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Measuring Residential Real Estate Liquidity

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There are many factors, other than price alone, that may affect the liquidity of real estate. This study develops a liquidity measure based on the Cox proportional hazard technique, a statistical model widely used in the epidemiologic and social sciences. The odds ratio, along with an estimate of market value for a home, are used to construct a liquidity measure. This measure can extract from the data a rich statistical profile of the variables that affect liquidity.

INTRODUCTION

Wood and Wood [22] define liquidity as "the inverse of the amount of time that elapses between the decision to sell a security and the receipt of the full market value by the seller." In this paper we construct a measure of housing liquidity related to this definition, but instead of examining the expected time on the market, our measure is based on the relative odds ratio. This ratio can be interpreted as the relative probability of sale for any two houses at a particular instant in time. If the relative odds ratio between a house of interest and a "typical house" equals two, for example, then the house of interest would be twice as likely to sell as the "typical" house at any point in time. The relative odds ratio will depend on characteristics of the houses (lot size, number of baths, living area, neighborhood, etc.), their prices, and other factors such as the season when the houses are listed for sale. The relative importance of these determinants is

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clearly of interest to real estate brokers, the mortgage industry, developers and homeowners in general.

Envision the housing market as a continuum of potential buyers, each searching in one or more potential housing submarkets comprised of houses with a particular set of attributes or characteristics. Because the number of potential buyers and sellers (and their preferences) in each submarket can differ, the liquidity of houses in each submarket may differ as well. Therefore, as the attribute set changes, housing liquidity may be affected. The proportional hazards regression model can be used to estimate relative odds ratios for heterogeneous goods like housing and extract from the data a rich statistical profile of the market preferences that affect liquidity. These relative odds estimates can in turn be used to construct a liquidity measure.

The measure proposed here is nothing more than the odds ratio evaluated for each house at its full market price. The difficulty in implementing this measure is the problem of defining and assessing "full market price."

From the perspective of an appraiser full market price would be the same as "market value," defined as "the most probable price as of a specified date" . . . "after reasonable exposure in a competitive market."[1] From a statistical perspective, this might be translated as "the price that has X percent probability of selling by day Y." For example, this could be the price at which a home has a 75% probability of selling within ninety days. Clearly market value definitions are arbitrary with respect to the choice of X and Y.

Once defined, an expert appraiser could estimate market values and these numbers could be used to evaluate the odds ratios. This approach may not be practical and will suffer from appraisal error. Another approach would be to use a hedonic pricing model to estimate market values. While easier to implement, the estimates would suffer from errors from the hedonic model (e.g., omitted variables). In any event, if one can develop a reasonable estimate of "market value," that estimate can be used to calculate the relative odds ratio of houses at their market prices. This price-adjusted odds ratio can then be interpreted as a measure of relative liquidity.

A drawback to the liquidity measure proposed here lies in the definition of liquidity as the expected time to sale of a house priced at its market value. Although this definition is widely used, it is not precise without an exact definition of market

[1]See American Institute of Real Estate Appraisers [1 Glossary].

value. Lippman and McCall [17] define liquidity in the context of a search model, which is more appropriate for the problem of residential housing. They define liquidity as the expected time to sale of an asset conditioned upon the seller following an optimal marketing strategy. The seller will maximize the net present value from selling by choosing the list price, a stopping rule,[2] whether or not to sell using a real estate broker, and so on. These choices, and the resulting expected time to sell the house, will likely depend on the characteristics of the asset itself (lot size, living area, neighborhood, etc.), the characteristics of the particular seller (opportunity cost of capital, degree of risk aversion, disutility from showing the house to potential buyers, etc.), as well as the pools of potential buyers and competing sellers. In theory, if we knew enough about the structure of the market, we could calculate a liquidity measure based on Lippman's and McCall's notion of liquidity. Typically though, an analyst would not have access to such data. Our measure, although based on a less theoretically appealing definition of liquidity, can be easily implemented.

Previously researchers have examined time on the market, a variable closely associated with liquidity. Most studies of time on the market have used market segmentation, multiple regression models or probit models. In their research on pricing strategies, Miller and Sklarz [20] indicate the sellers' strategies take into account both price and selling time, but non-price influences on time on the market are not considered. Kang and Gardner [12], and Butler and Guntermann [5] examine the effects of other house features on the time on the market using traditional regression approaches. Haurin [10] models time on the market using a failure time model based on the Weibull distribution. Each researcher has sought to improve our understanding of factors that affect time on the market. However, time on the market is not quite the same as liquidity. This study will use the proportional hazards regression model (an alternative failure time model developed by Cox [6]) to construct a measure of relative liquidity.

In this paper we will illustrate how to construct a relative liquidity measure and study its properties. The plan of the paper is as follows: The next section contains a description of the proportional hazards model. Section three describes the construction of the liquidity measure and provides an example based

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[2]See, for example, Haurin [10] for a discussion of a stopping rule in a housing market search model.

on data for the Columbus, Ohio housing market. Section four discusses properties of the proposed liquidity measure. The last section details limitations of our liquidity measure and presents concluding remarks.

THE PROPORTIONAL HAZARDS MODEL

Construction of our liquidity measure will utilize the proportional hazards methodology. Cox [6] developed the proportional hazards (PH) model for analysis of problems with duration data, and since then it has been widely applied in the epidemiologic and social sciences. Biostatisticians routinely use the model to look at survival rates following various treatments for diseases such as cancers, cardiovascular diseases, and others. Although economists have studied the durations of both unemployment spells and strikes, most business researchers have not yet added the proportional hazard model to their repertoire of tools.[3]

The proportional hazards model has several advantages over alternative methods because it is semi-parametric and because it can accommodate censored data. Censoring refers to observations where sale time cannot be observed. There are several reasons why we may not be able to observe sale time for a house. For example, homes that have not sold during the data collection period are censored observations because we do not know how much longer it will take to sell them. Additionally, homes that were withdrawn from the market would be censored observations. Ignoring censoring gives rise to biased samples and can lead to incorrect inferences. The proportional hazards model is applicable to censored data sets only if there is independent censoring, i.e., as long as houses with a low probability of sale are no more likely to be censored than houses with a high probability of sale.

Central to the proportional hazards model is the hazard function. Let T be a random variable representing the length of time between the date when the house is put on the market and the date when the house is sold, and let $f(t)$ and $F(t)$ be the p.d.f.

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[3]Atkinson and Micklewright [3] have examined unemployment duration; Lancaster [15], and Kennan [13] look at strike duration; Green and Shoven study mortgage prepayment rates [8]. Kiefer [14] reviews the literature on statistical methods (including the proportional hazards model) to analyze economic duration data. Description and discussion of the PH model is included in several textbooks including Kalbfleisch and Prentice [11], Miller [21] and Lee [16].

and the cumulative p.d.f. of sale time, respectively. The hazard function, $h(t)$, can then be defined as:

$$h(t) \equiv f(t)/(1\text{-}F(t)). \tag{1}$$

The hazard represents the conditional probability of selling a house at time t, provided that the house has not sold until time t. From the definition, one can clearly see that specification of either the p.d.f. or cumulative p.d.f. completely specifies the hazard function (and vice versa).[4] The hazard function, however, is a natural way to study duration data because it entails specification of a structural model based on conditional probabilities. Therefore, we can look at the overall probability of not selling the house by t days as a sequence of probabilities for being unable to sell one day at a time. As Kiefer [14] states, "Conditional and unconditional probabilities are related, so the mathematical description of the process is the same in either case. It is the conceptual difference that is important in the modeling of economic duration data."[5] Here, the hazard approach will be a convenient way to look at how sale probabilities vary according to the length of time the house has been on the market.

The PH model is based on the assumption that the hazard functions are proportional and that the proportionality constant depends on the explanatory variables. Thus, if $h(t,X)$ is the hazard function representing the conditional probabilities of sale for a house with explanatory variables X, then the PH model assumes that

$$h(t,X) = \exp(\beta X)h_0(t). \tag{2}$$

Beta represents PH regression coefficients and $h_0(t)$ is the baseline hazard function.[6] In this framework, the conditional probabilities of sale for any two houses are proportional, regardless of what time frame we are considering. So, by assumption, if a house in one neighborhood has twice the likelihood of sale in its first week on the market than does a house in another neighborhood, then the first house is also

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[4]The survival function, $(1-F(t))$, is also often used in failure time models. In the present context, the survival function would represent the probability of a house not being sold by time t. The survival function can easily be calculated given the hazard function.

[5]See Kiefer [14, p. 648].

[6]The baseline hazard represents the "shape" of the hazard function. It can be arbitrarily set to represent the hazard for any house. The hazard function for other houses will be proportional to this baseline hazard function.

twice as likely to sell in its second week in the market provided both houses have not sold during the first week. This ratio of conditional probabilities is called the hazard ratio or relative odds ratio. The PH assumption implies that the hazard ratios do not vary with time allowing us to estimate the proportionality factors without specifying the form of the baseline hazard function. For this reason, the PH model is often called a semi-parametric method.[7]

The PH model uses a likelihood approach to estimate the vector of beta coefficients from the hazard function. The conditional likelihood function is formed by first considering the conditional probabilities of sale at each sale time in the sample. Suppose that at time t_j one home in the sample, with explanatory variables X_j, was sold. Let $R(t_j)$ represent the set of observations with sale or censored times greater or equal to t_j. The probability that the house with X_j sells at t_j, given that we know that one house actually sold at t_j, is $h(t,X_j)/\{\text{sum of all } h(t,X_k)\}$, where k indexes all the houses in $R(t_j)$. Call this probability Π_j. According to the PH assumption in equation (2), Π_j reduces to:

$$\Pi_j = \exp(\beta X_j)/\Sigma[\exp(\beta X_k)]. \tag{3}$$

The conditional likelihood function is then formed by multiplying together the conditional probabilities Π_1, Π_2, Π_3, . . . where the subscript represents each sale time in the sample, with the Π's adjusted if there are ties (houses with the same sale times). Each Π_j is formed using only the observations that might have been sold at each sale time, j. Houses previously sold or censored houses would not be included in $R(t_j)$. The likelihood function is then maximized with respect to the beta coefficients to obtain the PH model estimates.[8]

Hypothesis testing can be conducted in a manner similar to the method used in logit models. A non-zero beta coefficient indicates that the explanatory variable affects the hazard rate. To see whether one or more of the betas are significantly different from zero, likelihood ratio tests are conducted.

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[7]Other failure time models make some assumption as to the form of the baseline hazard function. The Exponential and Weibull models are examples of parametric failure rate regression models. See Kalbfleisch and Prentice [11, pp. 30–38] for a description of these models.

[8]Chapter 6 of Miller [21] or Chapter 5 of Kalbfleisch and Prentice [11] provide a much more detailed discussion of how the likelihood function is formed, how ties are handled, and how the parameters of the model are estimated. The statistical software package, SAS, contains a procedure (PHGLM) which we use to estimate our PH model.

The PH model also will allow estimation of the odds ratio to further assess the importance of explanatory variables. The odds ratio is the ratio of the hazard functions:

$$h(t,X_1)/h(t,X_2)=\exp(\beta X_1)h_0(t)/\exp(\beta X_2)h_0(t) \tag{4}$$

or:

$$h(t,X_1)/h(t,X_2)=\exp(\beta(X_1-X_2)), \tag{4'}$$

where X_1 and X_2 are two different values of the variable X. To understand the interpretation of this ratio, consider the comparison of the hazard rates for a particular neighborhood versus the hazard rate for all houses in the sample. X then would represent a dummy variable equal to one (X_1) for the neighborhood of interest, or zero (X_2) for houses in other neighborhoods. The odds ratio, $\exp(\beta(1–0))$, or $\exp(\beta)$, can be interpreted as the odds of sale for houses in the neighborhood of interest relative to all houses in other neighborhoods. Thus, if the odds ratio equaled two, then houses located in the neighborhood in question would be twice as likely to sell on any given day.

CONSTRUCTION OF A LIQUIDITY MEASURE

The liquidity measure is simply the odds ratio evaluated at market prices. Thus, our measure can be interpreted as the relative odds of sale between two residences. Notice that this is a relative notion of liquidity. We do not look directly at the expected time to sell a house at its market value. Instead we measure the likelihood of sale of one house at its market value relative to another house at its market value.

To understand how to construct and interpret this measure, we present an example using data from the Columbus, Ohio housing market. To do this we must first estimate a proportional hazards model and a hedonic pricing model.

Sample Data

The sample studied consists of one hundred and three residential properties on the market in Columbus, Ohio during 1976. Time on the market varied from one day to two hundred days. Attributes collected included lot size, square feet of living area, number of bedrooms, baths, and several other attributes of quality or quantity, such as age and construction as brick or frame. Table 1 contains means and ranges for the variables in our sample.

TABLE 1

Sample Data Set

97 Uncensored Observations
6 Censored Observations

Variables	Sample Mean	Range Low	Range High
Time on Market (days)	66	1	200
List Price	$63,522	$28,500	$185,000
Sale Price	$60,016	$29,000	$175,000
Living Area (sq. ft.)	1800	900	4400
Bedrooms	3.5	2	6
Bathrooms	2	1	5
Lot Size (sq. ft.)	14244	2800	180000
Age	18.9	1	55
Dummy Variables			
Upper Arlington Neighborhood	0.50		
Winter	0.17		
Summer	0.16		
Spring	0.36		
Fireplace	0.96		
Swimming Pool	0.05		
Brick or Stone Construction	0.25		
Landscaping*	0.89		

*0 = Fair, 1 = Good, 2 = Excellent

Using this data set, a hedonic pricing model was developed using standard regression techniques, with sales price as the dependent variable.[9] The beta coefficients for our hedonic pricing model are contained in Table 2. While models with greater overall fit were possible, they included many insignificant variables. The variables actually used were also selected to minimize multicollinearity among the independent variables.

Table 3 contains the beta coefficients for the proportional hazards model. These coefficients represent variables that affect the time to sale: a negative beta means that increases in the variable reduce the hazard rate: a positive beta signals that increases in the variable increase the hazard rate. In our

[9]OLS may not be appropriate for data sets with a considerable number of censored observations because there may be selectivity bias. In this case the hedonic estimates ought to be estimated using a correction procedure suggested by Hekman. See Chapter 8 of Maddala [18] for a discussion of this procedure.

TABLE 2

Hedonic Pricing Model

Dependent Variable: Sale Price

Variable	*Beta*	St. Error	*t*-Value	Probability
Intercept	165			
Bedrooms	13565	2455	5.52	<0.01
Lot size (sq. ft.)	0.653	0.087	7.50	<0.01
Age	−405	125	3.24	<0.01
Brick or Stone Construction	10535	3945	2.67	<0.01
Landscaping	4367	1929	2.26	0.03
Upper Arlington	9568	3261	2.67	<0.01

Sample Size 97
F-Value 31.81
Adjusted *R*-Square 0.656

TABLE 3

Proportional Hazards Model

Dependent Variable: Time to Sale (days)

Variable	*Beta*	Std. Error	*Chi*-Squre	Probability	$Z : PH$
Summer	−1.50	0.40	13.82	<0.01	0.55
Spring	−0.84	0.24	12.54	<0.01	1.32
List Price	−0.000012	0.0000063	3.91	0.05	0.32
Bedrooms	0.55	0.20	7.33	<0.01	−0.10
Lot Size	−0.000048	0.000022	4.85	0.03	1.47
Landscaping	0.23	0.15	2.48	0.12	−0.52

97 Uncensored Observations
6 Censored Observations
−2 Log L.R. 695.9
Model *Chi*-Square 42.70 with 6 D.F.

example, listing the house in the spring or summer, increasing list price, and increasing lot size signal an increased hazard ratio, which implies a longer expected time on the market, ceteris paribus. An extra bedroom and better landscaping imply a shorter expected time on the market, ceteris paribus.

The last column of Table 3 (labeled $Z : PH$) contains a statistic to examine the validity of the proportional hazards assumption (see equation 2). Under the null hypothesis of proportional

TABLE 4

Liquidity Measure: The Price-Adjusted Odds Ratio

	Odds Ratio
House listed in the Spring*	0.43
House listed in the Summer*	0.22
House with an Additional Bedroom	1.47
Excellent Landscaping**	1.19
Lot with an Additional 5000 square feet	0.76

*Relative to a house listed in the fall or winter
**Relative to a house with good landscaping

hazards, the statistic will be a standard normal deviate. Therefore a $Z : PH$ with a magnitude of 1.91 indicates that we cannot reject the null hypothesis of proportionality at the 5% significance level.[10]

Our liquidity measure is based on the coefficients of both the proportional hazards model and the hedonic pricing model. Recall that the PH model odds ratio is defined as $\exp(\beta(X_1 - X_2))$, where β represents the PH coefficients, and X_1 and X_2 are the characteristics of the two houses to be compared. Using the estimated coefficients from the PH model, the relative odds ratio for any house relative to any other house is:

$$\begin{aligned} ROR = \exp[&-1.50{*}\Delta SUMMER - 0.84{*}\Delta SPRING \\ &- 0.000012{*}\Delta LIST\ PRICE + 0.55{*}\Delta BEDROOMS \\ &+ 0.23{*}\Delta LANDSCAPING - 0.000048{*}\Delta LOT\ SIZE], \end{aligned} \tag{5}$$

where the Δ signifies the difference between the values of each variable for the houses to be compared.

To calculate our relative liquidity measure, we compute the price-adjusted odds ratio, or the relative odds ratio for each house at market value.[11] The price-adjusted odds ratios in Table 4 were calculated using the preceding equation. For example, consider the relative odds ratio for two houses identical except

[10]See Harrell and Lee [9] for a detailed discussion of this test.

[11]Note that the liquidity measure can be constructed using an estimate of market value plus an estimate of the odds ratio. The estimate of market value could, for example, be obtained by appraisal. The estimate of the odds ratio could be obtained from an alternative failure time model such as the Weibull model.

that one has an extra bedroom and is listed at a price of \$13,565 more (to reflect the market value of the extra bedroom as estimated by the hedonic model in Table 2). The equation for the *ROR* reduces to:

$$ROR = \exp[-0.000012^*(13.565) + 0.55^*1] = 1.47. \qquad (5')$$

Therefore, we estimate that an additional bedroom will increase the sale probability on any given day to 1.47 times what the sale probability would have been without the extra bedroom. This number can be thought of as a measure of the "liquidity" added by an extra bedroom.[12]

Table 4 contains the estimates of our liquidity measure for each explanatory variable in our illustrative PH model. For the data set considered here, additional bedrooms and improved landscaping add to residential liquidity. Homes with larger lots were found to be less liquid. We also report a strong seasonal effect, with houses that are listed in spring or summer being less liquid.

THE LIQUIDITY MEASURE AND TIME ON THE MARKET

The measure of relative liquidity proposed here, the price-adjusted relative odds ratio, is clearly related to the expected time on the market. In the previous example, a house with an extra bedroom had a likelihood of sale on any given day that was 1.47 times what the sale probability would have been without the extra bedroom. Hence, the expected time on the market is lower for the house with an extra bedroom. Nevertheless, the odds ratio alone does not provide enough information to compute the expected time on the market. An estimate of either the survival function or the hazard function is required to calculate the expected sale time.

Table 5 contains estimates of both the hazard function and the survival function for a house with median values for the variables in our sample. The "median" house (a house with median values for all the independent variables in our data set) is

[12]Here bedrooms were entered as a single variable taking values from two to six bedrooms. The estimates from the PH model therefore represent the average effect of adding an additional bedroom. Alternatively, one could have coded the data using separate dummy variables for a two-bedroom house, a three-bedroom house, and so on. In this case the model would give separate estimates for the liquidity of adding any number of bedrooms within the sample range.

TABLE 5

Estimated Survival and Hazard for the Median House*

Time	Survival	Hazard
0	1.00	—
5	0.86	0.01
10	0.84	0.03
15	0.80	0.02
20	0.72	0.07
30	0.58	0.09
40	0.42	0.08
50	0.36	0.07
60	0.25	0.21
70	0.12	0.14
80	0.08	0.08
90	0.06	0.18
100	0.03	0.25
110	0.02	0.14
120	0.02	0.16

*The median house is listed in the fall or winter with: three bedrooms, good landscaping, a 9490 square foot lot and a list price of $54,540.

arbitrarily chosen to display the shape of the baseline hazard function. The hazard function represents the conditional probability of sale for the "median home" at any point in time, and the survival function represents the probability that a house will have not yet sold at any point in time. These estimates plus the PH beta coefficients allow us to calculate the survival function and the hazard function for any house of interest. Each hazard function will, by assumption, be proportional to the hazard function shown in Table 5. Equation (4′) therefore summarizes the relationship between the hazard for the "median house" and the hazard function for any other house. This relationship implies that the survival functions are not proportional, but rather related according to:[13]

$$S(t,X_1) = S(t,X_2)^{\exp\{\beta(X_1 - X_2)\}}. \tag{6}$$

The survival function for each house can be used to roughly estimate the expected sale time. Ths calculation can be carried out using simple numerical differentiation and integration procedures on a personal computer. The expected time to sale for the

[13]See Miller [21, pp. 2–3] for the derivation of equation 6.

TABLE 6

Expected Sale Times (at the Listing Date)

	Days
Median House*	39
Median House except:	
Listed in Spring	63
Listed in Summer	70
Extra Bedroom and List Price of $68,105	30
Improved Landscaping and List Price of $58,907	34
Extra 5000 Sq. Ft. of Lot and List Price of $57,805	46

*The median house is listed in the fall or winter with: three bedrooms, good landscaping, a 9490 square foot lot and a list price of $54,540.

median home and for the median home with ceteris paribus changes to the variables in our data set are shown in Table 6.[14]

For example, adding an extra bedroom to the median home (and increasing the cost of the home by $13,565 to reflect the increase in market value) reduces the expected sale time by nine days. Note that these calculations do not imply that adding an extra bedroom to a house other than the median will reduce expected sale time by a week. From the relative odds ratio, it is clear that expected sale time will be lower, but it may be lowered by more or less than a week depending on the other attributes of the houses.

CONCLUSION

The liquidity measure proposed in this paper is easy to calculate and interpret. It is potentially useful to study the magnitudes of factors that affect liquidity. It is also tempting to use the proportional hazard estimates to examine the effects of alternative pricing strategies on the time on the market. However, one must be careful when evaluating pricing effects. It does not make sense to apply the proportional hazards estimates to a house with an asking price far away from its market value as this would be applying estimates from the model beyond the sample range. For example, using our sample data set, a house priced

[14]These numbers are only ballpark estimates. Errors from estimating both the beta coefficients and the baseline survival function are compounded with errors from the numerical procedures due to the relatively small size of our data set.

$1000 less than its market price has an odds ratio of 0.98, a plausible estimate. A house priced $50,000 below market value, however, has an odds ratio of 0.55. This ratio is clearly too high, considering that the houses in this sample sell, on average, for $60,000.

Future research to determine the liquidity of various types of real estate in both active and thin markets will help expand our understanding of the liquidity premium in real estate markets.

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