41% in the South Side. Only a very small proportion of dwellings (around 7%) sold in the North Side are of traditional stone construction, compared with around a quarter in the South Side and East End and nearly 30% in the West End. This reflects the different periods of construction of the different areas and the different types of dwellings across the four submarkets. Most of the properties in the West End, South Side and East End are traditional tenement flats built around the turn of the twentieth century, whereas most of the properties in the North Side were constructed in the Post-War period. A homeowner in the North Side is therefore more likely to have access to a garden and have more rooms than in the other three submarkets,

Table 2 ■ Submarket dwelling and location characteristics (1999–2003).

	Average Values				
Variables:	West End	East End	South Side	North Side	Total
Price					
Selling price	£89,835	£48,327	£62,498	£50,703	£69,225
Price per room (flats)	£30,181	£13,774	£18,855	£13,224	£22,263
Price per room (houses)	£25,115	£17,989	£20,940	£17,965	£21,044
Attributes					
Flats	79.78%	63.56%	75.41%	58.64%	73.76%
Stone construction	28.91%	23.23%	25.30%	7.16%	24.97%
Number of bedrooms	1.97	1.98	2.04	2.22	2.02
Number of public rooms[a]	1.18	1.15	1.25	1.16	1.20
Garden	51.76%	56.14%	60.02%	69.88%	57.01%
Location					
Notable views	5.73%	2.25%	4.37%	5.43%	4.58%
Performance[b] of nearest school	44.85%	15.91%	26.98%	20.51%	31.56%
Km to Glasgow city centre	4.68	5.27	4.75	3.84	4.75
Marketing					
TOM	56.32	118.37	76.19	101.29	77.98
% Offers over sales	84.08%	65.82%	77.37%	60.27%	76.67%
% Fixed price sales	15.86%	33.11%	22.37%	39.38%	23.06%
Number of observations	4,154	1,953	4,365	810	11,282

Note: This table presents summary information at submarket level on selling price, price per room, dwelling attributes, location and marketing variables. The submarket boundaries are those used by GSPC, the largest consortium of estate agents in the West of Scotland.
[a] Number of rooms other than bedrooms, bathrooms and kitchens.
[b]Percentage of pupils gaining five or more awards at level five or above (three-year average for the period 2000–2002).
Source: School data were obtained from the Scottish Executive; all other results are from our GSPC data set.

and these differences affect the ambience of the neighborhood as well as the characteristics of individual dwellings.

While dwelling attributes may ostensibly be similar in the East, West and South Sides, there are considerable location and amenity differences that conspire to effect large price differentials. The landscape of the East End and South Side is relatively flat, and there are a large number of industrial and former industrial sites. The West End, on the other hand, is more hilly with relatively little industrial land use. As such, properties sold in the West End are more likely to have notable views than those sold in the East or South Sides. The West End also enjoys some of the nicest parkland and public space in Glasgow (notably

Kelvin Park and Art Gallery, the Botanic Gardens and the extensive grounds and listed buildings of the University of Glasgow). The South Side also benefits from notable public amenities such as the newly constructed Science Museum and the internationally renowned Burrell Collection museum located in the extensive landscaped grounds of Pollok House.

According to a simple linear distance measure, those that purchase properties on the North Side will, on average, be closest (3.8 km) to the amenities located in the city center (such as the Central and Queen Street train stations, Buchanan Street Bus station, one of the largest city center shopping areas in Europe, cinemas, theatres, restaurants, the Royal Concert Hall, city halls, the Gallery of Modern Art, Strathclyde University and the Mackintosh School of Art and the Royal Scottish Academy of Music and Drama), compared with properties in the West End (4.68 km), East End (5.27 km) and South Side (4.75 km). However, properties in the West End and South Side benefit from the circular underground rail link (the "Clockwork Orange"), and so, on balance, probably have better access to these central amenities (note that our estimate of the coefficient on the distance to Glasgow city center is more negative for the West End than in the other areas, see Table A1 in the Appendix, which is a curious result, symptomatic perhaps of imposing a mono-centric distance to center measure on a city that is asymmetric in shape and characterized by multiple centers of business activity).

One of the most significant differences across the four areas is the performance of local schools, a variable that has proved to be an important rationale for the existence of housing submarkets in the literature (see *e.g.*, Goodman and Thibodeau, 1998). We calculated the distance from each property transaction in our database to each school in the City of Glasgow and surrounding local authorities, and we then attributed to each of our transactions the exam results of the nearest school. Our results show that in the West End, the average performance of nearest school is almost 45% (*i.e.*, 45% of year four secondary school pupils have gained five or more awards at level five or above). This compares with test results of 27%, 21% and 16% for the nearest schools to properties sold in the South Side, North Side and East End, respectively.[10]

[10] We should note, however, that the education system in Glasgow is complex and a full account is beyond the scope of the current paper. For example, schools are grouped into three main categories: state Catholic, state Non-Denomitational and Independent (private) schools. Most schools fall into the second category and so of the three types of schools, Non-Denominational schools tend to have the smallest catchment areas. Catholic schools are fewer and further apart. They consequently have larger catchment areas. Private schools have their own entry rules and typically do not have comparable or coordinated catchment areas. As such, the distance-to-school effect is not straight forward since it interacts with religious conviction, financial resources and political

Empirical Analysis of the Hypotheses

Hypothesis 1: There is both duration dependence and nonmonotonicity in the hazard of sale, and these combine to preclude OLS, 2SLS, Probit/Heckman, Exponential and Weibull estimation of the probability of sale.

Of interest here is whether the probability of a property selling increases or decreases the longer it has been on the market. Looking at the life table in Table 3, we can see that for both the wider area of Strathclyde (which includes not only Glasgow but surrounding local authorities) and the Glasgow submarkets (the focus of the remainder of the article), around 10% of properties sell within the first two weeks, and around 40% sell within a month. After 180 days (approximately six months), little over 10% are still live, and this figure falls to less than 5% after a year and less than 2% after two years. For both Strathclyde and Glasgow, the hazard of sale is clearly duration-dependent and nonmonotonic, rising steeply in the first month and then falling gradually (with some evidence of a small rise at 300–330 days). This is confirmed when we look at the confidence intervals for the hazard rates. If we compare each confidence interval for Strathclyde with each confidence interval in the subsequent TOM duration, we find that none of them overlap until the 300–330 days interval. This is also true for Glasgow.

The smoothed hazard function presented in Figure 1 (estimated using Klein and Moeschberger's 1997 method) supports this general pattern, but demonstrates a more pronounced set of right hand "foothills." At first sight this serpentine hazard function looks like an aberration in the data or the consequence of overfitting. Further analysis, however, reveals that these foothills are in fact the product of a booming market and submarket differentials. Properties that have been on the market for a prolonged period may experience a "second wind" if the markets starts to boom, not because of a revival in marketing efforts, but because of a sea-level rise in the buoyancy of the market (note, *e.g*, in Figure 2 how the foothills all but disappear when the hazard function is plotted on single years of data and disappear without trace during the peak of the boom in 2002–2003).

Our conclusion, then, regarding Hypothesis 1 is that there is compelling evidence to suggest that the hazard of sale is both duration-dependent and nonmonotonic. This has important implications for the choice of hazard model

persuasion (Glasgow has strong socialist roots and many parents would object to private schooling on ideological grounds—more so than in Edinburgh, for example, where there are many more private schools per head of population), all of which are non-uniformly distributed across space. The situation is complicated further by the 'Placing Requests' system which allows parents to apply to a state school in a different catchment area.

Table 3 ■ Life table for time on the market (TOM) in Strathclyde and Glasgow (1999–2003).

TOM Interval (Days)		Strathclyde ($n = 27{,}623$) Cum. Failure	Hazard	95% CI		Glasgow ($n = 11{,}282$) Cum. Failure	Hazard	95% CI	
0	14	9.83%	0.0074	0.0071	0.0077	9.57%	0.0072	0.0068	0.0076
14	30	40.88%	0.0260	0.0255	0.0265	43.34%	0.0287	0.0278	0.0296
30	60	62.85%	0.0152	0.0148	0.0156	67.13%	0.0177	0.0171	0.0184
60	90	73.47%	0.0111	0.0107	0.0115	77.63%	0.0127	0.0120	0.0134
90	120	79.68%	0.0088	0.0084	0.0092	83.72%	0.0105	0.0097	0.0113
120	150	83.77%	0.0075	0.007	0.0079	87.17%	0.0079	0.0071	0.0087
150	180	86.83%	0.0069	0.0065	0.0074	89.35%	0.0062	0.0054	0.0069
180	210	88.98%	0.0059	0.0055	0.0064	91.33%	0.0069	0.0060	0.0077
210	240	90.95%	0.0065	0.006	0.0071	92.87%	0.0065	0.0055	0.0075
240	270	92.43%	0.0059	0.0054	0.0065	94.06%	0.0061	0.0050	0.0071
270	300	93.53%	0.0052	0.0046	0.0058	94.90%	0.0051	0.0041	0.0061
300	330	94.61%	0.0061	0.0054	0.0067	95.77%	0.0062	0.0050	0.0074
330	365	95.61%	0.0058	0.0051	0.0065	96.42%	0.0047	0.0037	0.0058
365	730	99.34%	0.0041	0.0039	0.0042	99.49%	0.0041	0.0038	0.0044
730	1095	99.79%	0.0029	0.0024	0.0033	99.82%	0.0026	0.0019	0.0034

Note: This table groups property sales into intervals of analysis time measured in days on the market. For each interval of TOM, the table lists the cumulative failure rate (the proportion of all properties in the data that have sold during the interval), the average hazard rate for the interval and the 95% confidence interval for the hazard rate. Results are presented for Glasgow and Strathclyde. For both Strathclyde and Glasgow, the hazard of sale is clearly duration dependent and nonmonotonic, rising steeply in the first month and then falling gradually (with some evidence of a small rise at 300–330 days).

used to analyze TOM. It means that studies that have used either Exponential or Weibull models (such as Zuehlke 1987, Haurin 1988, Yang and Yavas 1995, Jud, Seaks and Winkler 1996, Huang and Palmquist 2001, and Anglin, Rutherford and Springer 2003) may not be valid because neither of these models allow for the possibility of nonmonotonicity.

Hypothesis 2: Movements in the hazard curve (i) over the housing cycle and (ii) across space preclude unstratified proportional hazard regression; movements across space are also evidence of the existence of submarkets.

We find substantial shifts in the hazard function over time for Glasgow as a whole and for all submarkets. Figure 2 presents the results for the West End that neatly illustrate the metamorphosis of the hazard function during the upswing of the housing cycle. In 1999 the West End hazard function rises slowly until around 200 days and then remains relatively flat until around 700 days. In the following year, however, the hazard function has become considerably more peaked and skewed, and by 2002 a very steep hazard function emerges where the hazard rate for properties not sold after 200 days declines as rapidly as its initial rise. An almost identical curve is plotted for 2003. We found a similar, though less pronounced, pattern for the East End, the North Side and the South Side (not presented).

Our conclusion is that booming markets tend to have an early peak in the hazard function but also a steep decline soon after, which appears to confirm our intuition about the stigma effect being more potent during a boom. Our results confirm the finding of Jud, Seaks and Winkler (1996) that the hazard declines gradually following its zenith, but we find that the result is dependent on the phase of the market cycle. Such a degree of cyclical dependence in the hazard functions implies that there should be both stratification of hazard regressions over time and incorporation of covariate measures of the buoyancy of the market. Lawless (1982) likelihood ratio tests (presented in Section H2(i) of Table 5 below) confirm this conclusion by unanimously rejecting the null of a homogenous hazard function (the tests are run on the full five years of data, both for Strathclyde as a whole and for Glasgow and its composite submarkets). Note, however, that because our data only cover a market upswing, the generalizability of the result would need to be verified using data over a longer period.

Regarding variation across space, the life tables for TOM for individual areas presented in Table 4 show clear evidence for intra-urban disparity in the hazard function. For example, the hazard of sale for a property that has been on the West End market for between 30 and 60 days is 0.025, more than double that of properties in the East End, and more than 60% greater than the hazard of sale in the South Side and North Side. The likelihood ratio tests confirm that discrepancies exist between intra-urban areas for all periods in the data (Sig. $<$ 0.00001; see Section H2(ii) of Table 5). These results suggest that submarkets do indeed exist within a single metropolitan area, and that they are distinguishable not just by differences in attribute prices but also by marked heterogeneity in short-run dynamics. This is important because of its implication for the liquidity profile of housing assets across a city. Investors should not assume that the risk of selling delays of residential property in a particular city can be adequately described by the average TOM because, as we have shown, liquidity profiles vary systematically both over time and across space.

Examination of the kernel-smoothed hazard curves for each submarket reveals that they are most out of sync in 2000 (confirmed by the Lawless χ^2 value being higher for that year than any other single year—see Table 5), but we find that they converge as the boom continues (compare Panels (a) and (b) of Figure 3). Existing studies have tended to control for cyclical factors by including time and

Table 4 ■ Life table for time on the market (TOM) in Glasgow submarkets (1999–2003).

TOM Interval (Days)		Hazard of Sale by Submarket: West End	East End	South Side	North Side
0	14	0.0058	0.0055	0.0096	0.0053
14	30	0.0300	0.0198	0.0337	0.0205
30	60	0.0250	0.0114	0.0156	0.0140
60	90	0.0186	0.0094	0.0110	0.0116
90	120	0.0150	0.0081	0.0101	0.0090
120	150	0.0110	0.0071	0.0075	0.0062
150	180	0.0090	0.0048	0.0061	0.0058
180	210	0.0098	0.0066	0.0058	0.0070
210	240	0.0111	0.0045	0.0060	0.0084
240	270	0.0070	0.0055	0.0052	0.0102
270	300	0.0075	0.0043	0.0051	0.0047
300	330	0.0062	0.0060	0.0070	0.0033
330	365	0.0047	0.0041	0.0055	0.0038
365	730	0.0045	0.0040	0.0042	0.0037
730	1095	0.0023	0.0022	0.0030	0.0033
$n =$		4,154	1,953	4,365	810

Note: This table lists the average hazard of sale for each interval of TOM. Hazards are found to vary across submarkets and across intervals of TOM. The hazard rate tends to rise initially and then fall as TOM increases, confirming our hypothesis that the hazard of sale is subject to nonmonotonic duration dependence.

seasonal dummies. However, as these graphs show, different housing segments, even if they are within relative proximity to one another, can have markedly different-shaped hazard rates at different points in the cycle. Stratification over both space and time is therefore necessary if Cox proportional hazard regression techniques are to be applied (current applications of the Cox model have not taken into account this kind of nonproportionality—see, for example, Larsen and Park (1989) and Kluger and Miller (1990)).

Hypothesis 3: Institutional Idiosyncrasies can have a profound effect on the shape and position of the hazard curve.

Section H3(i) of Table 5 reports the results of likelihood ratio tests of homogeneity between Offers Over and Fixed Price sales for Strathclyde, Glasgow and Glasgow submarkets. For all the spatial units considered, the null of homogeneity is decisively rejected. Comparing the different χ^2 values, it would appear that the submarket with the largest discrepancy between Offers Over and Fixed Price hazards is the South Side, and in Figure 4, we present the hazard

Table 5 ■ Likelihood ratio tests for homogeneity between groups.

	(a) H2(i) H_0: homogeneity between years (Test run on full sample then on on partic. areas)			(b) H3(i) H_0: homogeneity between OO & FP[b] (Test run on full sample then partic. areas)		
	χ^2 [4]	Sig.	*n*	χ^2 [1]	Sig.	*n*
Strathclyde	8,805.7	0.000	27,623	5,532.2	0.000	26,754
Glasgow[a]	3,906.0	0.000	11,282	2,554.6	0.000	11,150
West End	588.6	0.000	4,154	462.3	0.000	4,139
East End	724.2	0.000	1,953	472.6	0.000	1,892
South Side	2,197.7	0.000	4,365	998.9	0.000	4,316
North Side	348.1	0.000	810	153.5	0.000	803
	(c) H2(ii) H_0: homogeneity between areas (Test run on Glasgow[a] for all years then on particular years)			(d) H3(ii) H_0: homogeneity between OO & FP[b] (Test run on Glasgow[a] for all years then on particular years)		
	χ^2 [3]	Sig.	*n*	χ^2 [1]	Sig.	*n*
1999–2003	852.4	0.000	11,282	2,554.6	0.000	11,150
1999	215.7	0.000	2,457	305.6	0.000	2,431
2000	218.9	0.000	1,395	275.9	0.000	1,328
2001	62.7	0.000	1,272	193.8	0.000	1,246
2002:	208.1	0.000	2,905	251.3	0.000	2,896
2003:	99.6	0.000	3,253	239.0	0.000	3,249

Note: This table presents the results of Lawless (1982) likelihood ratio tests for homogeneity of the hazard function between different subsets of the data. Panel (a) presents the results of tests for homogeneity across years, first in the whole sample and then in each submarket. Panel (b) presents the results of tests for homogeneity between Fixed Price (FP) and Offers Over (OO) sales, both in the full sample and also in each submarket. Panel (c) tests for homogeneity between areas in both the whole sample and individual years. Panel (d) tests for homogeneity between Fixed Price and Offers Over sales, both in the full sample and also in individual years.

[a]The four Glasgow submarkets combined.

[b]The number of Fixed Price sales decline as a proportion of all sales from 38.46% in 1999 to 34.64% in 2000, to 26.24% in 2001, to 15.40% in 2002 and to 13.36% in 2003.

function results for this submarket, first for 1999 (Panel (a)) and then for 2001 (Panel (b)).

The graphs show that, although the vertical difference between hazards remains during a boom, the shapes of the curves do tend to converge (they become increasingly proportional to one another). Note that because the number of Fixed

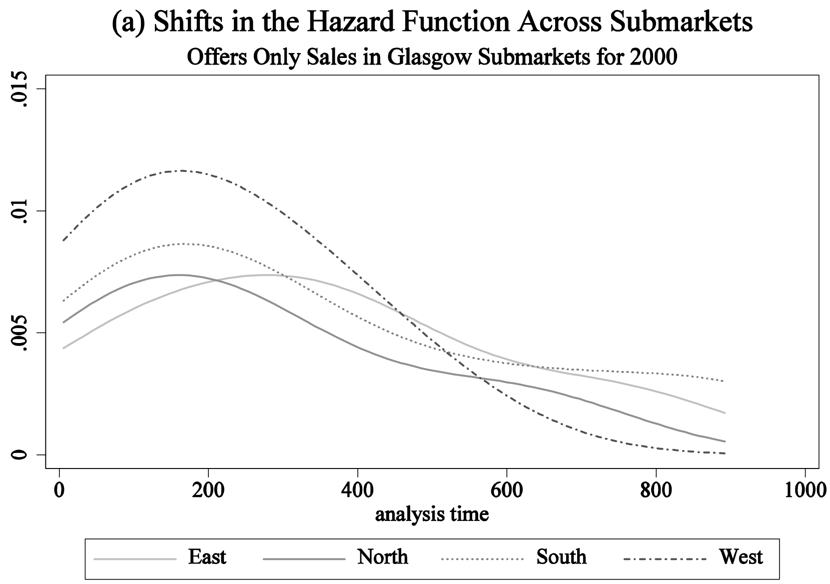
Price sales falls so rapidly during the course of the boom (the probability of switching to Fixed Price is itself contingent on the expected hazard of sale), there are sample size problems after 2001 for Fixed Price sales (*e.g.*, in 2003 the number of properties offered as Fixed Price that are still live after two months is just 59, falling to 12 properties after 4 months and zero properties after 10 months). Hence, we do not plot the graphs for the boom years 2002 and 2003. We do, however, present the likelihood ratio test results for all submarkets combined for each of the five years individually (and collectively) in Section 3(ii) of Table 5. Again the null of homogeneity is conclusively rejected in all cases.

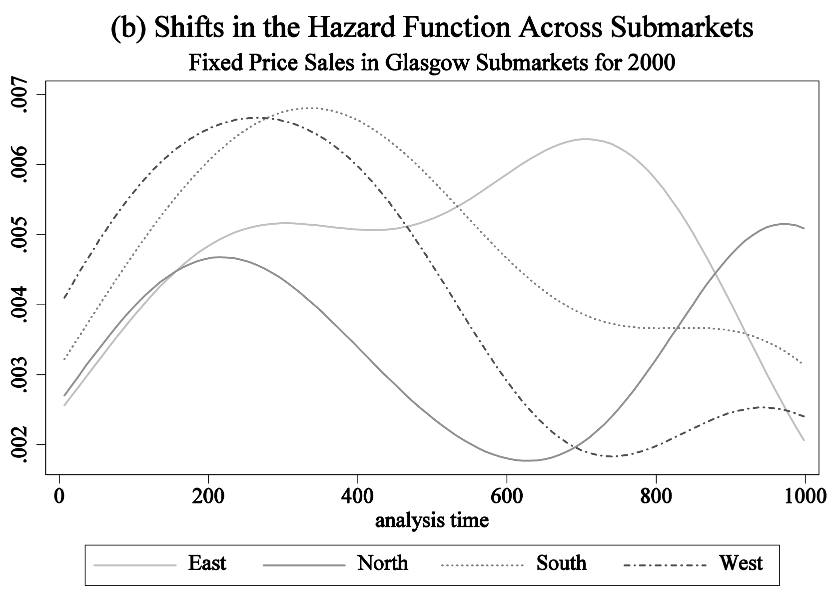
An important corollary of this finding is to ask how it affects the results from Hypotheses 1 and 2. One would expect that the argument for the existence of nonmonotonic duration dependence put forward in Hypothesis 1 would remain valid because the stigma effect does not disappear if one considers only Fixed Price or Offers Over sales (this is apparent in Figure 4).

However, one might expect the change in separate Fixed Price or Offers Over sales hazard curves to be different from that of a combined hazard curve because, as the market booms, fewer sellers will resort to Fixed Price sales (Offers Over marketing will increasingly produce a sufficiently rapid sale). Because we do not have data on when or whether individual sellers in our sample switch from Offers Over to Fixed Price sales, we cannot model the decision to switch from Offers Over to Fixed Price marketing at the individual household level. However, we do know that across the four submarkets, the proportion of Fixed Price sales falls from 38.46% in 1999 to 34.64% in 2000, to 26.24% in 2001, to 15.38% in 2002 and to 13.36% in 2003. This change in the proportion of Fixed Price sales during an upswing is likely to affect the relative shapes of the separate Fixed Price and Offers Over hazard functions. One might expect a similar metamorphosis of the hazard function over time for Offers Over sales, but without the initial right-hand humps evident when we examine all sales (because properties with very long TOM will have tended to switch to Fixed Price). This is confirmed in the first of the two diagrams in Figure 5 below where the right-hand humps remain for the Fixed Price hazard curves but not for the Offers Over hazard curves.

Regarding the question of whether or not one would still observe differences in the hazard function across submarkets if Offers Over sales were considered separately, one might expect the variation to persist but to be less pronounced because of differences in the propensity to switch to Fixed Price (Table 2 demonstrates the considerable variation the proportion of Fixed Price sales across submarkets: 15.86% in the West End, 22.37% in the South Side, 39.38% in the North Side and 33.11% in the East End). Figure 6(a) below confirms this:

Figure 6 ■ Hazard functions across submarkets: Offers Over vs. Fixed Price. Panel (a) plots the hazard function for each of the submarkets based on Offers Over sales alone. There is less of a difference in the hazard curves between submarkets than when the full sample is used (Figure 3(a)) or when the curves are plotted for Fixed Price sales (Figure 6(b)).





changes in the hazard curve across submarkets are less pronounced when one considers only Offers Over sales. Variation in the shape and position of the hazard curve remains equally pronounced, however, when we consider only Fixed Price sales (Figure 6(b)).

Conclusion

The article is the first published U.K. study of TOM to be based on a large data set and the first paper to attempt an in-depth analysis of the submarket heterogeneity of short-run marketing dynamics. We have employed Klein and Moeschberger's (1997) kernel-smoothed hazard functions, life table analysis and Lawless (1982) likelihood ratio tests to consider how the shape of the hazard function for marketing time changes over different phases of the housing cycle and across submarkets.

There are a number of conclusions we can draw from our analysis. First, we have shown that duration dependence (the tendency for the probability of sale to be contingent on how long a property has already been on the market) is linked to both the market cycle and the submarket structure of the urban housing market. Although the existence of duration dependence is not a new finding (it confirms the shape of the hazard function found in studies of U.S. house price sales, such as Jud, Seaks and Winkler 1996, though we find right-hand foothills in the hazard function during an upswing in the market), the implications of duration dependence have yet to be fully realized in the housing literature. It means, for example, that simple OLS or probit estimates of the probability of sale (*e.g.*,of the kind used in 2SLS and Heckman selection correction, used to create liquidity-adjusted price indices,) will not be entirely appropriate because they do not take into account the effect that marketing duration has on the probability of sale (they assume zero "duration dependence").

That the time dependence of the hazard of sale is found here to be non-monotonic is also important because it precludes the application of hazard regression models that assume monotonicity (such as Weibull, Exponential and Gompertz regressions). More appropriate modeling techniques would be ones that readily allow for such nonmonotonicity (*e.g.*, log-normal, log-logistic or semi-parametric hazard regressions.). So far, studies of time to sale appear to have overlooked the importance of the shape of the hazard function in deciding which estimation technique to use. Early studies of TOM applied OLS to TOM (Miller 1978, Kang and Gardner 1989) and even more recent papers have made use of OLS (particularly as the first step in 2SLS (see Forgey, Rutherford and Springer 1996 and Knight 2002). For the reasons already stated, OLS is inappropriate, however, for the analysis of TOM. Of the duration modeling techniques available, the most popular in the housing literature has been the

Weibull model (Zuehlke 1987, Haurin 1988, Yang and Yavas 1995, Jud, Seaks and Winkler 1996, Anglin, Rutherford and Springer 2003), but this does not allow for nonmonotonic duration dependency.

A second key insight from our study is that TOM analysis may provide evidence of the existence of submarkets and may further enrich our understanding of the nature and operation of those submarkets. We find, for example, that the hazard curve can vary significantly both in position and shape across intra-urban market areas. This adds support to the growing consensus (Goodman 1981, Watkins 2001, Goodman and Thibodeau 2003, Jones, Leishman and Watkins 2003) regarding the existence of submarkets by contradicting the notions of both a homogenous information set across the urban housing system and of spatially uniform adjustment over the business cycle. Our findings have implications for investors in terms of how they understand the nature of housing liquidity: any attempt to measure or control for liquidity variation that is based on an analysis of TOM will need to allow both for the *existence* of duration dependence and *shifts* in that dependence over time and space. In fact, there are implications for how hazard functions should be modeled in any multiple regression setting. For example, the homogeneity assumption of Weibull analysis and the "proportionality" assumption of Cox semi-parametric hazard regression (Larsen and Park 1989, Kluger and Miller 1990) are unlikely to hold, and so stratification by submarket is likely to be a necessary prerequisite. Shifts of this kind across submarkets are likely to undermine the generalizability of results from studies based on a single market and result in biased estimates in unstratified models of multiple submarkets. Tests for proportionality and application of appropriate correction methods are not typically used in the existing housing literature, but they could provide a means for future research to identify submarket boundaries.

We also find that, in a fluid-housing market, the hazard function shifts and evolves over time in a nonproportional way. This means that the phase(s) of the housing cycle in which TOM data are considered can have a profound effect on the results because the hazard function can evolve beyond recognition during the course of the cycle. The implication is that a regression model should also allow for nonproportionality over time and also include a covariate/accelerated hazard measure of the buoyancy of the local market. The great majority of existing studies have either employed samples drawn from two years or less (which again undermines the generalizability of results), or have failed to stratify by time. We recommend that future regression studies that are based on multiple submarkets also need to account for the fact that different submarkets included in the data may be at different phases of the housing cycle at any given moment. We also find that the institutional framework of a particular selling system (such as the difference between auctioned Offers Over and first come, first served

Fixed Price marketing in the Scottish system) can have a profound impact on the probability of sale and introduce further nonproportionality into the hazard function.

We wish to acknowledge the useful comments of Thomas Thibodeau and four anonymous referees. We are also grateful to GSPC for allowing us access to their data. We would further like to thank Gavin Wood for information on the Australian house-auction system, and Susan Smith for her helpful clarification of the Scottish conveyancing process.

References

Anglin, P.M., R. Rutherford and T.M. Springer. 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(1): 95–111.

Asabere, P., F. Huffman and S. Mehdian. 1993. Mispricing and Optimal Time on the Market. *Journal of Real Estate Research* 8(1): 149–156.

Banerjee, A.V. 1992. A Simple Model of Herd Behaviour. *Quarterly Journal of Economics* 107(3): 797–817.

Bikhchandani, S., D. Hirshleifer and I. Welch. 1992. A Theory of Fads, Fashion, Custom and Cultural Change in Information Cascades. *Journal of Political Economy* 100(5): 992–1026.

Chinloy, P. 1980. An Empirical Model of the Market for Resale Homes. *Journal of Urban Economics* 7: 279–292.

Cubbins, J.S. 1974. Price, Quality and Selling Time in the Housing Market. *Applied Economics* 6: 171–187.

Eklof, M. and A. Lunander. 2003. Open Outcry Auctions with Secret Reserve Prices: An Empirical Application to Executive Auctions of Tenant Owner's Apartments in Sweden. *Journal of Econometrics* 14: 243–260.

Fisher, J., D. Gatzlaff, D. Geltner and D. Haurin. 2003. Controlling for the Impact of Variable Liquidity in Commercial Real Estate Price Indices. *Real Estate Economics* 31(2): 269–303.

Forgey, F., R. Rutherford and T. Springer. 1996. Search and Liquidity in Single-Family Housing. *Real Estate Economics* 24: 273–292.

Gatzlaff, D.H. and D.R. Haurin. 1994. Measuring Changes in Local House Prices. *Journal of Urban Economics* 35: 221–244.

——. 1997. Sample Selection Bias and Repeat-Sales Index Estimates. *Journal of Real Estate Finance and Economics* 14: 33–50.

——. 1998. Sample Selection and Biases in Local House Value Indices. *Journal of Urban Economics* 43: 199–222.

Genesove, D. and J. Mayer. 1997. Equity and Time to Sale in the Real Estate Market. *American Economic Review* 87(3): 255–269.

——. 2001. Loss Aversion and Seller Behavior: Evidence from the Housing Market. *Quarterly Journal of Economics* 116(4): 1233–1260.

Gibb, K. 1992. Bidding, Auctions and House Purchase. *Environment and Planning* A 24: 853–869.

Glower, M., D. Haurin and P. Hendershott. 1998. Selling Time and Selling Price: The Influence of Seller Motivation. *Real Estate Economics* 26(4): 719–740.

Goodman, A. 1981. Housing Submarkets Within Urban Areas: Definitions and Evidence. *Journal of Regional Science* 21: 175–185.

Goodman, A.C. and T.G. Thibodeau. 1998. Housing Market Segmentation. *Journal of Housing Economics* 7: 121–143.

——. 2003. Housing Market Segmentation and Hedonic Prediction Accuracy. *Journal of Housing Economics* 12: 181–201.

Grigsby, W. 1963. *Housing Markets and Public Policy.* Philadelphia: University of Pennsylvania Press.

Haurin, D. 1988. The Duration of Marketing Time of Residential Housing. *AREUEA Journal* 16(4): 396–410.

Horovitz, J. 1992. The Role of the List Price on Housing Markets: Theory and an Econometric Model. *Journal of Applied Econometrics* 7: 115–129.

Huang, J. and R. Palmquist. 2001. Environmental Conditions, Reservation Prices, and Time on the Market for Housing. *Journal of Real Estate Finance and Economics* 22(2): 203–219.

Jones, C., C. Leishman and C. Watkins. 2003. Structural Change in a Local Urban Housing Market. *Environment and Planning* A 35(7): 1315–1326.

Jud, G., T. Seaks and D. Winkler. 1996. Time on the Market: The Impact of Residential Brokerage. *Journal of Real Estate Research* 12(3): 447–458.

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

Kalra, R. and K.C. Chan. 1994. Censored Sample Bias, Macroeconomic Factors, and Time on Market of Residential Housing. *Journal of Real Estate Research* 9(2): 253–262.

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

Klein, J.P. and M.L. Moeschberger. 1997. *Survival Analysis: Techniques for Censored and Truncated Data*. New York: Springer–Verlag.

Kluger, B. and N. Miller. 1990. Measuring Real Estate Liquidity. *AREUEA Journal* 18: 145–159.

Knight, J. 2002. Listing Price, Time on the Market and Ultimate Selling Price: Causes and Effects of Listing Price Changes. *Real Estate Economics* 30(2): 213–237.

Knight, J., C.F. Sirmans and G. Turnbull. 1998. List Price Information in Residential Appraisal and Underwriting. *Journal of Real Estate Research* 15: 59–76.

Krainer, J. 2001. A Theory of Liquidity in Residential Real Estate Markets. *Journal of Urban Economics* 49: 32–53.

Larsen, J.E. and W.J. Park. 1989. Non-Uniform Percentage Brokerage Commissions and Real Estate Market Performance. *AREUEA Journal* 17(4): 422–438.

Lawless, J.F. 1982. *Statistical Models and Methods for Lifetime Data*. New York: John Wiley and Sons.

Lee, E.T. 1992. *Statistical Methods for Survival Data Analysis.* New York: John Wiley and Sons.

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

Miller, N.G. 1978. Time on the Market and Selling Price. *AREUEA Journal* 6(2): 165–174.

Munneke, H.J. and A. Yavas. 2001. Incentives and Performance in Real Estate Brokerage. *Journal of Real Estate Finance and Economics* 22(1): 5–21.

Palm, R. 1978. Spatial Segmentation of the Urban Housing Market. *Economic Geography* 54: 210–221.

Pryce, G. 2004. *The Dynamics of Housing Submarkets: Measuring Duration Dependence in Time Off the Market.* Planning and Development Research Council Conference, University of Aberdeen, April.

Rapkin, C., L. Winnickand and D.M. Blank. 1953. *Housing Market Analysis.* Washington: U.S. Housing and Home Finance Agency.

Schnare, A. and R. Struyk. 1976. Segmentation in Urban Housing Markets. *Journal of Urban Economics* 3: 146–166.

Sirmans, C.F., G.K. Turnbull and J. Dombrow. 1995. Quick House Sales–Seller Mistake or Luck. *Journal of Housing Economics* 4(3): 230–243.

Stein, J. 1995. Prices and Trading Volume in the Housing Market: A Model with Downpayment Constraints. *Quarterly Journal of Economics* 110(2): 379–406.

Taylor, C.R. 1999. Time-on-the-Market as a Sign of Quality. *Review of Economic Studies* 66(3): 555–578.

Turnbull, G. and C.F. Sirmans. 1993. Information, Search and House Prices. *Regional Science and Urban Economics* 23: 545–557.

Watkins, C. 2001. The Definition and Identification of Housing Submarkets. *Environment and Planning A* 33: 2235–2253.

Yang, S. and A. Yavas. 1995. Bigger is Not Better: Brokerage and Time on the Market. *Journal of Real Estate Research* 10(1): 23–33.

Yavas, A. and S. Yang. 1995. The Strategic Role of Listing Price in Marketing Real Estate: Theory and Evidence. *Real Estate Economics* 23: 347–368.

Zuehlke, T.W. 1987. Duration Dependence in the Housing Market. *The Review of Economics and Statistics* 69(4): 701–709.

Appendix

Column one of Table A1 presents a hedonic ln(house price) regression based on the sales of 11,074 transactions across all four submarkets in Glasgow. All variables are statistically significant (t ratio greater than two). The final four columns present the results of the same regression run on each of the four submarkets separately. It can be seen that many of the coefficients vary substantially between the four areas (the coefficient on the number of bedrooms, *e.g.*, is 0.222 in the West End, 0.185 in the South Side, 0.171 in the East End and 0.159 in the North Side).

The results of Chow tests on the stability of coefficients across submarkets are presented in Table A2. The F values and associated significance levels unambiguously reject the null of homogenous coefficients across any of the two submarkets (the probability of falsely rejecting the null hypothesis of homogenous attribute prices is less than one-in-a-thousand). There is therefore strong evidence of variation in attribute-price across the four selected areas.

Table A1 ■ Hedonic log selling price regressions by submarket.

Variables	All 4 Submarkets	West End	East End	South Side	North Side
Dwelling is a house (rather than a flat)	0.16 (14.0)	0.08 (3.0)	0.32 (14.7)	0.24 (16.5)	0.30 (12.9)
Dwelling is main-door flat	0.17 (4.8)	0.11 (2.8)	0.00 (0.0)	0.16 (3.0)	−0.04 (−0.8)
Flat converted from a house	0.62 (20.0)	0.42 (13.3)	0.25 (1.4)	0.60 (14.7)	0.19 (1.3)
Detached bungalow	0.33 (10.4)	0.38 (4.9)	0.37 (7.7)	0.36 (7.7)	0.23 (5.7)
Semi-detached bungalow	0.20 (5.7)	0.34 (3.1)	0.04 (0.5)	0.26 (5.9)	0.13 (4.1)
Stone construction	0.06 (5.8)	0.07 (5.8)	−0.04 (−2.0)	0.06 (4.6)	−0.14 (−2.6)
Victorian	0.23 (6.0)	0.13 (3.3)	0.60 (6.6)	0.04 (0.9)	−0.29 (−6.1)
Has bay windows	0.22 (22.7)	0.17 (15.9)	0.06 (3.2)	0.16 (12.5)	0.03 (1.1)
Number of bedrooms	0.20 (31.9)	0.22 (22.4)	0.17 (13.9)	0.19 (25.6)	0.16 (10.6)
Number of public rooms	0.22 (18.4)	0.24 (10.0)	0.17 (9.9)	0.20 (19.1)	0.08 (2.0)
Dwelling is described as spacious	0.05 (5.5)	0.06 (5.3)	0.03 (1.7)	0.04 (3.2)	−0.04 (−1.7)
Conservatory	0.12 (3.8)	0.08 (1.2)	0.09 (1.7)	0.21 (4.7)	0.04 (0.9)
Has garage	0.17 (14.1)	0.17 (8.6)	0.18 (9.5)	0.20 (12.7)	0.15 (6.5)
Has garden	0.02 (2.1)	0.02 (1.7)	0.12 (6.2)	0.02 (1.8)	0.00 (0.1)
Has parking	0.10 (8.2)	0.07 (4.5)	0.04 (1.9)	0.09 (4.6)	0.10 (4.0)
Has gas central heating	0.14 (17.2)	0.12 (11.5)	0.12 (7.7)	0.13 (12.5)	0.01 (0.5)
Burglar alarm	0.04 (3.4)	0.06 (3.2)	0.10 (3.7)	0.04 (2.8)	0.07 (3.0)
Dwelling needs upgrading	−0.23 (−4.6)	−0.10 (−1.3)	−0.20 (−2.6)	−0.18 (−2.9)	−0.35 (−2.9)
Dwelling is described as "luxury"	0.27 (10.3)	0.13 (4.6)	0.08 (1.0)	0.31 (6.6)	0.09 (1.9)
En-suite bathroom facilities	0.26 (9.8)	0.19 (6.6)	0.12 (2.3)	0.15 (3.5)	0.26 (8.2)
Dwelling has notable views	0.10 (5.8)	0.05 (2.5)	0.02 (0.4)	0.06 (2.5)	0.07 (1.8)
Distance to center of Glasgow (km)	−0.06 (−23.2)	−0.10 (−33.0)	−0.02 (−4.9)	−0.06 (−14.1)	0.04 (4.0)

Table A1 ■ continued.

Variables	All 4 Submarkets	West End	East End	South Side	North Side
Spring	0.05	0.03	0.04	0.08	0.04
	(4.3)	(1.7)	(2.0)	(5.4)	(1.4)
Summer	0.11	0.08	0.08	0.11	0.09
	(9.0)	(5.2)	(3.7)	(6.9)	(3.3)
Autumn	0.11	0.06	0.09	0.12	0.11
	(9.2)	(4.3)	(3.9)	(7.8)	(3.8)
y2000	0.03	0.07	−0.04	0.01	0.08
	(2.1)	(4.2)	(−1.5)	(0.3)	(2.3)
y2001	0.16	0.14	0.10	0.09	0.11
	(11.4)	(8.9)	(3.4)	(4.5)	(3.8)
y2002	0.33	0.32	0.26	0.34	0.22
	(30.0)	(23.2)	(12.6)	(23.4)	(8.4)
y2003	0.51	0.49	0.47	0.53	0.41
	(46.4)	(31.8)	(22.8)	(37.9)	(16.4)
˙cons	9.96	10.47	9.66	9.92	9.73
	(426.9)	(276.3)	(245.6)	(324.1)	(161.7)
N	11074	4057	1912	4303	802
Adjusted R^2	0.52	0.642	0.669	0.634	0.708

Note: This table presents the results of hedonic ln(house price) regressions run on all four submarkets combined and then on each submarket separately. Coefficients (and hence attribute prices) vary considerably between submarkets. Figures in parentheses are t ratios based on White's standard errors.

Table A2 ■ Chow test results for equivalence of coefficients across two areas.

	West End	East End	South Side
East End	154.8	.	.
	0.000	.	.
South Side	98.5	28.7	.
	0.000	0.000	.
North Side	85.9	4.5	17.2
	0.000	0.000	0.000

Note: Figures in parentheses represent the significance values from F tests computed using the following formula: $F[r, df_U] = (RSS_R - RSS_U/r)\ /\ (RSS_U/df_U)$ where $RSS_R = RSS_1 + RSS_2$ where RSS_1 and RSS_2 are the residual sum of squares from samples 1 and 2 respectively, RSS_U is the residual sum of squares from samples 1 and 2 combined and $dfu = n_1 + n_2 - 2k$ where n is the sample size and k is the number of regressors. The null of equal coefficients is rejected in each case (significance < 0.001).