Real Estate Liquidity

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Residential real estate markets often go through "hot" and "cold" periods. A hot market is one where prices are rising, liquidity is good in that average selling times are short, and the volume of transactions is higher than the norm. Cold markets have just the opposite characteristics—prices are falling, liquidity is poor, and volume is low. In this paper I provide a theory to match these observed correlations. I show how liquidity depends on the value of the housing service flow, which in turn reflects the aggregate state of the economy. I use data from the San Francisco Bay Area to investigate the relationship between marketing times and state variables such as the interest rate and job growth.

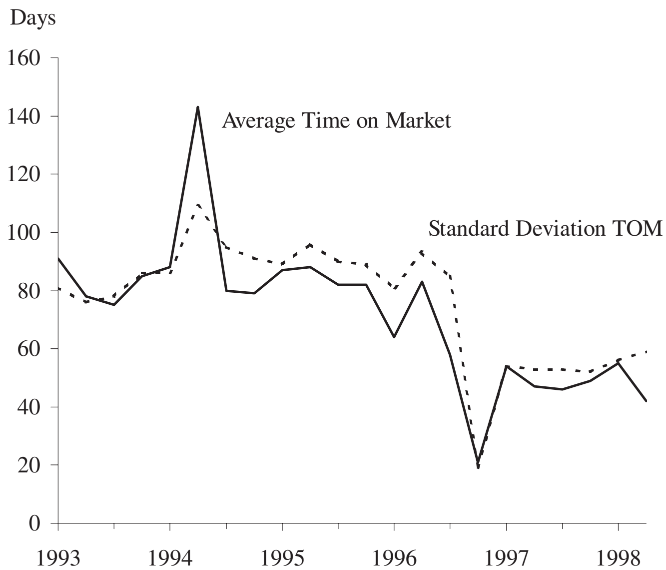
The amount of time required to sell a house is one of the more actively studied topics in real estate economics. The time to sale is inextricably linked to the pricing of real estate assets; thus, its importance to individual members of the economy cannot be overemphasized.

Researchers have few good theories about what should govern the time to sale. In most models of asset prices, time to sale is exactly zero. This is a consequence of the market-clearing condition that is often required to pin down equilibrium. But any model where the market clears must abstract from frictions, and frictions in the real estate market are so notoriously severe that they cannot be ignored. For example, unlike participants in financial securities markets, sellers of houses typically know much more about the asset for sale than prospective buyers know. In addition, buyers generally do not reveal how much they are willing to pay for a given house. Furthermore, each buyer in the market may be different, both in terms of financial means and tastes for the real estate good. And, most importantly, the real estate market is decentralized; buyers and sellers who want to trade must undergo a (sometimes costly) search process in order to complete a transaction.

In this paper I discuss some of the theoretical issues involved with modeling the time to sale of real estate assets. The key question I will address is why marketing periods for houses fluctuate so much over time (see Figure 1). It is not surprising that house *values* fluctuate over time and over different states of nature. Variation in interest rates and employment opportunities should cause variation in the value of the housing service flows provided by homeownership. But most economic theory predicts that fluctuations in fundamentals should be immediately reflected in prices. That is, if the value of a house changes by a certain amount, the price of the house should change by the same amount. The real estate market does not appear to work this way. Rather, when house values decline, sellers are slow to drop their prices. Thus, marketing times increase and the volume of sales declines. These are all features of a cold real estate market. The hot market has just the opposite characteristics. Real estate prices are typically rising during hot markets. However, prices do not appear to rise fast enough, as suggested by the fact that houses are quickly snapped up after they are brought to market.

FIGURE 1

AVERAGE TIME ON MARKET
IN SELECTED BAY AREA MUNICIPALITIES



SOURCE: East Bay Regional Data

The model developed in this paper is similar in structure to search models developed for real estate markets by Arnott (1989), Wheaton (1990), and Williams (1995). Stein (1995) also studies hot and cold real estate markets, but from a very different perspective. In Stein's model, cold markets arise from credit market frictions. Whereas in this paper, hot and cold markets arise from search frictions and asymmetric information.

The paper is organized as follows. In the first section, I outline a theory of real estate prices and liquidity that captures the hot and cold markets phenomenon. The model used here is a search-theoretic model where prices and liquidity are derived from the maximizing behavior of both buyers and sellers. Agents who live in houses consume housing services or housing dividends. Trade in houses takes place because individuals are vulnerable to idiosyncratic shocks that sever the match with their house. This might happen because of a change in household size or a job transfer. When an agent loses his match, he moves out immediately and puts the old house up for sale. As a seller, the agent prices the house so as to maximize the expected value of having the house on the market. At the same time, the agent is temporarily homeless and must search for a new house to live in. As a potential buyer, the agent searches until he finds a house that offers him enough utility net of price to warrant leaving the market. Since both buyers and sellers are optimizing, price and liquidity are determined endogenously. When the per period housing service flow is allowed to vary, liquidity also varies so as to match the observed correlations between prices, liquidity, and sales volume.

In Section II, I use data from the San Francisco Bay Area housing market to investigate the determinants of time on the market. In this empirical exercise, the intent is not to test hypotheses or even to select between different models of the real estate transaction. Rather, the exercise is a reduced form investigation into the relationship between time on the market and certain economic variables and asks whether these relationships are consistent with the theory developed in Section I.

I. THEORETICAL MODELS OF TIME ON THE MARKET

The basic structure of a search model is a setting where a large number of agents engage in bilateral trade. The central assumption is that agents do not gather in a single market place where they view all assets for sale. Rather, agents form expectations about the kinds of transactions that are feasible in the economy and then meet potential trading partners sequentially. The challenge is to characterize agents' decision rules in this environment. For example, based on the expectations a seller might have of how much buyers are willing to pay for a house, the seller must decide when to accept a bid and when to reject it. The fundamental tradeoff for a seller, then, is to weigh the benefits of further searching against the costs of delaying the sale. The benefits of continued searching are obvious: a buyer may arrive who attaches greater value to the house. The delay associated with continued search can be costly because (a) the agent delays consumption and (b) once the agent rejects an offer, it is uncertain when, if ever, the next "good" offer will arrive.

A One-sided Search Problem

A simple example may help illuminate the basic structure of the search model.[1] Suppose that an agent with a house for sale receives bids on the house one at a time. The agent believes that house prices are drawn from the continuous distribution F and that draws from the distribution of prices (i.e., offers) are i.i.d. For simplicity, assume that once the agent has sold his house, he takes the cash from sale and exits the economy.

1. This section borrows from Lippman and McCall (1986) and Sargent (1987).

The lifetime expected utility of a seller with offer price p in hand can be expressed recursively by

$$v(p) = \max\left[p, \beta\int_0^\infty v(y)dF(y)\right]. \qquad (1)$$

Lifetime expected utility is either the price p the seller receives from an immediate sale or it is the discounted expected utility of putting the house up for sale next period —whichever is greater. The parameter β is the seller's discount factor.

Equation (1) is an example of a Bellman's equation. Note that v is increasing in p and that the quantity $\beta\int_0^\infty v(y)dF(y)$ is a constant. It follows that there exists a price p^*, called the *reservation price,* such that

$$p^* = \beta\int_0^\infty v(y)dF(y) \ . \qquad (2)$$

The optimal decision rule in this problem is for sellers to accept all offers at least as high as p^* and to reject all offers below p^*.

This search model is flexible. It should be apparent that it is possible to set up the problem from either the buyer's or the seller's perspective. The important point to notice, however, is that the model implies that time on the market depends solely on F, the distribution of the bid arrival process. It is legitimate to ask where the seller's beliefs about F actually come from. If buyers were to realize that sellers accepted all offers above p^*, then no buyer would ever offer more than p^*. This type of equilibrium quickly collapses when parties on both sides of the transaction are allowed to behave optimally.

A Two-sided Search Problem

A more natural way to model trade in housing markets is to view both buyers and sellers as searchers. Towards this end, I will sketch the outline of a two-sided search model.[2] Suppose that houses, like any asset, have value because they produce a flow of services and assume that this service flow accrues to the homeowner each period for as long as the owner lives there. If the owner leaves the house, then the house ceases to yield a service flow and the owner proceeds to sell the house and look for a new house himself. Thus, when an agent leaves the house, the decisionmaking problem is to specify a pricing rule for the old house and a search strategy that will be utility maximizing. To make the problem interesting, assume that not all agents have the same preferences for houses that they visit. Differences in housing tastes imply that the search process may take time.

2. This model and its properties are developed in Krainer and LeRoy (1998).

Proceeding more formally, assume there are a large number of risk-neutral agents in an economy where the traded goods consist of a consumption good and houses. The consumption good serves as the numeraire. There is no new construction and no depreciation of the existing housing stock. An agent who owns and lives in a house enjoys a per period housing service flow, ε, that is constant for as long as an agent stays in the house. When an agent vacates a house and searches for a new one, she draws a new ε from the uniform distribution F on the interval [0,1].[3] Draws from this distribution by potential buyers are independent.

Trade in houses occurs because agents lose their "match" with their houses. This happens for purely exogenous reasons (e.g., the arrival of children, the departure of children), and occurs with probability $1 - \pi$ each period. For the moment, this is the only kind of uncertainty in the model. Once a homeowner loses the match, the house ceases to provide a service flow to its owner, and the owner puts it on the market, attempting to sell it for as much as possible.

Each period, a potential buyer visits the empty house. At this time, she draws from F and determines how much she likes the house. The seller sets a take-it-or-leave-it price before he learns anything about the buyer.[4] It is assumed that buyers face no financial constraints. If the buyer chooses to buy, she pays the asking price immediately and starts to receive housing services at the beginning of the next period. Thus, houses are priced ex-dividend, as is the convention in the asset pricing literature. If the buyer chooses not to buy, she does not consume any housing services in that period and searches again in the next.

Figure 2 contains a schematic of the timing of events for a buyer and seller pair of agents. The agents meet at the beginning of the period. All cash flows and consumption takes place at this time. Upon visiting the house, the buyer observes the idiosyncratic dividend ε yielded by this particular house and the listing price. If the buyer chooses to buy, then she pays the seller the cash price immediately. The house begins to yield dividends to its new occupant in the beginning of the next period. If the buyer chooses not to buy the house, then the house lies empty and the buyer is homeless for the period. The seller relists the house and the buyer visits a different house in the following period.

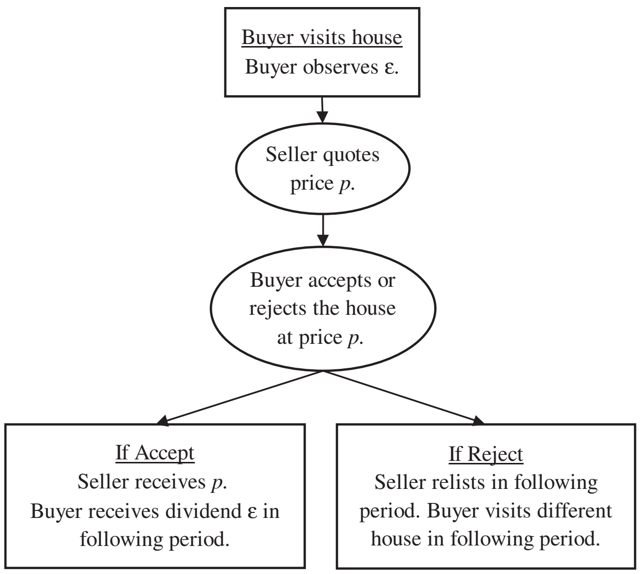
The steady state equilibrium in this economy consists of utility maximizing decision rules for both buyers and sellers. Let q be the expected value of having a house on the

3. From here on sellers of houses will be male and buyers female.

4. Real world housing transactions, of course, are accompanied by hard bargaining. Take-it-or-leave-it pricing should be viewed as a Nash bargaining game where the seller has all the bargaining power.

FIGURE 2

DECISIONMAKING BETWEEN SELLER/BUYER PAIR



market and let $\mu(p)$ be the probability that a house will sell when the list price is p. The seller chooses a price to solve

(3) $$q = \max_{\tilde{p}}\{\mu(\tilde{p})\tilde{p} + (1-\mu(\tilde{p}))\beta q\}.$$

With probability μ the seller receives the asking price for the house. Otherwise the seller puts the house back on the market and tries to sell it again in the next period. The parameter β is a discount factor.

The first order condition that yields the optimal price p is

(4) $$\frac{d\mu}{dp}(p-\beta q)+\mu(p)=0.$$

The retail price of housing, p, and the expected value of having a house on the market (or the wholesale price of housing), q, are determined in equations (3)–(4) in terms of μ, the probability of sale function. This is the key point of departure between one-sided search models where μ is taken exogenously and the two-sided models where μ is derived endogenously.

We now describe the optimal behavior of a buyer. We start first with an agent who currently has match ε and is scheduled to consume the housing service flow at the beginning of the next period. Define $v(\varepsilon)$ to be the lifetime expected utility of owning a house yielding service flow ε,

(5) $$v(\varepsilon) = \beta(\varepsilon + \pi v(\varepsilon) + (1-\pi)(q+s)).$$

The agent will consume next period's housing service flow with certainty. With probability π the match will persist for another period and the homeowner will continue to consume ε. The match will fail next period with probability $1-\pi$. In this case, the agent must put the house on the market and begin to search again. The house selling process, as we saw above, yields q in expected value. The agent is also free to search for a new house at this point. The value of this recovered search option is denoted by s. Note that this is the *value* of a house to a particular agent. The value of a house to an owner depends solely on the service flow ε and is very different from the *price.*

If we consider a buyer who is contemplating buying a house with service flow ε for price p, then the optimal strategy is to buy if the expected value of the house net of price is greater than the option to search again next period. That is,

(6) $$v(\varepsilon) - p \geq \beta s.$$

This problem has the same form as the seller's problem in the one-sided search model above. Since v is strictly increasing in ε and βs is constant, there exists an ε^* such that a searching agent is indifferent between buying a house for the quoted price p and searching again next period. That is, there exists an ε^* such that

(7) $$v(\varepsilon^*) - p = \beta s.$$

The service flow ε^* is the *reservation service flow,* and plays the same role in the search process as the reservation price discussed above.

A searching agent continues searching if she draws $\varepsilon < \varepsilon^*$ and buys if she draws $\varepsilon \geq \varepsilon^*$. Therefore, we can write the expected value of search as

(8) $$s = F(\varepsilon^*)\beta s + (1-F(\varepsilon^*))\left(\int_{\varepsilon^*}^{1} v(\varepsilon)dF(\varepsilon) - p\right).$$

In order to close the model we note that the probability of sale is simply the probability of drawing $\varepsilon \geq \varepsilon^*$, or $\mu = 1 - F(\varepsilon^*)$, or

(9) $$\mu = 1 - \varepsilon^*,$$

when F is the uniform distribution on [0,1].

Equilibrium is a price of housing p, an expectation of the value of a house on the market q, an expectation of the outcome from the search process s, a reservation service flow ε^*, and a belief about the probability that a buyer will purchase a house μ when the price is p. All these variables must satisfy equations (3), (4), (7), (8), and (9). The equilibrium is a Nash equilibrium: the actions of both sellers and buyers are best responses to each other. Standard fixed-point arguments can be used to prove the existence of equilibrium. The nonlinear nature of the system of equations makes it difficult to solve the system analytically, but it is routine to solve for the equilibrium numerically.

The primary object of interest in this model is the time a house is on the market. Given the per period probability of sale, μ, it is straightforward to derive the expected time on the market,

$$TOM = \frac{1-\mu}{\mu} \quad (10)$$

The immediate observation is that *TOM* is an expected *remaining* duration. This expectation is a constant. It does not depend on the time a house already has spent on the market. This lack of time dependence is a consequence of the choice to abstract from all financing constraints. Sellers in this model are never forced to drop their prices and sell so as to finance a downpayment on another house.

Also, since there is no aggregate risk in the model, note that there can be no state dependence in *TOM*. But aggregate risk can easily be incorporated in the model by redefining the housing service flow to consist of an idiosyncratic component ε and an aggregate component *x,*

$$d = \varepsilon + x \quad (11)$$

The idiosyncratic component ε has the same interpretation as before. The variable *x* is aggregate in that all agents who live in houses receive exactly the same *x.* We assume that *x* is a stochastic process that can take on one of two values, a high value x^H and a low value x^L. Assume that *x* is a first-order Markov process with transition probability $1 - \lambda$. Thus,

$$\Pr(x' = x^k \mid x = x^k) = \lambda \text{ for } k = L, H. \quad (12)$$

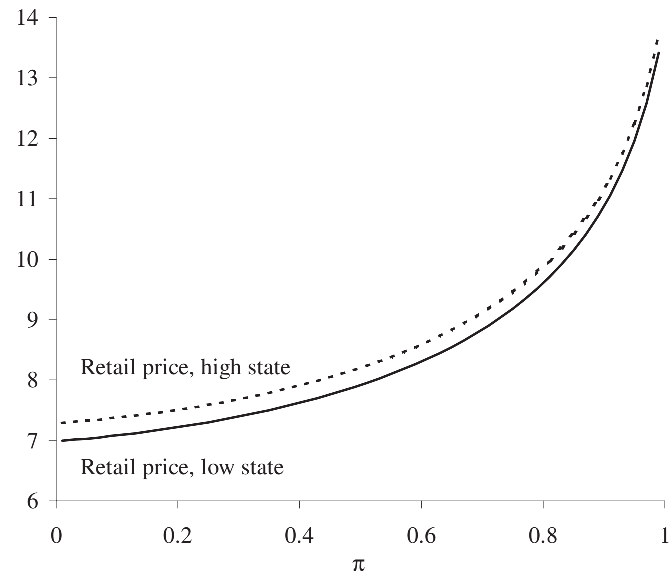
I adopt this specification because prices of individual houses tend to move together with those in the same neighborhood, city, or even within a broader geographical region. Since it is unlikely that idiosyncratic tastes vary much over time, it makes sense to model this covariation by assuming a common component in all housing service flows. The variable *x* is meant to reflect the aggregate state of the economy. A more concrete interpretation of *x* could include amenity levels such as school quality or the level of crime in the area.[5] It is also possible to interpret *x* as a location-specific component in the housing service process that reflects the value of land. Under this interpretation, shocks to the productivity of the land or to job growth filter their way into house prices through *x.*

By adding a random variable *x* to the housing service flow, the equations above that define equilibrium are adjusted to become functions of *x.* Figures 3 and 4 show simulated values of the pricing function $p(x)$ and the probability of sale function $\mu(x)$ for different values of π. Note that for all values of π, $p(x^H) > p(x^L)$ and $\mu(x^H) > \mu(x^L)$. Evidently, good liquidity corresponds to periods when the value of the housing service flow is high and prices are high. Since houses are more likely to sell during these periods, on average, more houses do sell and the volume of sales is greater in this state than in the low state. Thus, the model is able to match the observed correlations between liquidity, prices, and volume. Krainer (1999) argues that this is a natural outcome in markets where asset values fluctuate and agents must search for trading partners. When *x* is high and the value of housing is correspondingly high, sellers raise their prices, but not so high as to choke liquidity. In this kind of environment, sellers demand liquidity because if they fail to sell, they risk the possibility that the state of the economy changes and that they will be forced to sell on less advantageous terms. Likewise, in cold markets when *x* is low, sellers do not demand liquidity. That is, they do not drop their prices to maintain liquidity. Rather, it is optimal to keep prices high. Failure to sell in a cold market is not costly if sellers expect the state of the economy to improve. Thus, it is optimal for sellers to follow the old dictum and wait out a cold real estate market.

The modeling assumption that drives these results is the inability of sellers to hedge changes in the opportunity cost of failing to sell their houses. As stated above, pricing a

FIGURE 3

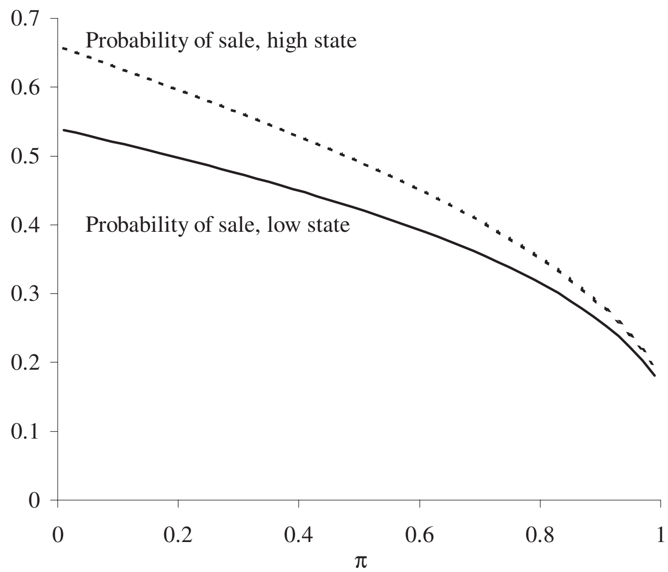
Pricing Function
($\beta = 0.95$, $x^L = 0$, $x^H = 0.4$, $\lambda = 0.8$)



5. See Gabriel, Mattey, and Wascher (1996).

FIGURE 4

PROBABILITY OF SALE FUNCTION
($\beta = 0.95$, $x^L = 0$, $x^H = 0.4$, $\lambda = 0.8$)



house high in a hot market is risky because the state variables of the economy are stochastic. Sellers are anxious to sell quickly in hot markets because they do not want to be caught with an empty house during a cold market. If sellers are allowed to rent out empty houses at a price that is perfectly correlated with the value of the housing service flow, then fluctuations in liquidity completely disappear and real estate prices incorporate all changes in real estate values. That is, expected returns for the marginal buyer are constant. The fact that moral hazard discourages many homeowners from renting out their empty houses suggests that fluctuating liquidity is a natural feature of owner-occupied real estate markets.

II. EMPIRICAL STRATEGIES FOR STUDYING TIME ON THE MARKET

The model developed above is overly simplistic for the sake of tractability. There are two parameters in the model: $1 - \pi$, the per period probability of moving, and $1 - \lambda$, the per period probability that the state variable x changes value. The model places no restrictions on these probabilities except that they lie between zero and one. The chief result of the model is the joint derivation of a probability of sale function $\mu(x)$ and a pricing function $p(x)$ that implies that house prices, liquidity, and transaction volume be positively correlated, as in fact they are in the data. As far as causation, the model is silent and simply assumes that the evolution of the state variable x drives the economy. The remainder of this paper is devoted to searching for candidate x variables and assessing their ability to "explain" time on the market in a reduced form setting.

The most prevalent technique for studying durations of any kind is the use of hazard models.[6] The hazard function specifies the time t probability of an event occurring at time T, given that the event has not yet occurred. Formally, the hazard function is defined as

$$\theta(t;x) = \lim_{dt \to 0} \frac{\Pr(t \le T < t + dt | t \le T, x)}{dt} . \tag{13}$$

As in the theoretical section, x is a vector of covariates that influence the hazard function.[7]

The probability of selling a house in a given period is analogous to the per period hazard rate. All predictions about how the probability of sale varies with time and with other variables are really predictions about the shape of the hazard function. In the model presented in this paper, the probability of sale is independent of how long the house has been on the market, implying that the hazard function is a constant function of time. The model predicts that the probability of sale depends on the aggregate state of the economy. Thus, one should detect a statistically significant relationship between the marketing times and variables such as employment growth and interest rates.

The first specification of the hazard function that I consider is the exponential hazard given by

$$\theta(t;\, x) = \gamma \exp(x'\xi) . \tag{14}$$

Here, x is a vector of covariates and ξ a vector of parameters. The parameter γ is the underlying hazard rate, or the baseline hazard, which results when all covariates take on zero value. Note that the exponential hazard function, like the probability of sale function developed above, does not depend on time.

Since the constant hazard model is likely to be too constraining for empirical work, I also consider a generalization of the exponential hazard, the Weibull hazard function, given by

$$\theta(t;\, x) = \gamma\alpha(\gamma t)^{\alpha-1} \exp(x'\xi) . \tag{15}$$

6. See Kalbfleisch and Prentice (1980) and Lancaster (1990) for extensive discussion of hazard model estimation.

7. It also is possible to make the covariates functions of time. This specification is useful for problems such as modeling the time to mortgage prepayment, where the time path of interest rates influences the decision. In this study, average times to sale are sufficiently short (two months), so I have elected not to incorporate time-varying covariates.

The Weibull model is characterized by a scale parameter α, which, together with time t, determines the slope of the hazard function. If $\alpha > 1$ then the hazard is increasing, meaning that houses that have already been on the market a long time are more likely to sell. Increasing hazards might be observed if sellers lowered their asking prices after a long duration on the market. The opposite situation obtains if $\alpha < 1$. A decreasing hazard might result from buyers inferring that houses with long marketing times are lemons. The Weibull hazard reduces to the exponential hazard in the special case of $\alpha = 1$.

The third specification that I consider, the Cox model, is semiparametric in nature. Suppose that the hazard function for a particular house i takes the form

$$\theta_i(t; x) = \theta_0(t)\exp(x'\xi) \ . \tag{16}$$

Here, $\theta_0(t)$ is the baseline hazard. Given another house j, the hazard ratio takes the form

$$\frac{\theta_i(t;x)}{\theta_j(t;x)} = \exp(\Delta x'\xi) \ , \tag{17}$$

where Δx is the difference between the covariates associated with the two houses. The Cox model is semiparametric because estimation of ξ does not require one to specify the functional form of the underlying hazard $\theta_0(t)$.

All three specifications are examples of proportional hazard models. This model class is particularly useful because it enables researchers to compute easily how the hazard rate of otherwise identical houses varies with changes in one of the covariates. For example, in the Cox model, if x_1 is the mortgage interest rate (in percentage terms), then $\exp(\xi_1)$ is the relative likelihood that the same house will sell when the interest rate is one percentage point higher.

Data and Results

The data are from East Bay Regional Data (EBRD), a multiple listings service that covers Alameda County, Contra Costa County, and parts of Solano County. EBRD collects these data for, among other purposes, calculating the median house price in a given market, tracking the volume of sales, and providing member realtors with data to price houses using comparables. The data range from winter 1992 to spring 1998. This sample period corresponds to nearly one complete real estate cycle for the Bay Area.

I use data from six adjacent East Bay municipalities: Alameda, Albany, Berkeley, Emeryville, Oakland, and Piedmont. The raw dataset contains 29,305 observations. Of this total, 14,303 (49 percent) of the listings culminated in sales. The remaining listings were either allowed to expire or were withdrawn by the seller. In cases of withdrawals and expirations, the observation is treated as right-censored at the termination date. There are many instances where an owner lists a house, withdraws it, and then relists the house later.[8] In this case, I treat the first listing as a censored observation and calculate time on the market to be the time elapsed between the second (or final) listing and the sale.

Each observation in the dataset includes the original list price, the final sale price, as well as property-specific information such as the address, the type of structure (single-family detached or condominium) the number of baths, the number of bedrooms, square footage, age, and whether or not the property is covered by a homeowner's association. The dataset also includes the dates of original listing, the pending date or the date escrow is opened, and the closing date. For this study, time on the market corresponds to a marketing time. Thus, time on the market is calculated as the time elapsed between the original listing and the pending date. Summary statistics of the variables are set forth in Table 1.

The theory presented here suggests that time on the market depends on the aggregate state of the economy. In practice, the relevant set of state variables will include local economic variables and financial market variables. Homebuyers require a downpayment in order to purchase a house. Accordingly, variables that contribute to household wealth, such as the growth in personal income and the growth in employment, are candidates for covariates. Of these two variables, housing economists traditionally concentrate on the growth in local employment, because job creation not only adds to household wealth, but also stimulates housing demand due to the migration of households into the market to fill the newly created jobs. Growth in employment also may reflect an increase in local productivity, which should affect house prices if land is a part of the production function. The job growth data are provided by the Bureau of Labor Statistics.[9] As can be seen in Figure 5, Bay Area job growth has risen steadily over the course of the sample period. Leading into the hot market, local job growth was dramatic, eclipsing the national average.

Financial market variables also will affect the housing market because most people finance their housing purchases. Thus, the level and expectations about future mortgage interest rates will be important in the housebuying decision. The mortgage interest rate data used in this study are taken from Freddie Mac's (Federal Home Loan Mortgage Corporation) primary mortgage market survey. Figure 6

8. The second list price is usually, but not always, lower than the first. Anecdotally, realtors report that sellers who withdraw a house oftentimes perform mild renovations before relisting, such as painting the interior or improving the landscaping.

9. The Bay Area reporting region consists of San Francisco, Oakland, San Jose, Santa Rosa, and Vallejo-Fairfield-Napa MSAs.

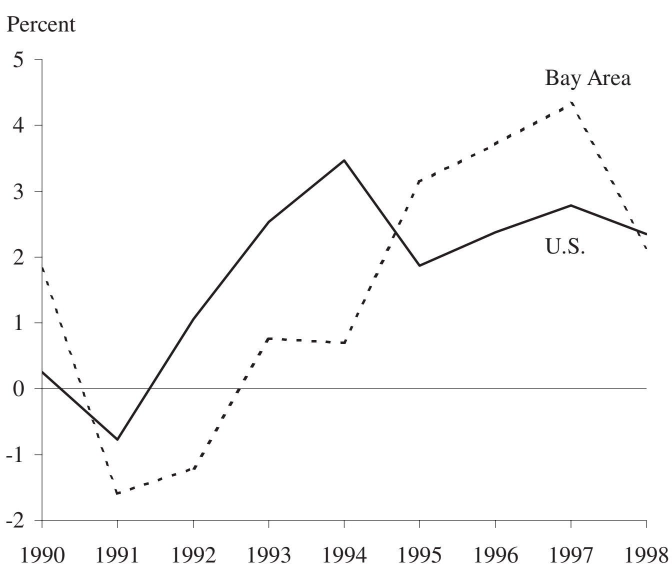
TABLE 1

SUMMARY STATISTICS
SAMPLE CHARACTERISTICS OF HOUSES SOLD, 1992–1998

VARIABLE	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
Bedrooms	2.70	0.94	1	9
Bathrooms	1.61	0.73	1	7
Square feet	1,575	744	420	11,067
Age	58	31	0	99
List price	244,354	171,287	14,900	3,950,000
Sold price	237,340	165,244	10,000	3,300,000
Time on market	68	78	1	816
Condominium	0.144			
List in summer	0.268			
Observations	14,303			

FIGURE 5

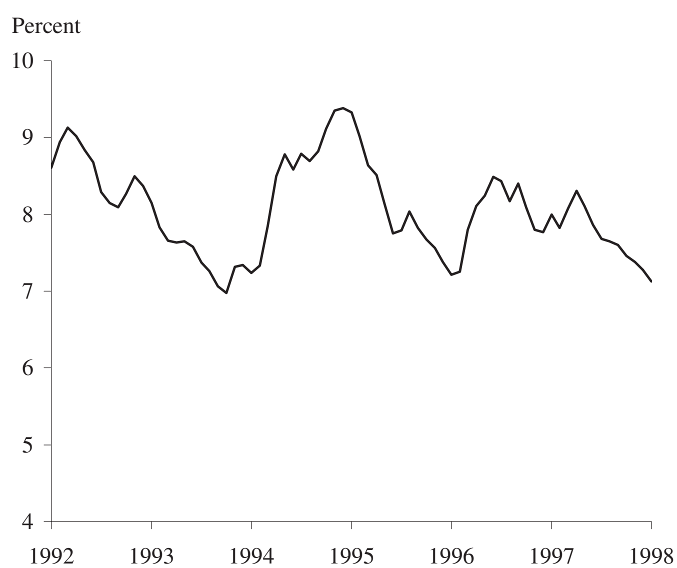
ANNUAL JOB GROWTH



SOURCE: Bureau of Labor Statistics

FIGURE 6

EFFECTIVE COST OF MORTGAGE FINANCE



SOURCE: FHLMC

plots the benchmark mortgage rate plus an adjustment for points charged. I have assumed that one point is worth ten basis points. I use this composite measure rather than each variable separately because there appears to have been a break in the points series during the winter of 1997—precisely the time when the Bay Area real estate market was heating up.

Ignored in the analysis up to this point is the notion that the real estate market is highly segmented by type and quality of the housing unit. Most realtors will testify that high priced houses and houses with unusual configurations have a longer waiting time on the market—allegedly because the demand is much thinner in these submarkets. No such segmentation exists in the theoretical model. However, it is possible to recast the degree of heterogeneity in housing characteristics either as a statement about the distribution of the housing service flow ε or as a statement about the waiting time until a potential buyer visits the house for sale. That is, it is possible to assume that potential buyers for a certain type of house arrive every $n > 1$ periods instead of every period. Either way, in equilibrium, thinning out the market should cause the expected time on the market to increase.

Empirically, we can study how time on the market depends on features of the house in question by constructing an index that measures the degree to which a house is unusual. Following Haurin (1988), this index takes the form

$$I_i = \sum_{j=1}^{J} \varphi_j \left| h_{ij} - \bar{h}_j \right| . \tag{18}$$

In this specification a house i is defined by j different characteristics. The atypicality of house i is measured by the sum of the absolute deviations of the house's characteristics from the sample means of the characteristics. These deviations, in turn, are weighted by the shadow prices of the house characteristics, φ_j. I assume that the shadow prices can be estimated from the hedonic pricing function

$$p_i = \varphi_0 h_{i1}^{\varphi 1} h_{i2}^{\varphi 2} \cdots h_{iJ}^{\varphi J} . \tag{19}$$

The results from the hedonic regression are in Table 2. The price and house characteristic variables are in logs. I also included dummy variables for the year and season of listing.

The good fit and statistical significance of the explanatory variables in the table are typical of hedonic regressions. On the whole, the signs of the regression coefficients are not surprising. For example, houses with more square footage and more bathrooms command higher prices. The coefficient on the bedroom to square footage ratio is negative. At first, this may seem puzzling as houses with more bedrooms might be thought to be more valuable. However, a large number of bedrooms per square foot is an indicator

TABLE 2

HEDONIC REGRESSION

$\log(p) = \varphi_0 + \varphi_1 \log(h_1) + \ldots + \varphi_J \log(h_J) + v$

VARIABLE	COEFFICIENT	STANDARD ERRORS
Intercept	4.827	0.107
Bathrooms	0.147*	0.012
Bedrooms/sq feet	–0.181*	0.015
Square feet	0.904*	0.015
Age	–0.065*	0.004
Condominium	–0.113*	0.012
Piedmont	0.488*	0.021
$\bar{R}^2$	0.61	
$F(14, 14288)$	1,567	

* Statistically significant at the 1% level.

that the house may be a rental property. The age of a house has a negative effect on its price. The interpretation of the age coefficient, however, is complicated. On the one hand, old houses can fall into disrepair or may not offer the same kitchen size or amount of closet space as more modern houses do. Alternatively, age also can serve as a proxy for an established neighborhood and have a positive effect on the house price

In the specification above, prices are allowed to vary over time. But note that house characteristics are held constant. Wallace (1996) points out that new construction and remodeling can lead to large changes in the means of housing characteristics. We can imagine similar problems of drift over time if we were to generalize the hedonic function to include quality of life variables.[10] While the East Bay has a dynamic housing market, it is unlikely that these mean shifts are important over this relatively short sample period.

Model Estimation

Once the atypicality variable has been constructed, it is possible to study the effects of various economic factors on time on the market. The estimation results are set forth in Table 3. All models are estimated by maximum likelihood.

The parameter estimates in Table 3 reflect the influence of the covariates on the hazard rate. Thus, a positive coefficient implies that the covariate is positively related to liquidity. The first point to notice is that, not only are the signs

10. Gabriel, Mattey, and Wascher (1996 and 1999) study whether changes in amenities can explain migration patterns.

TABLE 3

HAZARD MODELS

	EXPONENTIAL	WEIBULL	COX
Intercept	–3.517*	–2.583*	
	(0.115)	(0.117)	
Atypicality	$-1.04e^{-7}$ *	$-8.42e^{-8}$	$-7.07e^{-8}$
	$(5.08e^{-8})$	$(5.24e^{-8})$	$(5.29e^{-8})$
Piedmont	0.460*	0.458*	0.464*
	(0.050)	(0.051)	(0.050)
Term spread	0.277*	0.257*	0.250*
	(0.018)	(0.018)	(0.018)
Effective mortgage rate	–0.334*	–0.313*	–0.305*
	(0.015)	(0.015)	(0.015)
Employment growth	0.114*	0.102*	0.098*
	(0.009)	(0.009)	(0.009)
α		0.791	
		(0.006)	
$\chi^2(k)$	705	630	603

NOTES: Standard errors are in parentheses.
* Significant at the 5% level.

of the estimated coefficients the same across the three different model specifications, but the estimates themselves are quite similar. Recalling that the exponential hazard model is just a special case of the Weibull model when $\alpha = 1$, we might think that the similarity in the coefficients is evidence in favor of the exponential hazard. However, a formal test of the hypothesis that $\hat{\alpha} = 1$ is rejected.[11]

As expected, the degree to which a house is atypical harms the liquidity of the asset. But note that the measured effect of atypicality is extremely small in all three models. We must bear in mind, however, that this coefficient measures the influence of the *index* on the hazard rate and thus depends on the way the index has been constructed. The negative coefficient implies that houses with characteristics far from the mean are less liquid. Thus, unusually configured houses are less liquid than houses with more standard configurations. It is important to note that the negative sign on this coefficient does not imply that adding another bathroom reduces the house's liquidity.

Whether or not the house is in Piedmont has a positive effect on liquidity. This is not surprising, as Piedmont is thought to be a desirable place to live for, among other reasons, the quality of its schools. The statistical significance of this location-specific variable does, however, serve as a reminder that neighborhood effects are important in real estate markets and can create omitted variable problems in statistical estimation.

Intuitively, high interest rates reduce the purchasing power of potential buyers in the market, and the data clearly support this notion. The coefficient on the effective cost of mortgage finance is –0.334 and is statistically different from zero. This result suggests that when interest rates rise and housing becomes less affordable, sellers do not automatically lower their prices so as to maintain the liquidity of the market.

The term spread is defined to be the difference between the yield on the 30-year Treasury bond and the 3-month Treasury bill at the time of sale. This variable is meant to capture expectations about the future path of interest rates. If the expectations hypothesis is correct, then a steeply sloped term structure suggests that short-term rates will rise in the future. Of course, if the slope of the term structure is steeply sloped, then long-term interest rates (i.e., mortgage interest rates) also are likely to be high, and we might expect the coefficient on the term spread variable to be negative. However, the level of long-term rates is already controlled for by the mortgage interest rate variable. The positive coefficient on the term spread can be interpreted to mean that sellers are anxious to execute their trades before an expected change in rates. Thus, they are anxious to execute their trades before the change in state. Sellers price their houses so that they are liquid, and buyers search less.

The other local economic variable expected to influence the housing market is a measure of changes in wealth. While income growth and consumption in a narrowly defined region are difficult to measure accurately, employment growth is measured relatively more cleanly. In all three model specifications, the estimated coefficient on job growth is positive—markets that have experienced recent growth tend to be more liquid. Job growth affects the housing market directly by its impact on demand. New jobs often draw new workers into the area who will need housing. New jobs also might reflect a strong and stable economy, prompting existing homeowners to trade up. The link to the theory is that in settings where housing demand is strong, it is optimal for sellers to price their houses so as to be liquid.

One particularly useful feature of the Cox model is that the estimated coefficients can be used to calculate relative odds ratios. To do this, we compare the estimated hazard rates for two houses that are identical except for differences in one of the covariates. The covariates of primary interest are the two external covariates—the job growth variable and the interest rate variable. The experiment is to compare house liquidity at the height of the hot market (7 percent effective interest rate and 3.5 percent job growth) to predicted liquidity when these covariates take on their

11. The 95% confidence interval for $\hat{\alpha}$ is [0.79, 0.81].

mean values. I also look at liquidity for a cold market scenario (10 percent interest rate and zero percent job growth). The results from this exercise are contained in Table 4.

For the case of single-family detached housing, a house is 1.34 times more likely to sell on any given day if the effective mortgage rate is 7 percent than it would if it were for sale when the effective rate was the sample average of 8 percent. Similarly, a 10 percent effective mortgage rate makes the house only 0.55 times as likely to sell on a given day, relative to the sample average. The estimated hazard rate is much more sensitive to interest rates than it is to job growth. For single-family houses, a house that is selling when the six-month job growth rate has been 3.5 percent (annualized) is 1.18 times more likely to sell than if it were listed during a time with average job growth (1.9 percent).

One interesting piece of evidence that emerges from the analysis is confirmation that the single-family housing market and the condominium market behave differently over the course of the real estate cycle. In terms of time series averages, the mean time on the market for a house is 95 days, while the mean time for condominiums is 124 days. The two markets also behave differently with respect to shocks. Note from Table 4 that the job growth sensitivities of the two markets are comparable, with the single-family housing liquidity slightly more volatile with respect to changes in the job growth rate. The responses of liquidity are more pronounced to interest rate shocks. The per period probability of sale of a condominium is 1.41 times higher when the effective mortgage rate is 7 percent, as opposed to a house that is 1.34 times as likely to sell during this low interest rate environment. This finding seems to agree with the idea that the condominium market has a different clientele from the single-family housing market. Condominium buyers, at least in the San Francisco Bay area, tend to be younger households for whom the binding constraint is meeting a monthly mortgage payment and, in particular, coming up with a downpayment.

TABLE 4

Relative Odds Ratios

	Houses only	Condominiums only
House in Piedmont	1.59	—
7% effective interest rate	1.34	1.41
10% effective interest rate	0.55	0.50
Zero job growth	0.83	0.86
3.5% job growth	1.18	1.14

Note: Standard errors are in parentheses.

Robustness

Two primary questions arise from the empirical work. First, it is striking that the relationship between house characteristics and time on the market is so weak.[12] In part this finding reflects the fact that large, atypical houses make up only a small fraction of the total observations in this sample. Perhaps understandably, final transaction data involving these houses often goes unrecorded. It is also possible that this weak relationship is due to the atypicality measure itself. One way to test whether the atypicality index is an adequate way of summarizing the relevant information about house characteristics is to insert observed house characteristics directly into the hazard function and study their influence on the hazard rate. Table 5 contains the estimates of the hazard function when the atypicality index is replaced by the number of bathrooms, the ratio of bedrooms to square footage, and the number of square feet.

Table 5 reveals that the coefficient estimates on the number of bathrooms and the square footage are not statistically significant from zero. In contrast, there is a strong negative relationship between liquidity and the ratio of bedrooms to square footage. This is not too surprising, as we already noted in the hedonic regression (Table 2) that this variable was strongly related to price. The estimated coefficients on the job growth variable are not markedly different from the specification where atypicality was measured by a single index. It is interesting, however, to note in Table 5 that the interest rate coefficients are much smaller in absolute value than in the original specification.

A second critique of the empirical work is that the estimated relationships between house marketing times and the covariates may not be robust, but rather are influenced by a low frequency time trend in the data. Recalling Figure 1, there has been a downward trend in the time on the market series beginning in the winter of 1994 and persisting to the end of the sample period in 1998. To address this concern, I add a time trend to the list of covariates and reestimate the models in Table 3. The results are contained in Table 6.

Once again, the coefficient on the atypicality index is insignificantly different from zero. The estimated coefficients on the interest rate and job growth variables retain the same signs as before. However, the estimated coefficients on the interest rate variables are slightly smaller in absolute value than in Table 3. The relationship between the job growth

12. It is possible to argue that the house characteristics collected in this dataset—the number and kinds of rooms and the size—are not the most important characteristics. Characteristics such as the neighborhood quality, nearby amenities, and other intangible qualities will influence price and liquidity, but remain essentially unobservable to the econometrician.

TABLE 5

HOUSING CHARACTERISTICS IN THE HAZARD FUNCTION

	EXPONENTIAL	WEIBULL	COX
Intercept	–3.913*	–2.890*	
	(0.141)	(0.143)	
Bath	–0.015	–0.019	–0.023
	(0.016)	(0.016)	(0.016)
Bed/square feet	–260.128*	–258.802*	–257.688*
	(17.168)	(17.343)	(17.430)
Square feet	$6.29e^{-7}$	$4.71e^{-6}$	$8.61e^{-6}$
	$(1.45e^{-5})$	$(1.50e^{-5})$	$(1.53e^{-5})$
Piedmont	0.351*	0.348*	0.351*
	(0.052)	(0.051)	(0.051)
Term spread	0.146*	0.257*	0.143*
	(0.017)	(0.018)	(0.017)
Effective mortgage rate	–0.198*	–0.197*	–0.195*
	(0.014)	(0.014)	(0.014)
Employment growth	0.161*	0.135*	0.126*
	(0.009)	(0.009)	(0.009)
α		0.801	
		(0.006)	
$\chi^2(k)$	1,218	976	907

NOTES: Standard errors are in parentheses.
* Significant at the 5% level.

TABLE 6

HAZARD MODELS WITH TIME TREND

	EXPONENTIAL	WEIBULL	COX
Intercept	13.982*	7.865*	
	(1.208)	(1.223)	
Atypical	$-1.58e^{-7}$ *	$-1.39e^{-7}$ *	$-1.33e^{-7}$ *
	$(5.78e^{-8})$	$(5.91e^{-8})$	$(5.96e^{-8})$
Piedmont	0.514*	0.497*	0.496*
	(0.051)	(0.051)	(0.051)
Term spread	0.115*	0.122*	0.127*
	(0.017)	(0.017)	(0.017)
Effective mortgage rate	–0.163*	–0.175*	–0.179*
	(0.015)	(0.015)	(0.014)
Employment growth	0.284*	0.211*	0.126*
	(0.013)	(0.013)	(0.009)
α		0.809	
		(0.006)	
$\chi^2(k)$	1,094	723	627

NOTES: Standard errors are in parentheses.
* Significant at the 5% level.

variable and liquidity is strengthened when a time trend is included in the hazard function. While these differences in coefficient estimates appear to be small, the differences are important in economic terms. Recall from the odds ratio exercise in Table 4 that changes in liquidity due to a unit change in the value of a covariate, say x_1, is calculated not as ξ_1, but as $\exp(\xi_1)$.

III. CONCLUSION

In this paper I develop a search model of the real estate market where prices and liquidity are determined endogenously. When the value of the housing service flow is allowed to fluctuate, liquidity also fluctuates. In periods when the housing service flow is high, sellers do not raise their prices to take full advantage of the increase. Rather, they demand greater liquidity so as to complete the sale before the market turns against them. In periods when the housing service flow is low, sellers do not drop their prices in order to achieve the same amount of liquidity as in the hot market. Rather, prices are sticky because sellers find it optimal to "fish" for a buyer who attaches an unusually high private value to the house. This fishing takes time, and the market becomes cold. This behavior by sellers is optimal because the opportunity cost of failing to sell in a cold market is relatively low—a seller can always wait until the next period hoping to sell in a better market.

Using data from the San Francisco Bay Area, I search for variables that drive the value of the housing service flow postulated in the theoretical section. I establish a statistical link between time on the market and the interest rate, the slope of the term structure, and the job growth rate. I detect a weak relationship between liquidity and the degree to which a house is atypical.

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