The Repeat Time-On-The-Market Index*

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Abstract

We propose two new indices that measure the evolution of housing market liquidity. The key features of both indices are a) their ability to control for unobserved heterogeneity exploiting *repeat* listings, b) their use of censored durations (listings that are expired and/or withdrawn from the market), and c) their computational simplicity. The first index computes proportional displacements in the home sale baseline hazard rate. The second estimates the relative change in median marketing time. The indices are computed using about 1.8 million listings in 15 US urban areas. Results suggest that both accounting for censoring and controlling for unobserved heterogeneity are key to measure housing market liquidity.

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1 Introduction

The importance of housing to local markets and the macroeconomy is unquestionable. Not surprisingly, substantial efforts are made to monitor and measure housing market conditions. While perhaps home prices receive the most attention, a large battery of other indicators that are regularly produced (such as, housing starts, number of sales, vacancy rates, interest rates and mortgage originations, among many others) are widely used by researchers, regulators, investors and even the general public. Surprisingly, as far as we know, there are no official indices that rigorously and periodically measure housing market liquidity.

While it is not straightforward to conceptually define and measure the liquidity of an asset such as housing, the works of Lippman and McCall (1986) and Lin and Vandell (2007) suggest that the first and second moments of "time on the market," the time it takes a home to sell, are key factors to assess housing liquidity risk. Accurate measurement of time on the market (TOM) can be vital to assess housing market conditions. For example, consider two markets with identical homes, with the same price levels and appreciations rates. In the first market, it takes the median home two weeks to sell, while, in the second market, it takes four months. Moreover, TOM is more volatile and has been increasing in the second but not in the first market. Would a rational investor buy a property in the first or second market? Would a homeowner be more likely to put her home in the first or second market? This simple illustrative example highlights the fact that liquidity alone can affect the optimal decisions of buyers, sellers and investors in the real estate market. Despite its importance, we are not aware of any attempts to systematically and *rigorously* measure the evolution of TOM.

The lack of official measures of TOM (and housing liquidity) is probably not due to data constraints. In the U.S. and in many other developed countries, the marketing of real estate properties is centralized in a multiple listing system where sellers post their properties and their asking prices. This system typically records the date when a property is listed and the date when it is sold. This information allows one to compute the number of days that any home stays on the market. In fact, many real estate associations in the U.S. provide statistics such as median or mean TOM as part of their reports. As is the case with unconditional mean and median prices, however, changes in unconditional TOM over time are confounded by changes in the quality of homes being sold in each period.

In this paper we develop two new indices that measure the evolution of TOM in the housing market. The key features of both indices are a) their ability to control for unobserved heterogeneity exploiting *repeat* listings, b) their use of censored durations (listings that are expired and/or withdrawn from the market), and c) their computational simplicity. If all properties that were listed were to find a buyer (i.e., if there were no censored observations), the same conventional approach used to compute repeat sale price indices could be used to estimate a TOM index that accounts for unobserved heterogeneity. [1] Expired and withdrawn listings are, however, a common feature of real estate markets. For instance, in a suburb of Washington DC (Fairfax County, VA) as much as 60 percent of listings expired and/or were withdrawn during the peak of the financial crisis. Similar patterns are found in San Diego, Las Vegas, Miami and 11 other MSAs in the U.S. that we analyze.[2] Descriptive statistics suggest that censoring drastically changes with market conditions: it remains low during housing booms and peaks during busts. Hence, conventional methods based on repeat sales need to be modified to account for censoring. This is the main objective and contribution of our paper.

Intuitively, censoring of home listings can severely impact estimates of the mean or median TOM. TOM durations are only observed for homes where this duration is no larger than a censoring duration that represents the patience of the home seller. Not only does this censoring lead to a downward bias in estimates of mean or median TOM, but an increase

[1]The classical approach to compute housing price indices uses repeat sales and a simple linear regression model to control for unobserved housing heterogeneity (Bailey, Muth, and Nourse, 1963). Influential extensions to this method are described in Case and Shiller (1987) and Case and Shiller (1989). The repeat sales approach has been used in recent studies to measure changes in income (Rosenthal, 2014) and changes in rents (Ambrose, Coulson, and Yoshida, forthcoming).

[2]Our empirical analysis exploits individual residential real estate listing records in 15 separate US urban areas. The dataset contain about 1.8 million observations. Details about the sample are provided in Section 3.

in the distribution of TOM that is not matched by an increase in the distribution of sellers' patience will lead to a larger percentage of listings that expire or are withdrawn and hence more severe censoring. To illustrate empirically the effects of ignoring censoring issues when computing changes in TOM, we estimate (unconditional) median TOM with and without accounting for censoring in each of our regions of interest. Results strongly suggest that ignoring censoring leads to significantly different assessments about changes in the distribution of TOM. For example, the median TOM of properties that were listed in Fairfax County during 2007 and *sold* thereafter was about 60 days. This number is almost 3 times lower than the estimate of the median TOM of all 2007 listings when censored durations are included in the estimation. In all areas, the variance of median TOM of completed durations is much lower than the variance of median TOM when censored observations are accounted for. In our view, any method developed to produce a TOM index should incorporate censored observations.

Accounting for *observed* housing heterogeneity, such as home size, number of bathrooms, and other home characteristics in a duration model is relatively straightforward. Applying the re-weighting procedure suggested by DiNardo, Fortin, and Lemieux (1996), we estimate quality adjusted TOM distributions and show that, in Fairfax County, controlling for observed housing characteristics does not substantially change the estimate of the TOM distribution. Controlling for unobserved heterogeneity, however, has been shown to be important when estimating home price indices (Wallace and Meese, 1997) and may also be important when computing TOM indices.

We propose two models that can be used to correct for unobserved heterogeneity using *repeat* listings. The main intuition is straightforward. Just as it is the case with repeat sales home price indices (Bailey, Muth, and Nourse, 1963), one can use the TOM of properties that have been on the market in more than one period to "difference out" the unobserved heterogeneity. In the presence of random censoring, however, the conventional methods employed to construct a repeat sale index no longer apply, and need to be adapted for this specific application.

Our first index amounts to a logit regression for whether the TOM corresponding to the second listing exceeded the TOM corresponding to the first listing.[3] We show that this approach provides a natural analogue to the repeat sales regression used to construct a home *price* index. The model underlying this construction assumes that the hazard rate evolves proportionately over time, and that a home's unobserved heterogeneity shifts its baseline hazard by the same amount in all time periods. This assumption essentially implies that unique features of a home make it always more (or less) likely to sell relative to the market's baseline hazard. This index controls for unobserved heterogeneity in a transparent manner, incorporating censored durations in the estimation process and estimating the "repeat proportional hazard index" using a computationally straightforward procedure.

The repeat proportional hazard index provides an estimate of the gross percentage increase in the hazard rate relative to a base period. This index is estimated in all of our 15 areas of interest and results are reported in Section 5.1.4. The index provides valuable insights about trends in housing liquidity and shows that liquidity is subject to substantial variation over time. For example, in Fairfax County, the index increased by a factor of 5 between 1997 and 2000, and decreased by the same factor between 2004 and 2007. In San Diego, the index was at its lowest levels in 2007 and steadily increased thereafter; by the end of 2012, it was almost 8 times higher than in 2007. The other areas we study exhibit similar levels of volatility. We compare our index with a simple hazard ratio computed using a Cox regression. While the overall trend of both indices is much alike, there are some important differences. Generally, the RPHI is more volatile than the unconditional hazard ratio, increasing faster during "booms" and decreasing faster during "busts".

The second index we propose in this paper is based on a log-linear specification for the TOM. This type of specification in a duration model is known as an accelerated failure time (AFT) model (see, e.g., Kalbfleisch and Prentice, 2011). The AFT specification models

[3] This logit regression is computed on a subsample of the homes. Conditioning on this subset of homes turns out to be innocuous. See Section 5.1.3 for details.

the median of (log) TOM as a function of period-specific shifters as well as a home-specific unobserved heterogeneity term, which is assumed to be time-invariant. The period-specific shifters are used to construct the "repeat median TOM index." The AFT model suggests that, absent censoring, we could simply estimate a fixed effects regression using the difference in the log TOM (i.e., a repeat sales regression). Instead we use the Kaplan-Meier procedure (Kaplan and Meier, 1958) to first estimate the difference in the median[4] log TOM between two listings *conditional on the home being listed in two particular periods*. That is for each pair of time periods, t and $t + k$, we select the set of repeat listings that were put on the market in period t for the first time and in period $t + k$ for the second time and, using only this subset of observations, we estimate the median log TOM in each period using the Kaplan-Meier correction for censoring and take the difference. We repeat these calculations for every pair of periods in our sample. Then, in a second step, we run a simple OLS regression to estimate the repeat median TOM index.

The repeat median TOM index (RMTI) measures the relative change in the median TOM in the current period relative to a base period. Results, reported in Section 5.2.2, are qualitatively similar to results of the first index: In all areas we study, liquidity is highly volatile, but it is significantly lower during the housing bust period (2007 - 2008). We compare the RMTI with a simple ratio of unconditional medians and find substantial differences: it seems that controlling for unobserved heterogeneity affects the estimate of median TOM.

This paper provides the first rigorous measures of liquidity in the housing market that attempt to improve on the simple and conventional median time-on-the-market measure. While unobserved heterogeneity alone could be accounted for using a repeat sales formulation, as is common for home price indices, we find that it is also empirically important to account for observations of TOM that are censored when the home is withdrawn from the market. We propose two methods which are both novel contributions as measures of liquidity.

[4] We work with the median because the mean is typically not identified by the Kaplan Meier estimator.

The first index uses an econometric method, previously used to account for heterogeneity and censoring in duration models in different contexts, in a novel application. The second index uses a novel econometric procedure that contributes to the literature in econometrics that attempts to relax the proportional hazards assumption. The combined empirical evidence suggests that controlling for unobserved heterogeneity using repeat listings is important to measure changes in housing marketing time.

The rest of the paper is structured as follows. The next section discusses the relationship between our work and the literature. Section 3 describes the data and computed descriptive statistics. In Section 4, we discuss the censoring problem and investigate observable heterogeneity among homes. In Section 5 we develop our two new indices that incorporate censored observations as well and account for unobserved heterogeneity. In Section 6 we conclude.

2 Literature Review

The indices developed in this paper build on an extensive literature on unobserved heterogeneity in duration models. Duration models with unobserved heterogeneity have been used in economics to model unemployment spells (Heckman and Borjas, 1980; Flinn and Heckman, 1982), auto accidents (Abbring, Chiappori, and Pinquet, 2003), child mortality (Ridder and Tunali, 1989; Olsen and Wolpin, 1983), and brand-switching behavior (Gönül and Srinivasan, 1993), among other applications.[5] This literature traditionally focused on the distortions caused by unobserved heterogeneity when it takes the form of a random effect, independent of covariates (Lancaster, 1979; Heckman and Singer, 1984; Trussell and Richards, 1983; Heckman and Honoré, 1989). A classical random effect model in our application would assume that the distribution of unobserved housing heterogeneity does not vary over time. But it is precisely the potential for the quality of the homes listed to vary over time that we wish to control for in our analysis.

[5] Duration models have been used to study *observed* heterogeneity in housing time on the market (see, e.g., Haurin, 1988; Glower, Haurin, and Hendershott, 1998).

Instead the methods used in this paper assume a fixed effects model – where unobserved heterogeneity may be correlated with covariates. Application of a standard fixed effects regression (which would amount to a repeat sales regression in our context) is not possible because of the presence of random censoring. There are two solutions proposed in the literature that are relevant for our model. Ridder and Tunali (1999) propose a stratified partial likelihood in a proportional hazards model.[6] Their method has been applied in studying child mortality with family fixed effects (Ridder and Tunali, 1999) and to study spatial differences in unemployment duration using location fixed effects (Gobillon, Magnac, and Selod, 2011). As shown by Lancaster (2000), the stratified partial likelihood approach amounts to a logit regression for whether the TOM corresponding to the second listing exceeded the TOM corresponding to the first listing. We extend this insight by showing that in our model of repeat listings the method is equivalent to a repeat sales logit regression. This is a novel contribution of our paper, which allows the estimation of the repeat proportional hazard index.

Honoré, Khan, and Powell (2002) suggest adapting a method for fixed censoring (Honoré, 1992) by integrating over the distribution of the censoring variable. Both papers use an accelerated failure time model as an alternative to the proportional hazards model. Their approach however requires that the censoring variable be independent of all covariates. The implication of this assumption in our context would be that the distribution of sellers' patience does not vary over time, which is not a reasonable assumption. We avoid this because the only covariates in our model are indicators for the time period in which each listing occurred. We plug in conditional Kaplan-Meier estimates rather than a single unconditional estimate. After an initial step that estimates the conditional median log TOM for each listing pair we employ the standard repeat sales regression. Lindgren (1997) also takes a conditional Kaplan-Meier approach but not in a repeated duration model and does not allow for unobserved heterogeneity. The present paper is apparently the first to apply such an

[6]Ridder and Tunali (1999) extend an idea also discussed in Kalbfleisch and Prentice (1980), Chamberlain (1985) and Lancaster (2000).

approach to a fixed effects model.

The methods developed in this paper can be readily applied to estimate operational measures of housing liquidity in the literature (for example, Lippman and McCall, 1986; Lin and Vandell, 2007).

3 Data and Conventional Descriptive Statistics

In most developed countries, including the U.S., real estate agents collect rich information about the marketing process of housing sales. The data are collected in a database system known in the U.S. as Multiple Listing Services (MLS). These data contain details about each listing and each transaction. Besides the asking price, sale price and home characteristics, the specific dates when the listing was posted and when the home was sold (or when the listing was withdrawn from the market) are generally available. This allows researchers to compute the time that a property stays on the market (time-on-the-market TOM).

Our data come from two sources. Metropolitan and Regional Information Systems (MRIS) provided us with MLS data from Fairfax County, VA.[7] Data contain information for all housing listings in this county that were listed on the MLS between January 1, 1997 and December 31, 2010. Fairfax MLS data contain pricing, TOM as well as detailed characteristics about the properties such as the number of rooms, bathrooms, age, type of home and address. Because the location of each property is observed, one can compute aggregate statistics at any level of geographic aggregation. More importantly, we can track if the same property is listed and/or sold in multiple periods.

Our second source of data is CoreLogic Solutions, LLC (CoreLogic). CoreLogic collects MLS data from more than 100 MSAs, verifies the consistency of the information and produces a series of indicators (available in its Real Estate Analytics Suite). Collecting MLS data from different U.S. regions is not easy. Besides legal agreements with each MLS regional

[7]Fairfax County is part of the Washington, D.C. metropolitan statistical area and is located in northern Virginia. According to the 2010 U.S. Census, Fairfax hosts more than one million residents and over 380,000 housing units. Fairfax also ranks as one of the richest and best-educated counties in the U.S.

association, a careful data validation process is needed because there are no set guidelines about database structure (variable names, etc.). CoreLogic provides this service. CoreLogic allowed us to work with their individual housing listings in 14 MSAs that were posted on the MLS between January 2004 and February 2013. The MSAs in our sample include large and medium urban areas in the East, Middle, and Western regions of the U.S.[8] CoreLogic data include information about pricing and the specific dates when the listing entered and exited the market. While we do not observe any of the property's characteristics, the data contain a unique property identifier. This allows us to track listings/sales of the same property over time.

We exclude from our two samples listings with unusually high or unusually low listing prices (top and bottom 1 percent during each year), observations that stayed on the market for more than two years, and observations with missing data. After this cleaning process, we are left with about 0.3 million listings in Fairfax County, and 1.4 million listings in the sample of 14 U.S. MSAs. A list of the urban areas, the number of listings, and a description of the sample period is available in Table 1. About 58 percent of all listings in the overall sample end up in a sale; the other listings either expire or are withdrawn from the market. Many properties are listed on the MLS more than once. We call these cases *repeat* listings and note that there are almost 1 million of them.

Before we present descriptive statistics, we need to discuss how time-on-the-market is defined. Both data sets include the date when a listing is first posted on the MLS, the date when the property was taken off the market (when the contract was signed) as well as the date when the transaction was closed (which is typically between 4 and 12 weeks after the contract agreement). We define TOM as the difference between the listing date and the contract date.

We first show *conventional* descriptive statistics, that is, the kind of statistics that are

[8]The MSAs we analyze include Ann Arbor, MI, Boulder, CO, Durham, NC, Honolulu, HI, Las Vegas-Paradise, NV, Medford, OR, Miami-Miami Beach-Kendall, FL, New Orleans-Metairie-Kenner, LA, Olympia, WA, San Diego-Carlsbad-San Marcos, CA, San Luis Obispo-Paso Robles, CA, Santa Barbara-Santa Maria, CA, Toledo, OH and Youngstown-Warren-Boardman, OH-PA.

typically computed and published by MLS associations. These include the mean and median TOM as well as the volume of sales. Importantly, the mean and median TOM are calculated just for the sample of properties that have been sold. The top panels of Figures 1 and 2 present these statistics for Fairfax County, and five representative MSAs from our U.S. areas: Las Vegas, San Diego, Miami, Honolulu and New Orleans.[9] The statistics have been computed for each quarter to illustrate within-year seasonality. The swings in expected duration in Fairfax County clearly coincide with the housing market boom and bust. Expected TOM in Fairfax decreased drastically in the late 1990s and remained rather low until the end of 2005. It increased back to the 1990's levels in 2007 and slowly dropped thereafter. What it is surprising is that, even during the midst of the financial crisis expected TOM is only about two and a half months, and median duration does not exceed 60 days. The other areas show similar patterns. For example, median TOM in San Diego increases about three times between the first quarter of 2004 and 2010, but is never less than 120 days; in Miami, median TOM after 2007 remains low (less than 4 months) and exhibits a decreasing trend; and, expected duration in Honolulu peaks in 2009 but is never above 5 months.

While interesting, the patterns shown in the top panels of Figures 1 and 2 can be misleading. The distribution of TOM of properties that are sold may be quite different than the unconditional distribution. The bottom panels in these figures display the share of listings that are withdrawn and/or expired in each of these areas. When the market is strong, most listings find a buyer. When the market slows down, however, a higher fraction of listings are withdrawn form the market. For example, in Fairfax County, while about 90 percent of properties listed in 2003 found a buyer, over half of properties listed in 2006 were withdrawn. Similar patterns are found in Las Vegas, San Diego and other areas we analyze. In the next section, we compute TOM statistics using information from both listings that were sold and listings that were withdrawn and/or expired.

[9] Descriptive statistics for other areas are available upon request.

4 Censoring and Observed Heterogeneity

In this section, we begin with a formal setup for our problem. This setup will be used in all sections hereafter. Then, we use the Kaplan-Meier estimator to compute the unconditional distribution of TOM. Finally, we estimate quality adjusted TOM statistics, where the characteristics of the housing stock are assumed to remain fixed at those from the properties listed in a base period.

4.1 Basic setup

Let Y_{it} denote the time home i would spend on the market before closing if listed in period t for $i = 1, \ldots, n$ and $t = 1, \ldots, T$. Our goal is to measure how the distribution of Y_{it} varies with t. Generally we only observe $Y_i^s := Y_{it_i^s}$ for $s = 1, \ldots, S_i$ where S_i is the number of times home i is listed for sale in the time frame observed and t_i^s is the period in which home i was listed the s^{th} time it was listed. Sometimes listings are removed without the home being sold. As we noted in the previous section, during some periods the fraction of listings that do not terminate in a sale is greater than 50%. To model this let C_i^s denote the censoring time for the s^{th} observed listing of home i, that is, the length of time after which the home will be withdrawn if it has not been sold. Then for each listing we observe $V_i^s = \min\{Y_i^s, C_i^s\}$ as well as $d_i^s = \mathbf{1}(Y_i^s < C_i^s)$.

4.2 Unconditional TOM

First, rather than considering repeat listings of the same home we pool the data. Let $m = 1, \ldots, M := \sum_{i=1}^n S_i$ index each listing in the sample and let Y_m denote the observed time on the market for listing m and t_m denote the time period associated with this listing. If observation m is the s^{th} listing for home i in the sample then $t_m = t_i^s$. We first want to estimate the distribution of $Y_m \mid t_m = t$ for each $t = 1, \ldots, T$. If unobserved heterogeneity across homes informs listing decisions then this will differ from the distribution of Y_{it}.

In this section, the main difficulty that we address in estimating the distribution of $Y_m \mid t_m = t$ is that some listings are censored and hence we only observe (V_m, d_m, t_m) where C_m is the censoring time for observation m, $V_m := \min(Y_m, C_m)$ and $d_m = \mathbf{1}(Y_m < C_m)$. Censoring introduces a downward bias in median time on the market measures – homes that are sold before being removed from the market are less likely to be in the right tail of homes that take a long time to sell. Both the median of the distribution of $V_m \mid d_m = 1$ and the median of the distribution of V_m will be biased downward relative to the median of Y_m.

To adjust for censoring we use the Kaplan-Meier estimator. It can be viewed as a reweighting of the data based on the distribution of censored observations (Efron, 1967). The procedure effectively splits each censored observation into two partial observations at C_m and $+\infty$ each receiving weights according to the probability that the censored observation is above or below each given quantile.

Formally, if C_m is independent of Y_m conditional on t_m then $Pr(V_m = y, d_m = 1 \mid V_m \geq y, t_m) = Pr(Y_m = y \mid Y_m \geq y, t_m)$. The left-hand side of this equation is observed in the data and the right-hand side is the hazard function for $Y_m \mid t_m$, $h_{Y_m|t_m}(y \mid t)$. The distribution function is identified since $F_{Y_m|t_m}(y \mid t) = 1 - \exp(-\int_0^y h_{Y_m|t_m}(s \mid t)ds)$. The Kaplan-Meier estimator is based on this argument.

To account for censoring, we use the sample of all listings: those that were sold and those withdrawn from the market. As we previously discussed, for units that are sold, we compute TOM as the difference between the date when an offer was accepted and the date when the listing was posted. When a listing is withdrawn from the market or it expires without a sale, we compute the time between the initial listing and withdrawal, and treat it as a censored observation. Then, for each quarter, we obtain an estimate of the median TOM from the Kaplan-Meier estimate of the TOM distribution. In the top panels of Figures 3 and 4 these estimates are compared to the median TOM among the homes that sold. Results strongly confirm our priors that accounting for censoring drastically affects the estimate of TOM statistics. For example, the median TOM in Fairfax County in 2007 is close to 6 months, about three times larger than the *conventional* estimate. In all other areas, the estimate of median TOM increases substantially when withdrawn listings are accounted for.

The Kaplan-Meier approach described above assumes only that censoring is independent. We could instead use the Cox (1972) partial likelihood estimator to estimate shifts over time in the hazard function, rather than changes over time in the median TOM, under a proportional hazard assumption. The Cox proportional hazard model makes no assumptions about the functional form of the baseline hazard and its coefficients can be easily used to compute displacement in the baseline hazard over time.

For each urban area in our sample, we estimate a Cox hazard model. The dependent variable is TOM and the covariates are binary indicators that take the value of 1 if a home was listed in a particular period (quarter) in the sample. We then choose a base period (2010 q1) and compute the hazard ratio between each period t and the base. A hazard ratio of 1.5 in period t would imply that the probability that a homeowner sells her home (given that the home is still on the market) is 50 percent higher than in the base period. The model is estimated both using only finished durations, and also incorporating censored observations. Results shown in the bottom panels of Figures 3 and 4 confirm that accounting for censoring can substantially change our assessment about the evolution of housing liquidity. For example, in Fairfax County, accounting for censoring leads to a less volatile estimate of the hazard ratio; and, in most other areas, there are significant differences between the two hazard ratio estimates.[10]

In sum, any statistic that measures the evolution of TOM should account for censored observations.

[10] Notice that in all areas there is an increase in the unadjusted hazard ratio during the last sample period. This is mechanically produced by the sampling procedure. Data were collected at the end of the sample period. Hence, properties that are listed and sold during the last quarter in the sample (recent listings) must have been sold quickly. These patterns are corrected when censored observations are accounted for.

4.3 Conditional TOM

In the previous section no attempt was made to control for housing heterogeneity. That is, the set of homes listed in one period could be much different than the set of homes listed in another. Differences in TOM could reflect changes in the composition of homes for sale rather than changes in market conditions. This is the same concern that motivates the use of hedonic and repeat-sales methods to estimate housing price indices. In this section, we follow the methods proposed by Carrillo and Pope (2012) to estimate changes in median TOM and shifts in the hazard rate while controlling for *observed* housing heterogeneity.

Carrillo and Pope (2012) show how to compute (quality adjusted) time on the market distributions and hazard functions using MLS data. In particular, the duration distribution and hazard function during each period is simulated assuming that housing units have the same characteristics as homes in a base period. The simulation is based on the decomposition methods proposed by DiNardo, Fortin, and Lemieux (1996) and the Kaplan-Meier estimator (Kaplan and Meier, 1958). This method permits estimation of the distribution of TOM while controlling both for censoring and observed heterogeneity. To keep our exposition self-contained, technical details of the method are provided in an appendix.

For each period t in Fairfax County, we simulate the distribution of time-on-the-market assuming that the characteristics of housing units remain constant as those prevalent in the first quarter of 2000 (the base period).[11] We denote this counterfactual distribution as $\hat{F}_t$. We then estimate the counterfactual median TOM in each period. Results are shown in Figure 5. The dashed and solid lines display the median and counterfactual median, respectively. Controlling for observed heterogeneity does not substantially change our estimate of the median TOM. This is not surprising since previous studies have found that housing characteristics do not explain much of the variation of housing marketing time.[12]

[11]The characteristics included in the model are the home's age (9 categories), number of bathrooms, bedrooms and indicators for the home's type.

[12]Typically, the coefficient of determination in log-linear TOM regressions is typically very low (for example, Levitt and Syverson, 2008), and structural models have a hard time predicting TOM (Horowitz, 1992; Carrillo, 2012).

5 Censoring and Unobserved Heterogeneity

We have shown so far that accounting for censoring affects TOM statistics by a large amount, while controlling for observed housing characteristics does not. In this section, we estimate changes in TOM while explicitly controlling for *unobserved* heterogeneity. As we mentioned before, there is an extensive literature on unobserved heterogeneity in duration models where it is generally assumed that the unobserved heterogeneity is a random effect (Heckman and Singer, 1984; Trussell and Richards, 1983; Heckman and Honoré, 1989). This approach is not appealing in our context for the following reasons. First, if we let unobserved heterogeneity be a random effect we would implicitly assume that its distribution does not vary over time, a somewhat strong assumption in the context of the housing market. Second, estimation results could be affected by the modeling choices (for example, parametric vs. non parametric specifications of the unobserved heterogeneity). Finally, these methods tend to be computationally intensive and may not work when the number of observations is very large (hundreds of thousands of observations). Our goal in this section is to propose housing liquidity indices that control for unobserved heterogeneity, account for censored durations and, more importantly, are computationally easy to implement.

We propose below two models that can be used to correct for unobserved heterogeneity using *repeat* listings. The main intuition is straightforward: Just as it is the case with repeat sales home price indices (Bailey, Muth, and Nourse, 1963; Case and Shiller, 1987), one can use the TOM of properties that have been on the market in more than one period to "difference out" the unobserved heterogeneity. Because TOM is subject to random censoring, however, the conventional methods employed to construct a repeat sale index no longer apply, and need to be adapted for this specific application.

5.1 The Repeat Proportional Hazard Index

A mixed proportional hazards model for the duration of time on the market is defined by the following hazard function for home i if listed in period t.

$$\lambda_{it}(y) = \exp(\beta_t)\lambda_{0i}(y) \tag{5.1}$$

The first factor, $\exp(\beta_t)$, allows the hazard function to vary proportionately depending on the time period listed and $\lambda_{0i}(\cdot)$ is a home-specific baseline hazard function. If we normalize $\beta_1 = 0$, $\lambda_{0i}(y)$ is the hazard function for home i if it is placed on the market in this initial period. Thus, according to this model, fluctuations in the housing market contribute to variation in time on the market through parallel shifts in the hazard functions.

The baseline hazard function is allowed to vary across homes. This represents unobserved heterogeneity in homes. If Y_{it} is observed for every (i, t) pair then this is a standard mixed proportional hazards model and can be consistently estimated on pooled data using the Cox (1972) partial likelihood estimator, as discussed briefly in Section 3.2. This estimator is also valid under the sampling scheme assumed here if $\lambda_{0i}(\cdot)$ and t_i^s are independent because in that case the distribution of $Y_i^s \mid t_i^s = t$ is characterized by the hazard function λ_{it}. If $\lambda_{0i}(\cdot)$ and t_i are correlated then the distribution of $Y_i^s \mid t_i^s = t$ is distorted by selection effects. In this section we discuss an extension of Cox (1972) due to Ridder and Tunali (1989, 1999) that uses variation among separate listings for the same home to eliminate the fixed effect, $\lambda_{0i}(\cdot)$.

5.1.1 No censoring

The structure of the proportional hazards model allows us to difference out the unobserved heterogeneity using repeat listings of the same home. In this section we describe this differencing solution when there is no censoring. We show how to account for censoring in Section 5.1.2. The hazard function in equation (5.1) is the hazard corresponding to the conditional distribution $Y_i^s \mid t_i^s = t, \lambda_{0i}(\cdot)$. Let $\Lambda_{0i}(y) := \int_0^y \lambda_{0i}(s)ds$ denote the baseline integrated hazard function. It follows then that

$$-\ln(\Lambda_{0i}(Y_i^s)) = \beta_{t_i^s} + \varepsilon_i^s$$

where $-\varepsilon_i^s \mid t_i^s \sim EV1(0,1)$. This is a standard result for the proportional hazard model. If $\lambda_{0i}(y) = \exp(\alpha_i)\lambda_0(y)$ then we have $-\ln(\Lambda_0(Y_i^s)) = \beta_{t_i^s} + \alpha_i + \varepsilon_i^s$ suggesting that differencing will remove the unobserved heterogeneity. However, the baseline hazard function is generally not known so a standard fixed effects strategy is not feasible. Instead we obtain identifying information from the order statistics since $Y_i^s \geq Y_i^{s'}$ if and only if $\ln(\Lambda_{0i}(Y_i^s)) \geq \ln(\Lambda_{0i}(Y_i^{s'}))$.

Before deriving the result we state the following two conditions which are assumed.

Assumption 5.1.

For each pair of listings, s and $s+1$,

(i) $Y_i^s \mid t_i^s, t_i^{s+1}, \lambda_{0i}(\cdot) =_d Y_{it_i^s} \mid \lambda_{0i}(\cdot)$ *and* $Y_i^{s+1} \mid t_i^s, t_i^{s+1}, \lambda_{0i}(\cdot) =_d Y_{it_i^{s+1}} \mid \lambda_{0i}(\cdot)$

(ii) Y_i^s, Y_i^{s+1} *are independent conditional on* $t_i^s, t_i^{s+1}, \lambda_{0i}(\cdot)$

The first condition is what is known as a strict exogeneity condition in panel data models. It requires that both the listing date of a given listing and the date of the other listing in the pair are exogenous. This assumption could potentially be problematic but is likely harmless in our application.[13] The second condition is innocuous as it states essentially that any dependence between listings of the same home is accounted for by the home-specific hazard, or "fixed effect", $\lambda_{0i}(\cdot)$.

Under the first condition ε_i^s and ε_i^{s+1} are independent and under the second condition

[13] In particular, it is plausible that t_i^{s+1} depends on Y_i^s; the longer the listing is on the market before it sells, the later the next listing date will be. If this was a serious concern we would expect the results to be sensitive to restrictions of the sample to exclude observations with $t_i^{s+1} - t_i^s < c$, where c is an arbitrary cutoff. In results not reported in the paper we have found that this is not the case.

both $-\varepsilon_i^s$ and $-\varepsilon_i^{s+1}$ are distributed $EV1(0,1)$ conditional on $t_i^s, t_i^{s+1}, \lambda_{0i}$. Therefore,

$$\begin{aligned}
Pr(Y_i^{s+1} \geq Y_i^s \mid t_i^s = t_s, t_i^{s+1} = t_{s+1}) & \\
&= Pr(\ln(\Lambda_0(Y_i^{s+1})) \geq \ln(\Lambda_0(Y_i^s)) \mid t_i^s = t_s, t_i^{s+1} = t_{s+1}) \\
&= Pr(\varepsilon_i^{s+1} - \varepsilon_i^s \geq \beta_{t_{s+1}} - \beta_{t_s} \mid t_i^s = t_s, t_i^{s+1} = t_{s+1}) \\
&= \frac{\exp(\beta_{t_s})}{\exp(\beta_{t_s}) + \exp(\beta_{t_{s+1}})}
\end{aligned}$$

This suggests that the β_t can be estimated through a logit regression where the dependent variable is $\mathbf{1}(Y_i^2 > Y_i^1)$. This has been proposed by Lancaster (2000) and Chamberlain (1985) and is based on an extension of Cox (1972) due originally to Ridder and Tunali (1989).

Ridder and Tunali (1989) show that the probability that a particular duration ends after y days conditional on at least one at-risk duration ending after y days takes the same form. The at-risk durations at time y are those which last at least y days. Specifically, the probability that the s^{th} listing ends after y days conditional on at least one of the listings for home i that lasts at least y days ending after y days is given by

$$\frac{\exp(\beta_{t_s})}{\sum_{s' \in R_i(Y_i^s)} \exp(\beta_{t_{s'}})}$$

where $s' \in R_i(y)$ if and only if $Y_i^{s'} \geq y$. This is the general form of the partial likelihood used in Ridder and Tunali (1989), Ridder and Tunali (1999) and Gobillon, Magnac, and Selod (2011). The partial log likelihood function is:

$$l(\beta) := \sum_{i=1}^{n} \sum_{s=1}^{S_i} \log \left(\frac{\exp(\beta_{t_i^s})}{\sum_{s' \in R_i(Y_i^s)} \exp(\beta_{t_i^{s'}})} \right)$$

The partial likelihood estimator which maximizes this function, $\hat{\beta}$, has been studied by Ridder and Tunali (1999). They provide regularity conditions under which this estimator is consistent and asymptotically normal. Note however that if we consider pairs of two listings for each home then these properties are inherited from standard results on maximum likelihood as the estimator is equivalent to the logit estimator described above.

5.1.2 Accounting for censoring

This estimator is not feasible in the presence of censoring. If only homes with all listings uncensored are used, the estimator is biased. To describe the estimator we use to construct our RPHI index first recall that d_i^s is an indicator denoting whether the home is sold and V_i^s denotes the observed duration, that is, the minimum of the TOM and the censoring time. To incorporate the censored observations and obtain an estimator that is (asymptotically) unbiased, the likelihood is adjusted to:

$$l(\beta) := \sum_{i=1}^{n} \sum_{s=1}^{S_i} d_i^s \log \left(\frac{\exp(\beta_{t_i^s})}{\sum_{s' \in \tilde{R}_i(V_i^s)} \exp(\beta_{t_i^{s'}})} \right)$$

where $s' \in \tilde{R}_i(v)$ if and only if $V_i^{s'} \geq v$.

As shown in Ridder and Tunali (1999), this new partial likelihood estimator is valid under three conditions – independence of the multiple listings conditional on observed (t_i^s) and unobserved ($\lambda_{0i}(\cdot)$) heterogeneity, strict exogeneity of the regressors, $\{t_i^s\}$, and independent censoring. As in the previous section we adapt Ridder and Tunali (1999) to a logit estimator that works with pairs of listings. We assume the following three conditions.

Assumption 5.2.

For each pair of listings, s and $s+1$,

(i) $Y_i^s \mid t_i^s, t_i^{s+1}, \lambda_{0i}(\cdot) =_d Y_{it_i^s} \mid \lambda_{0i}(\cdot)$ *and* $Y_i^{s+1} \mid t_i^s, t_i^{s+1}, \lambda_{0i}(\cdot) =_d Y_{it_i^{s+1}} \mid \lambda_{0i}(\cdot)$

(ii) $(V_i^s, d_i^s) \perp\!\!\!\perp (V_i^{s+1}, d_i^{s+1})$ *conditional on* $t_i^s, t_i^{s+1}, \lambda_{0i}(\cdot)$

(iii) Y_i^s *and* C_i^s *are independent conditional on* $t_i^s, \lambda_{0i}(\cdot)$

The first condition is identical to the strict exogeneity condition in Assumption 5.1 and the second condition is a slight generalization of the independence condition in Assumption 5.1. The third condition is the standard assumption of independent censoring. In fact, condition (iii) may be viewed as even more innocuous than the independence assumption underlying the Kaplan-Meier estimator as it assumes that censoring is independent conditional on the home-specific unobserved heterogeneity.

Under Assumption 5.2, the probability that the s^{th} listing is uncensored and ends after y days conditional on one of the listings in $\tilde{R}_i(y)$ being uncensored and ending after y days is given by

$$\frac{\exp(\beta_{t_s})}{\sum_{s' \in \tilde{R}_i(y)} \exp(\beta_{t_{s'}})}$$

Consider the case where there are only two listings. Evaluating the above for each s at $y = Y_i^s$ produces one (non-trivial) likelihood contribution for each i corresponding to the s with $V_i^s = \min\{V_i^1, V_i^2\}$. If $d_i^s = 0$ then the likelihood contribution is 0 and home i does not contribute at all to the likelihood function. However, if $d_i^s = 1$ then home i contributes the term

$$\frac{\exp(\beta_{t_i^s})}{\exp(\beta_{t_i^1}) + \exp(\beta_{t_i^2})}$$

regardless of whether the other listing for home i is censored or not.

Thus, as Lancaster (2000) demonstrates in a brief remark, in the case where we use only the first two listings for each home the partial likelihood function takes the form

$$\sum_{i=1}^{n} W_i \mathbf{1}(V_i^2 > V_i^1) \log\left(\frac{\exp(\beta' X_i)}{1 + \exp(\beta' X_i)}\right) + W_i \mathbf{1}(V_i^1 > V_i^2) \log\left(\frac{1}{1 + \exp(\beta' X_i)}\right)$$

where X_i is a vector of dummy variables, X_{it} for $t = 2, \ldots, T$, where $X_{it} = 1$ if $t_i^2 = t$, $X_{it} = -1$ if $t_i^1 = t$ and $X_{it} = 0$ otherwise and W_i is equal to 1 if neither duration is censored or if only the smaller of the two durations is censored, and is equal to 0 otherwise. The estimator $\hat{\beta}$ which maximizes this partial likelihood function is identical to the coefficient estimators from a logit regression of the binary indicator $\mathbf{1}(V_i^2 > V_i^1)$ on X_i *on the subsample* *of observations with* $W_i = 1$.

5.1.3 Implementation: Proportional Hazard Index

The procedure to estimate the coefficients β_t is straightforward and can be summarized as follows.

- Step 1: Identify the relevant sample of repeat listings (observations where $W_i = 1$). We focus first on listings that appear in more than one period. Among this set of repeat listings, we select those properties with completed durations in both periods or if only the smaller of the two durations is censored.
- Step 2: Calculate the dependent variable. Using the sample defined in the previous step, we estimate an indicator that takes the value of 1 if $Y_i^2 \geq Y_i^1$, and zero otherwise.
- Step 3: Estimation of a logistic model. The dependent variable is the indicator computed in the previous step, and the covariates are the variables in vector X_i.

5.1.4 Results: Repeat Proportional Hazard Index (RPHI)

In the proportional hazard model we take $\mu_t = \exp(\beta_t)$ as the repeat proportional hazard index (RPHI) which can be interpreted as the gross percentage increase in the hazard rate since the initial period. The index is pegged at $\mu_0 = 1$. In other words, if $\mu_t = 1.5$ the probability that a home listed in period t will sell on any given day, conditional on still being on the market, is 50% larger than it would be if it had been listed in the base period. The RPHI is estimated in all 15 MSAs in the sample and results are displayed in Table 2. In all areas the index has been normalized so that it equals 1 in the first quarter of 2010. There is significant variation in the RPHI both across areas and over time.

It is useful to compare the RPHI with the simple unconditional hazard ratio computed in Section 4.2. The hazard ratio discussed in Section 4.2 has the same interpretation as the RPHI and is estimated incorporating both censored and non-censored durations; however, it does not account for unobserved heterogeneity. The evolution of both of these variables is displayed in the top panels of Figures 5 and 6. While the overall trend of both indices is much alike, there are some important differences. For example, in Fairfax County, the RPHI during a booming market (in 2000) is much higher than the unconditional hazard ratio. Such patterns would arise if the types of homes that were listed in this particular period were especially hard to sell (less liquid) due to their unique features. On the contrary, in a slow market (2007), the unconditional hazard ratio is higher than the RPHI suggesting that homes being listed during "bad times" were, due to their unobserved characteristics, more liquid than the average home in the sample. This translates into a RPHI that is more volatile that the unconditional hazard ratio. These patterns seem to be persistent in the other urban areas.

In sum, just as it is the case with repeat-sales home price indices, controlling for unobserved heterogeneity is key to measure the evolution of the baseline hazard rate.

5.2 A Repeat Median TOM Index

An alternative method is based on the accelerated failure time model $\log(Y_i^s) = \beta_{t_i^s} + u_i^s$ with $u_i^s = \alpha_i + \varepsilon_i^s$. This generalizes a proportional hazards model with a constant hazard function by allowing the distribution of ε_i^s to be unrestricted. This suggests that

$$\log(Y_i^2) - \log(Y_i^1) = \beta' X_i + \tilde{\varepsilon}_i$$

where X_i is as defined in Section 4.1.2 and $\tilde{\varepsilon}_i = \varepsilon_i^2 - \varepsilon_i^1$. If $E(\tilde{\varepsilon}_i \mid X_i) = 0$ and there is no censoring then the usual fixed effects regression estimator will consistently estimate β.

A similar approach is still possible in the presence of censoring. First we make the following assumption.

Assumption 5.3.

(i) $Med(\alpha_i + \varepsilon_i^s \mid t_i^s, t_i^{s+1}) = Med(\alpha_i + \varepsilon_i^{s+1} \mid t_i^s, t_i^{s+1})$

(ii) Y_i^s *and* C_i^s *are independent conditional on* t_i^s, t_i^{s+1} *and* Y_i^{s+1} *and* C_i^{s+1} *are independent conditional on* t_i^s, t_i^{s+1}

The first condition combines something like the strict exogeneity condition of Assumption 5.2(i) and a stationarity condition. To see this, note that it follows if (i) $\varepsilon_i^s \mid \alpha_i, t_i^s, t_i^{s+1} =_d \varepsilon_i^s \mid \alpha_i, t_i^s$ and $\varepsilon_i^{s+1} \mid \alpha_i, t_i^s, t_i^{s+1} =_d \varepsilon_i^s \mid \alpha_i, t_i^{s+1}$ and (ii) $\varepsilon_i^s \mid \alpha_i, t_i^s =_d \varepsilon_i^{s+1} \mid \alpha_i, t_i^{s+1}$. Under condition (i) β is identified if $Med(\log(Y_i^s) \mid X_i)$ is identified because

$$Med(\log(Y_i^2) \mid X_i) - Med(\log(Y_i^1) \mid X_i) = \beta' X_i$$

Moreover, $Med(\log(Y_i^s) \mid X_i)$ will generally be identified under independent censoring (condition (ii)), as described in Section 4.2. An important caveat is relevant if there is a value $\bar{y}$ such that all observations with durations exceeding $\bar{y}$ are censored. In this case the u quantile of the distribution is only identified for $u \leq \bar{u}$ where $\bar{u}$ is the proportion of the durations that exceed $\bar{y}$. If $\bar{u} < 1/2$ then the median is not identified. However, we do not observe this problem in the housing markets we study in this paper.

5.2.1 Implementation: Median Index

The model is estimated in a two step procedure. First we select a set of repeat listings: those that were put on the market in period t for the first time and in period $t+k$ for the second time. Using only this subset of observations (that includes both completed and censored durations) we estimate the median log TOM separately in *each* period by carrying out the Kaplan-Meier estimator. We can then compute the difference in the median log TOM between periods t and $t+k$. Note that unobserved heterogeneity dissapears when the difference in median log TOM is computed (as long as assumption 5.3 holds.) We repeat these calculations for every other pair of periods in our sample. Then, in a second step, we run a simple OLS regression to estimate β. The procedure to estimate the repeat median TOM index is summarized below:

- Step 1: We estimate $Med(\log(Y_i^2) \mid X_i) - Med(\log(Y_i^1) \mid X_i)$ by carrying out the Kaplan-Meier procedure conditional on $t_i^1, t_i^2 = t_1, t_2$ for each pair of t_1, t_2 such that $t_1 < t_2$. For each observation i we then have an estimate $\widehat{\delta M}_i$ of $Med(\log(Y_i^2) \mid X_i) - Med(\log(Y_i^1) \mid X_i)$.

- Step 2: We run an OLS regression of $\widehat{\delta M}_i$ on X_i to estimate β.

As we mentioned in the introduction, this procedure can be viewed a as a repeat sales quantile (median) regression that makes use of an the accelerated failure time (AFT) assumption (see, e.g., Kalbfleisch and Prentice, 2011) and uses a conditional Kaplan-Meier estimator to correct for censoring in a first stage.

5.2.2 Results: Repeat Median TOM Index

A repeat sales index for home prices, such as the Case-Shiller index, is created by taking $\hat{\mu}_t = \exp(\hat{\beta}_t)$. This transformation is natural in that context because $\exp(\beta_t)$ represent the gross market return between the initial period and period t. Here we will use the same construction for the index though the interpretation as a gross return is less salient.

In the accelerated failure time model we take $\mu_t = \exp(\beta_t)$ and define it as the repeat median TOM index (RMTI). Notice that a larger index value represents an increase in the time on the market. For example, if $\mu_t = 1.5$ then the median time on the market would have been 50% larger in period t compared to the base period. The RMTI is estimated in all 15 MSAs in the sample and results are displayed in Table 3. In all areas the index has been normalized so that it equals 1 in the first quarter of 2010. As it was the case with the RPHI, the RMTI exhibits significant variation both across areas and over time.

In the bottom panels of Figures 5 and 6 we show the inverse of the RMTI in selected urban areas. We plot the inverse (rather than the level) of the RMTI to facilitate a direct comparison with the RPHI above. These two indices can be compared as they both represent rates at which the time on the market changes over time. As expected, in all areas the RMTI and the RPHI seem extremely highly correlated. In fact, if the baseline hazard function is constant then the two models coincide and the two indices estimate the same thing.

We compare the RMTI with a simple ratio of unconditional medians. The unconditional medians have been estimated using the Kaplan-Meier estimator and censored durations but do not account for housing unobserved heterogeneity. The RMTI and the unconditional median ratio follow a similar trend. In some areas, the trends are almost identical (Fairfax County) while in others there are substantial differences (Miami and New Orleans, for example). As it was the case with the repeat proportional hazard index, controlling for unobserved heterogeneity is important when measuring the evolution of the median TOM.

6 Conclusions

This paper develops the first measures of liquidity in the housing market that are based on repeat listings. Important features of the two indices we propose are their ability to control for unobserved heterogeneity exploiting *repeat* listings, and their use of censored durations. The first index, the RPHI, computes proportional displacements in the home sale baseline hazard rate. This index is based on an econometric model that has been used on other contexts; the application of this method to the measurement of real estate liquidity is one of the main contributions of our paper. The second index, the RMTI, estimates the relative change in (quality adjusted) median TOM. The RMTI uses a novel econometric procedure that contributes to the literature in econometrics that attempts to relax the proportional hazards assumption. We compute the indices using listings data from 15 US urban areas including Miami, San Diego, Las Vegas, and a suburb of Washington D.C. The combined empirical evidence suggests that to measure housing liquidity it is key to account for observations that are censored when the home is withdrawn from the market and to control for unobserved heterogeneity using repeat listings.

We also highlight the computational transparency and simplicity of both indices. The RPHI can be estimated using a simple logistic regression, while the RMTI can be estimated with a simple two step procedure that combines the estimation of median TOM in each period and an OLS regression. Given the availability of MLS data, we hope that the application of our methods is a straightforward task. Periodic reporting of such indices should be useful to investors, regulators, home buyers and home owners to assess housing market conditions and make informed decisions.

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A Appendix

A.1 Derivation of Measures

We estimate quality-adjusted time-on-the-market distributions for each quarter-area combination in our sample. The method used to compute the distributions follow Carrillo and Pope (2012), who combine the Dinardo, Fortin and Lemieux (1996) (DFL) with the Kaplan-Meier (1958) estimator. This allows the DFL decomposition to work in cases where the dependent variable is subject to random censoring. To keep our exposition self-contained, we carefully review the decomposition method.

Let Y be our variable of interest (the time a listing stays on the market) and t_0 and t_1 refer to the two mutually exclusive periods (quarters) in each of the areas we analyze. The cumulative probability function of Y in period t_0 is defined as

$$F(y|T = T_0) = \Pr(Y \leq y|T = t_0) = \int F(y|x, T = t_0)h(x|T = t_0)dx \tag{A.1}$$

where T is a random variable describing the period from which an observation is drawn and x is a particular draw of observed attributes of individual characteristics from a random vector of housing characteristics X. $F(y|x, T = t_0)$ is the (conditional) cumulative distribution of Y given that a particular set of attributes x have been picked, and $h(x|T = t_0)$ is the probability density of individual attributes evaluated at x. The cumulative probability function of Y in period t_1 is defined similarly.

Suppose we would like to assess how the distribution of Y (marketing time) in period t_1 would look if the individual attributes x (number of bathrooms, bedrooms and age, for example) were the same as in period t_0 (the base quarter). We denote this counterfactual as $F_{t_1 \to t_0}$ and express it symbolically as[14]

$$F_{t_1 \to t_0} = \int F(y|x, T = t_1)h(x|T = t_0)dx \tag{A.2}$$

Using Bayes' rule, DFL recognized that

$$\frac{h(x|T = t_0)}{h(x|T = t_1)} = \frac{\frac{\Pr(T=t_0|X=x)}{\Pr(T=t_0)}}{\frac{\Pr(T=t_1|X=x)}{\Pr(T=t_1)}} = \frac{\frac{\Pr(T=t_0|X=x)}{1-\Pr(T=t_0|X=x)}}{\frac{\Pr(T=t_0)}{1-\Pr(T=t_0)}} = \tau_{t_1 \to t_0}(x) \tag{A.3}$$

One may use Equation A.3 to substitute $h(x|T = t_0)$ in Equation A.2 and thereby obtain Equation A.4.

$$F_{t_1 \to t_0}(y) = \int F(y|x, T = t_1)h(x|T = t_1)\tau_{t_1 \to t_0}(x)dx \tag{A.4}$$

Notice that this expression differs from Equation A.1 only by $\tau_{t_1 \to t_0}(x)$. DFL refer to $\tau_{t_1 \to t_0}(x)$ as "weights" that should be applied when computing the counterfactual distribution

[14]The subscript $t_1 \to t_0$ indicates that the attribute data from period t_0 will be "replaced" by data from period t_1.

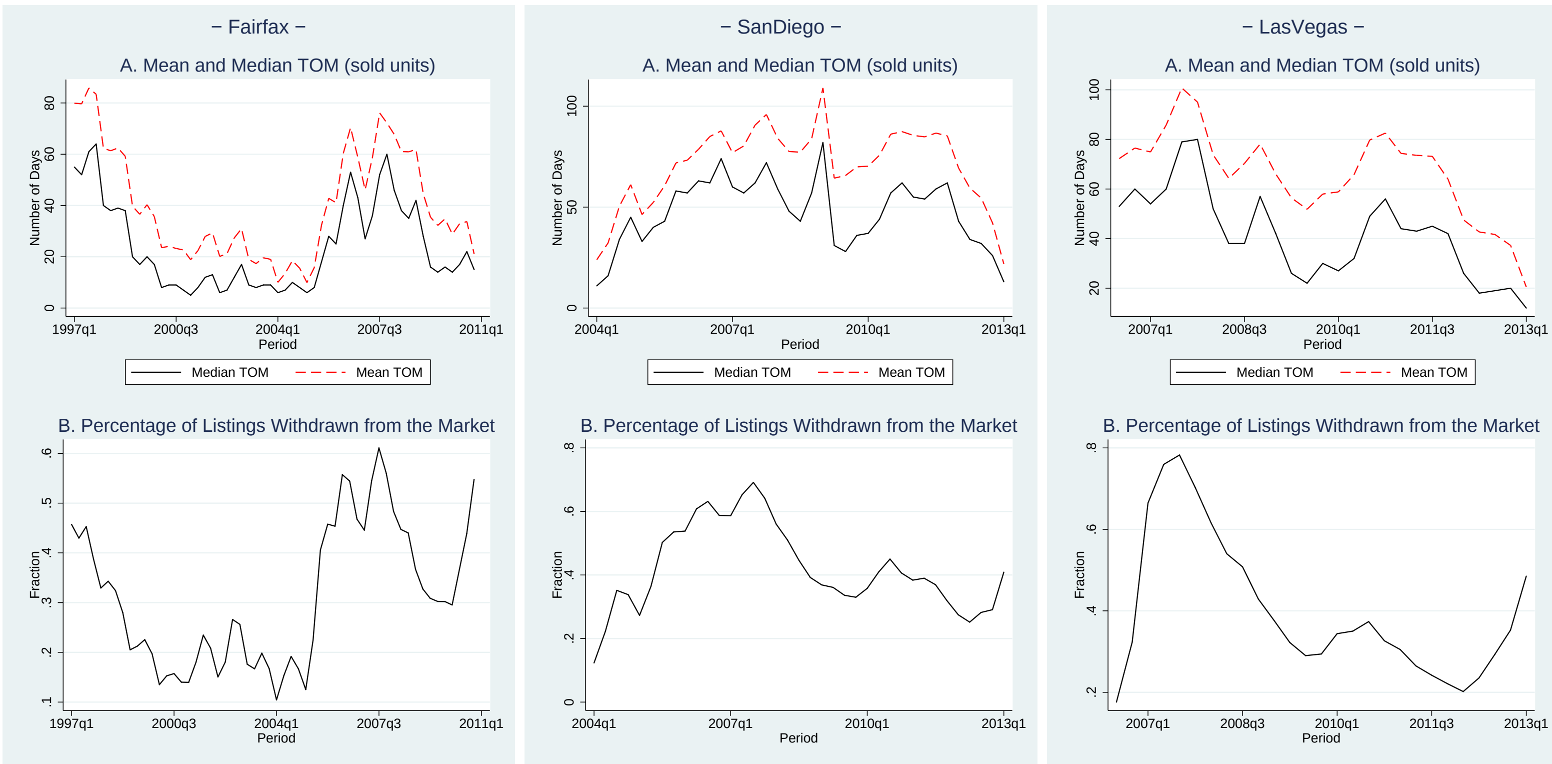
of our variable of interest. However, given that the weights are unknown, they need to be estimated.

Carrillo and Pope (2012) note that the DFL method described above cannot be directly used in this application because marketing time is subject to random censoring; that is, some properties are not sold and withdrawn from the market. Because the random variable Y (marketing time) is subject to random censoring, the counterfactual distribution can be computed using the Kaplan-Meier estimator, with sampling weights given by $\tau_{t_1 \to t_0}(x)$.

To be specific, we summarize the estimation algorithm for the counterfactual given that a random sample of N_0 and N_1 observations for periods t_0 and t_1 is available. Notice that in all steps described below the sample includes all censored and non-censored observations.

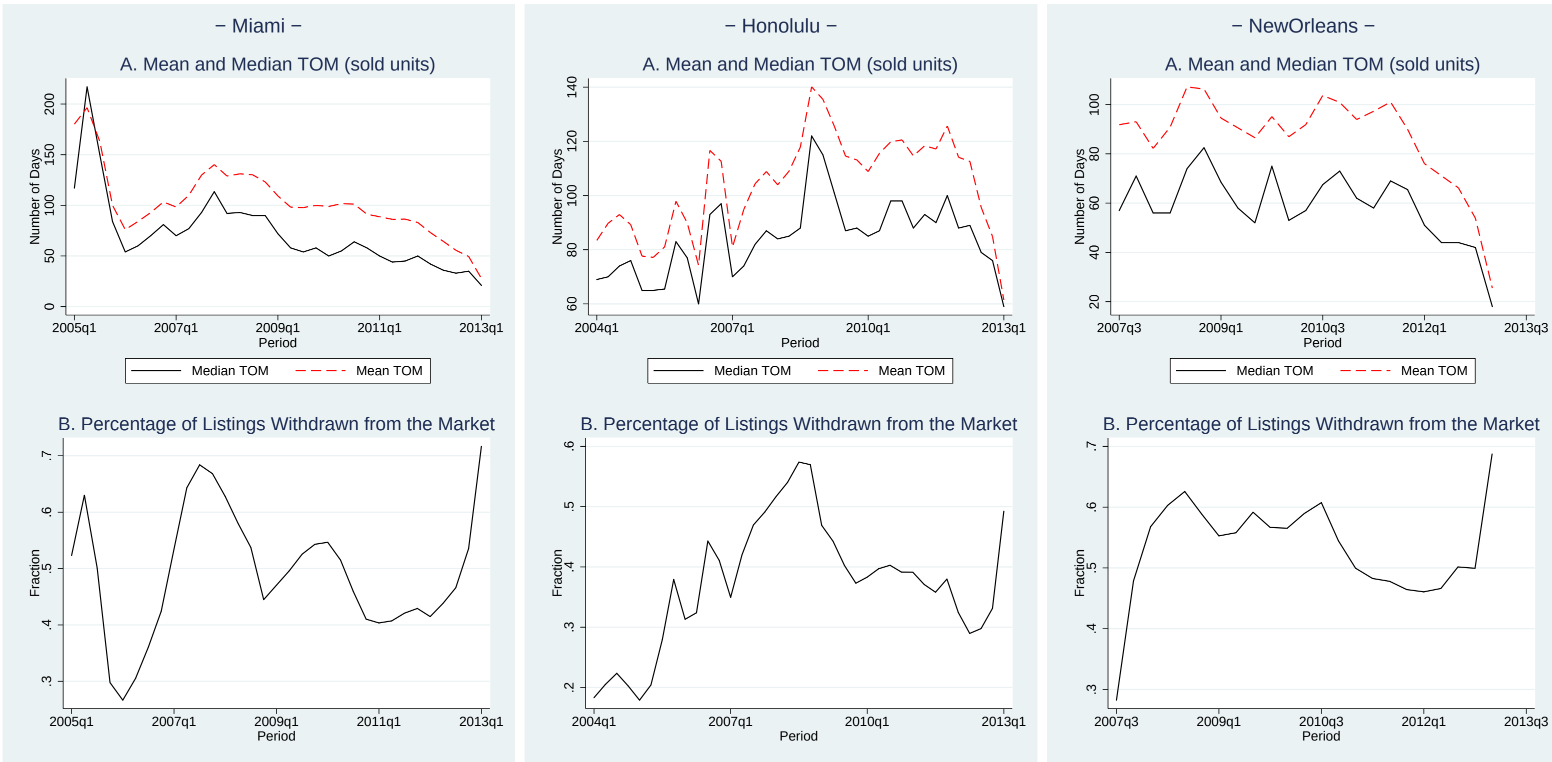
- Step 1: Estimate $P(T = t_0)$ using the share of observations where $T_i = t_0$; that is, compute: $\hat{\Pr}(T_i = t_0) = N_0/(N_0 + N_1)$.
- Step 2: Estimate $P(T = t_0|X = x)$, by estimating a logit model using the pooled data. The dependent variable equals one if $T_i = t_0$ and explanatory variables include the vector of individual attributes x_i.
- Step 3: For the subsample of observations where $T_i = t_1$, estimate the predicted values from the logit $\hat{\Pr}(T_i = t_0|X = x_i) = \exp(x_i\hat{\beta})/\left(1 + \exp(x_i\hat{\beta})\right)$, where $\hat{\beta}$ is the parameter vector from the logit regression. Then, compute the estimated weights $\hat{\tau}_{t_1 \to t_0}(x)$.
- Step 4: For the subsample of observations where $T_i = t_1$, compute a weighted empirical cumulative distribution function using the Kaplan-Meier estimator. Weights are given by $\hat{\tau}_{t_1 \to t_0}(x)$.

Figure 1:
Descriptive "Conventional" Statistics (part 1)



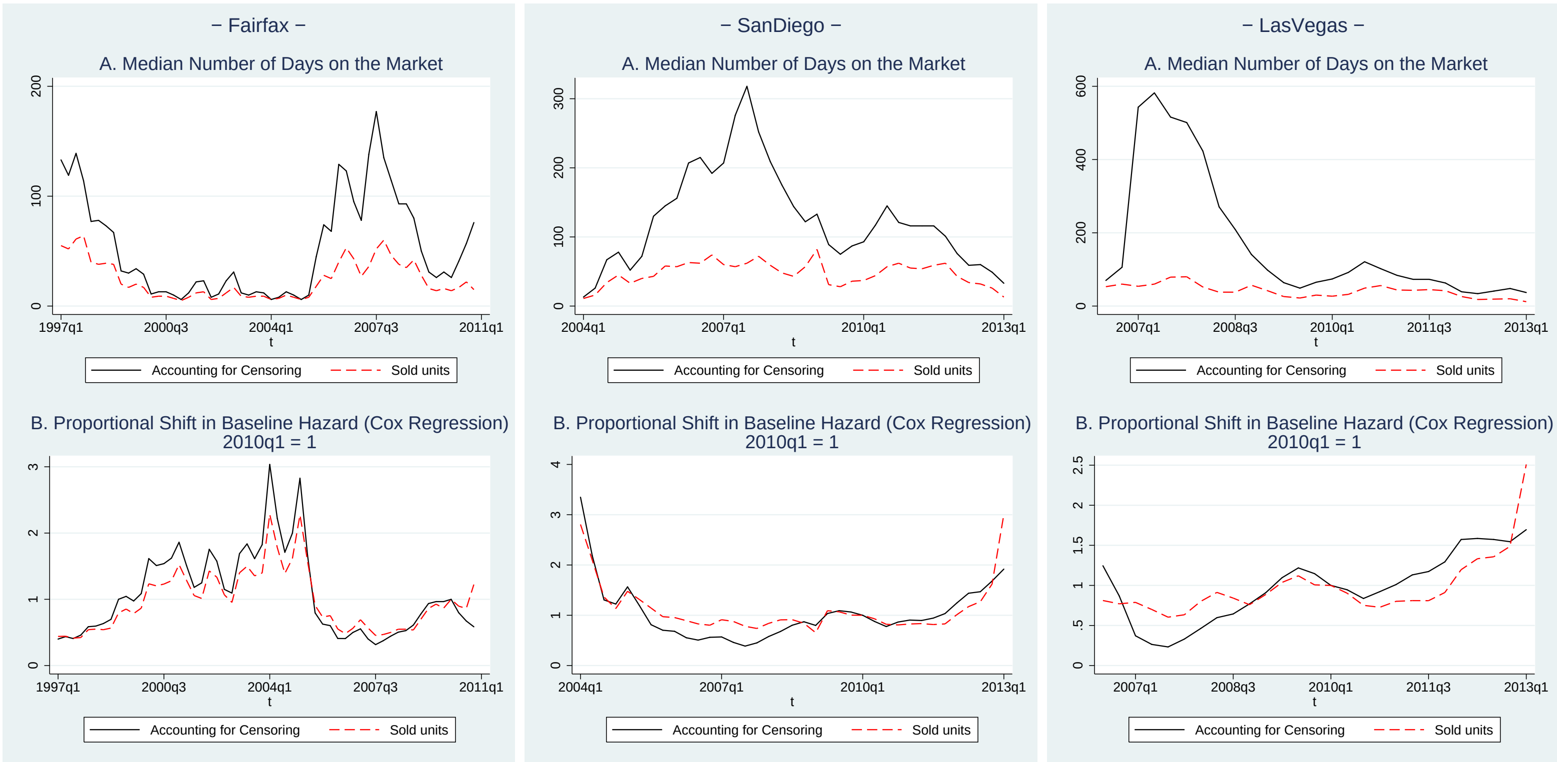
Notes: This figure presents descriptive statistics of the sample. Panel A computes the mean and median number of days that a home stays on the market (TOM). This is a "conventional" estimate that simply computes the mean and median TOM of finished durations (sold units). The second panel shows the share of total listings that are withdrawn from the market.

Figure 2:
Descriptive “Conventional” Statistics (part 2)



Notes: This figure presents descriptive statistics of the sample. Panel A computes the mean and median number of days that a home stays on the market (TOM). This is a “conventional” estimate that simply computes the mean and median TOM of finished durations (sold units). The second panel shows the share of total listings that are withdrawn from the market.

Figure 3:
Adjusting for Censoring When Computing TOM Statistics (part 1)

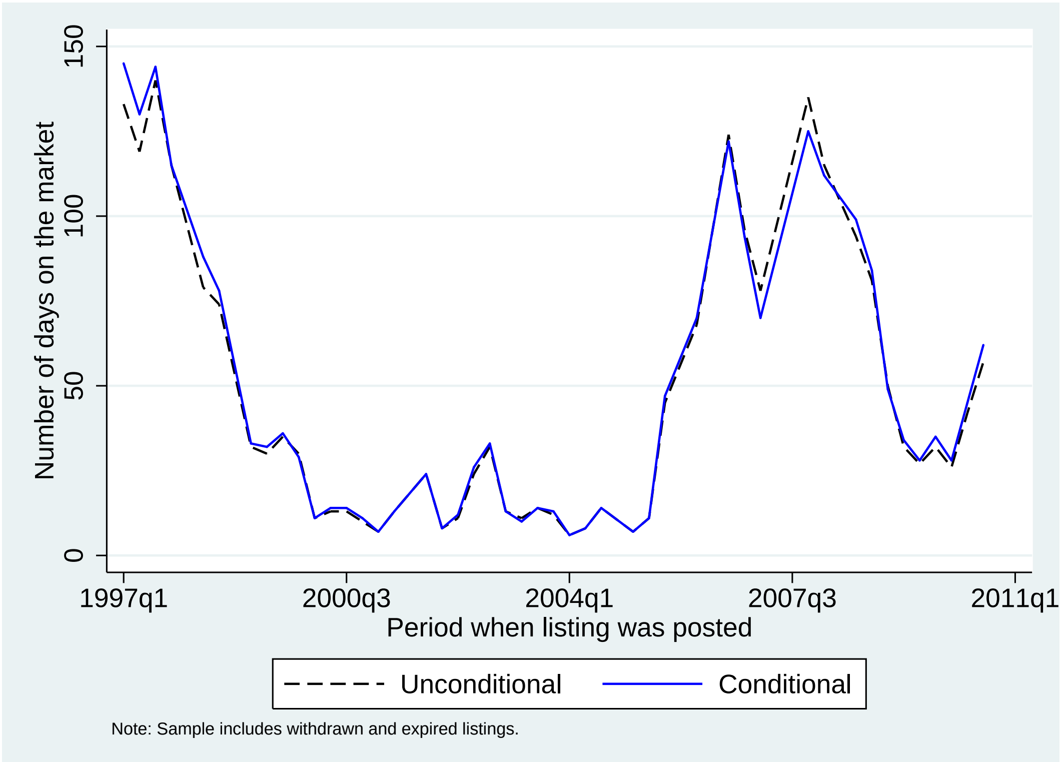


Notes: Panel A computes the median number of days that a home stays on the market (TOM). The "conventional" estimate simply computes the median TOM of finished durations (sold units). To account for censoring, a Kaplan-Meier estimator is used. For units that are sold, TOM is defined as the difference between the date when an offer was accepted and the date when the listing was posted. For censored observations, we compute duration as the difference between the date when the listing was posted and the date when it was withdrawn. In Panel B, a COX proportional hazard model is used to estimate changes in the baseline hazard relative to a base period (2010 q1). The "conventional" approach uses only the sample of finished durations (sold units). To account for censoring, proportional hazard models are estimated using both finished and censored durations.

Figure 4:
Adjusting for Censoring When Computing TOM Statistics (part 2)

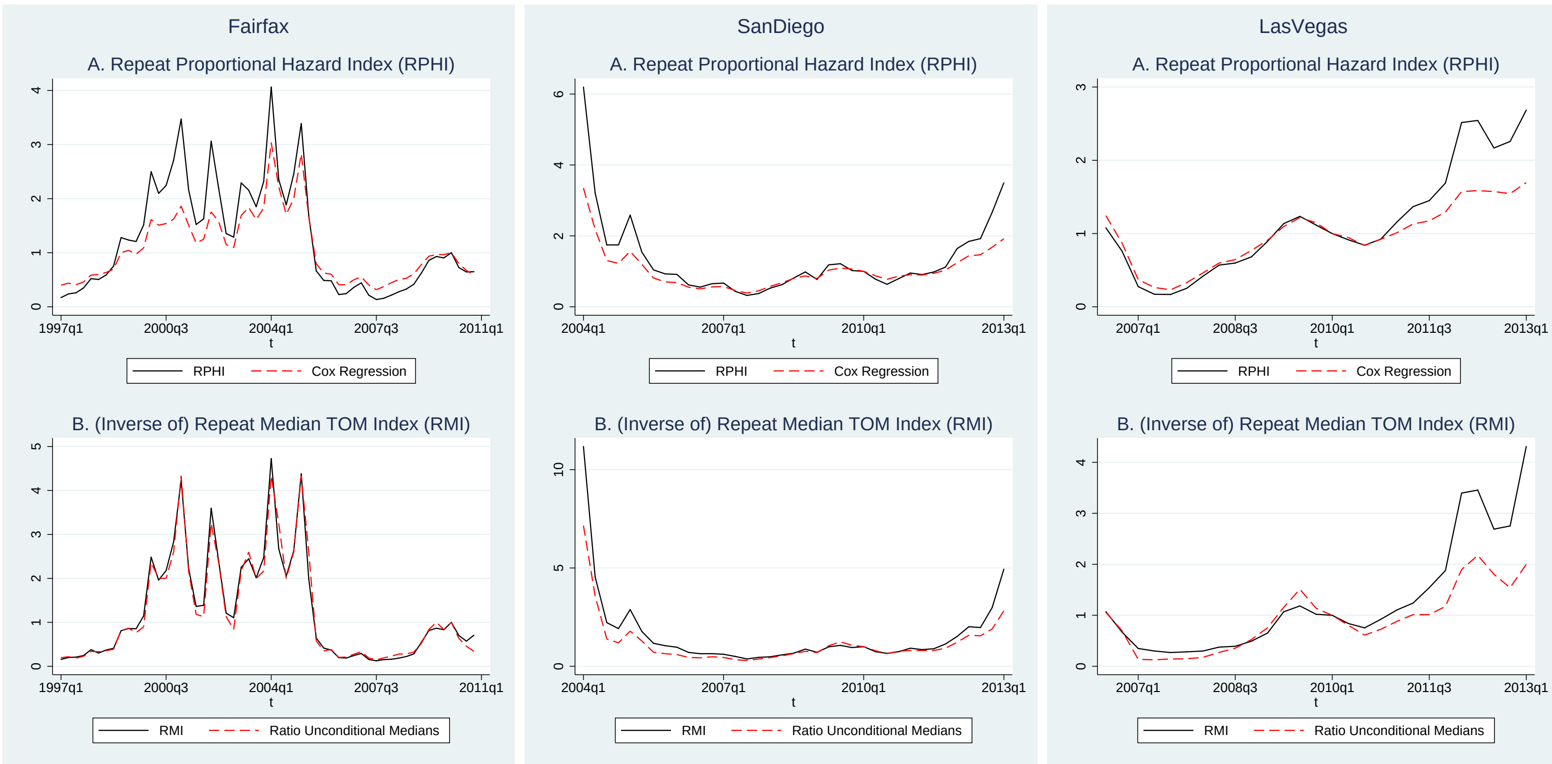
Notes: Panel A computes the median number of days that a home stays on the market (TOM). The "conventional" estimate simply computes the median TOM of finished durations (sold units). To account for censoring, a Kaplan-Meier estimator is used. For units that are sold, TOM is defined as the difference between the date when an offer was accepted and the date when the listing was posted. For censored observations, we compute duration as the difference between the date when the listing was posted and the date when it was withdrawn. In Panel B, a COX proportional hazard model is used to estimate changes in the baseline hazard relative to a base period (2010 q1). The "conventional" approach uses only the sample of finished durations (sold units). To account for censoring, proportional hazard models are estimated using both finished and censored durations.

Figure 5:
Controlling for Observed Heterogeneity: Conditional and Unconditional Median TOM
- Fairfax County, VA -



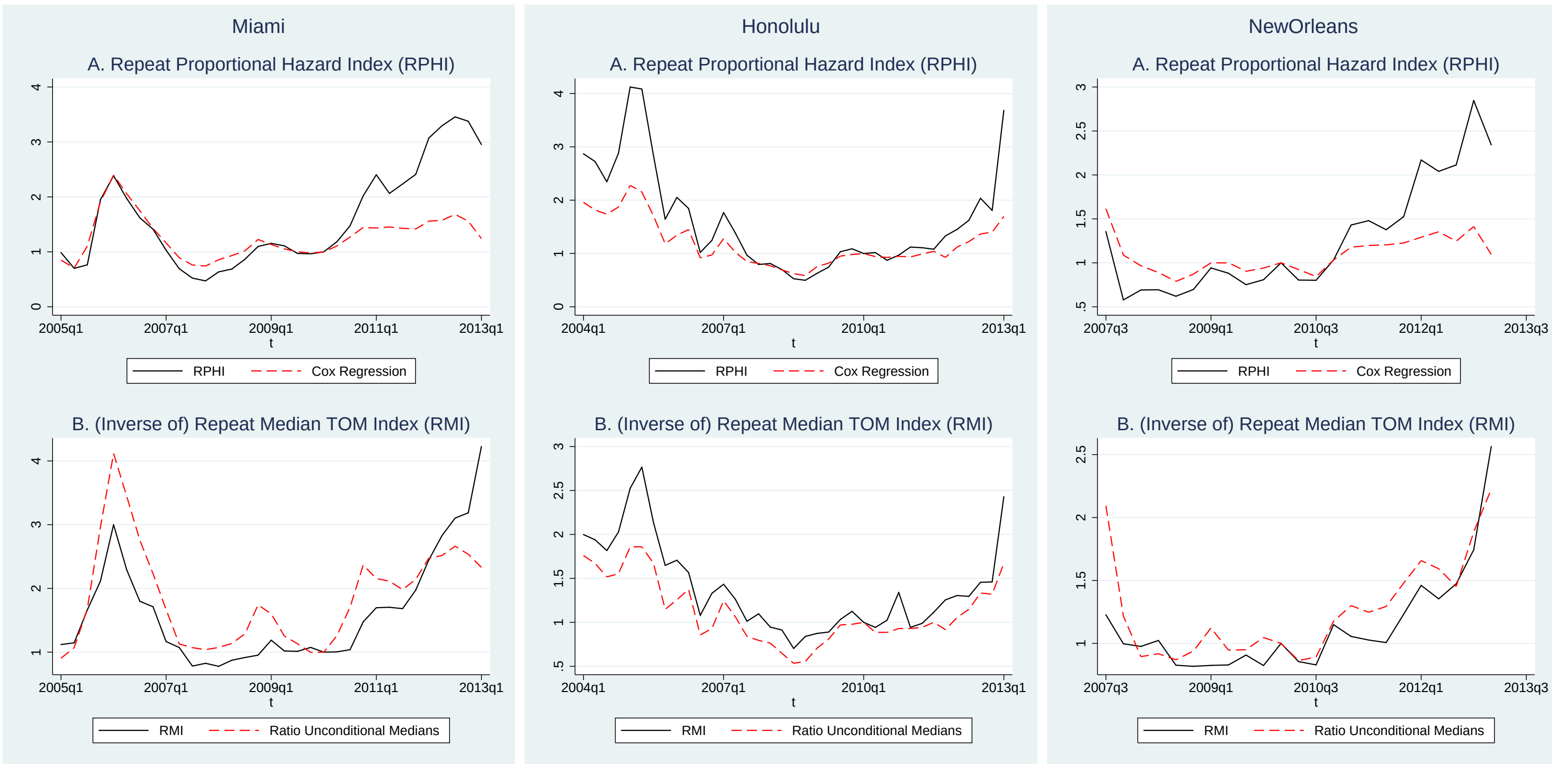
Notes: This Figure plots the evolution of the unconditional and conditional median TOM in Fairfax County. The unconditional median is computed using completed and censored durations and the Kaplan-Meier estimator. The conditional median is calculated using the re-weighting approach proposed by Dinardo, Fortin and Lemieux (1996). The conditional median TOM is simulated assuming that the characteristics of homes (age, structure type, number of bedrooms and bathrooms) remain constant as in a base period (2000 q1).

Figure 6:
Repeat Time-On-The-Market Indices (part 1)



Notes: Panel A computes the Repeat Proportional Hazard Index (RPHI). The index measures relative shifts of the baseline hazard after controlling for unobserved home's heterogeneity. For example, and index value of 1.5 in period t reflects a 50 percent increase in the home sale baseline hazard in period t relative to the base period (2010 q1). The RPHI is compared with a similar index based on a Cox- regression that does not correct for unobserved heterogeneity. Panel B shows the (inverse of) the Repeat Median TOM Index (RMI). We report the inverse of the RMI to facilitate comparison with the RPHI. The RPHI is compared with a simple index that compares the relative shift of the unconditional median TOM in period t relative to the base period.

Figure 7:
Repeat Time-On-The-Market Indices (part 2)



Notes: Panel A computes the Repeat Proportional Hazard Index (RPHI). The index measures relative shifts of the baseline hazard after controlling for unobserved home's heterogeneity. For example, and index value of 1.5 in period t reflects a 50 percent increase in the home sale baseline hazard in period t relative to the base period (2010 q1). The RPHI is compared with a similar index based on a Cox- regression that does not correct for unobserved heterogeneity. Panel B shows the (inverse of) the Repeat Median TOM Index (RMI). We report the inverse of the RMI to facilitate comparison with the RPHI. The RPHI is compared with a simple index that compares the relative shift of the unconditional median TOM in period t relative to the base period.

Table 1
Geographic and Time Coverage of Sample

	Urban Area	# Obs. all listings	# Obs. all home sales	# Obs. *repeat* listings	Period Begin	Period End
01	Ann Arbor, MI	45,044	21,101	27,642	2004q1	2013q1
02	Boulder, CO	47,177	26,923	27,510	2004q1	2013q1
03	Durham, NC	59,234	34,125	31,112	2004q1	2013q1
04	Fairfax County, VA	357,515	244,961	232,382	2007q2	2010q4
05	Honolulu, HI	85,511	54,350	46,670	2004q1	2013q1
06	Las Vegas-Paradise, NV	262,267	153,577	140,181	2006q3	2013q1
07	Medford, OR	26,138	16,315	13,247	2004q1	2013q1
08	Miami-Miami Beach-Kendall, FL	219,210	112,069	96,982	2005q1	2013q1
09	New Orleans-Metairie-Kenner, LA	79,845	36,869	43,446	2007q3	2013q1
10	Olympia, WA	35,416	21,733	18,351	2004q1	2013q1
11	San Diego-Carlsbad-San Marcos, CA	367,122	207,162	228,676	2004q1	2013q1
12	San Luis Obispo-Paso Robles, CA	27,506	19,044	11,747	2004q1	2013q1
13	Santa Barbara-Santa Maria, CA	29,054	20,085	13,929	2004q1	2013q1
14	Toledo, OH	65,873	35,673	33,599	2004q1	2013q1
15	Youngstown-Warren-Boardman, OH-PA	52,825	27,098	26,099	2004q1	2013q1

Notes: This table tabulates the number of observations in each area we study. The first column shows the total number of real estate listings reported on the MLS during the sample period. The second column shows the sale volume: the number of listings that end up in a sale. Column three shows the number of repeat listings: the number of properties that were listed more than once during the sample period.

Table 2
Repeat Proportional Hazard Index (RPHI) in Selected US MSAs

	AREA														
Period	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15
2002q1				3.062											
2002q2				2.191											
2002q3				1.355											
2002q4				1.288											
2003q1				2.291											
2003q2				2.156											
2003q3				1.851											
2003q4				2.317											
2004q1	1.425	0.844	1.442	4.064	2.870		2.930			1.636	6.199	3.040	3.878	2.829	1.146
2004q2	1.625	0.843	1.523	2.352	2.723		2.966			2.910	3.212	2.777	2.613	2.595	1.021
2004q3	1.409	0.830	1.376	1.885	2.345		3.317			2.625	1.745	1.708	2.111	1.852	1.094
2004q4	1.295	1.068	1.169	2.454	2.882		3.217			3.731	1.747	1.837	2.708	1.673	1.424
2005q1	1.696	1.300	2.133	3.388	4.122		3.956	0.987		4.228	2.585	2.242	1.967	2.568	1.488
2005q2	1.222	1.125	1.936	1.686	4.085		3.803	0.700		3.492	1.543	1.935	1.690	2.269	1.441
2005q3	0.781	1.020	1.463	0.665	2.833		2.344	0.763		3.682	1.042	1.673	1.278	2.058	1.066
2005q4	0.699	1.236	1.643	0.488	1.643		1.266	1.950		2.361	0.928	1.027	0.885	1.622	1.180
2006q1	0.734	1.208	2.171	0.481	2.052		1.690	2.384		2.897	0.914	1.035	0.950	2.132	1.406
2006q2	0.712	0.985	2.066	0.226	1.845		1.114	1.972		1.969	0.617	0.801	0.703	1.628	1.071
2006q3	0.495	0.843	1.646	0.245	1.020	1.078	0.759	1.619		1.693	0.556	0.870	0.610	1.244	0.938
2006q4	0.481	1.037	1.977	0.359	1.246	0.760	0.862	1.413		1.342	0.650	0.791	0.650	1.140	1.064
2007q1	0.534	1.511	2.270	0.443	1.767	0.276	1.152	1.030		1.774	0.670	1.108	0.748	0.947	1.110
2007q2	0.438	0.990	1.994	0.214	1.388	0.171	1.011	0.693		1.091	0.436	0.784	0.485	0.775	0.983
2007q3	0.561	0.883	1.154	0.135	0.968	0.169	0.580	0.523	1.356	0.945	0.321	0.579	0.465	0.564	0.871
2007q4	0.637	1.209	1.380	0.158	0.794	0.253	0.774	0.472	0.578	0.926	0.375	0.459	0.380	0.706	0.741
2008q1	0.756	1.324	1.318	0.215	0.812	0.417	0.487	0.636	0.692	1.096	0.528	0.637	0.651	0.942	0.968
2008q2	0.650	1.246	1.431	0.278	0.698	0.569	0.751	0.687	0.694	0.813	0.624	0.576	0.667	0.817	0.849
2008q3	0.688	0.914	1.119	0.328	0.527	0.597	0.887	0.865	0.620	0.875	0.811	0.689	0.699	0.777	0.836
2008q4	0.844	0.793	0.977	0.417	0.497	0.681	0.804	1.098	0.698	0.965	0.983	0.860	1.029	0.846	0.947
2009q1	0.917	0.870	1.145	0.623	0.627	0.894	0.688	1.155	0.942	0.937	0.772	0.910	0.787	1.143	0.944
2009q2	1.003	0.997	1.130	0.858	0.744	1.136	0.928	1.110	0.882	0.827	1.184	0.751	0.921	1.024	0.907
2009q3	1.249	1.064	1.250	0.930	1.033	1.235	1.039	0.972	0.752	1.127	1.216	1.099	0.862	0.942	0.937
2009q4	0.961	0.957	1.216	0.904	1.088	1.116	1.351	0.965	0.808	1.082	1.023	1.115	0.673	0.929	1.265
2010q1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2010q2	0.801	0.812	0.794	0.725	1.017	0.914	0.813	1.184	0.804	0.879	0.781	0.765	0.703	0.909	0.688
2010q3	0.779	0.572	0.713	0.645	0.872	0.840	1.078	1.474	0.802	1.052	0.635	0.905	0.595	0.766	0.657
2010q4	1.080	0.824	1.000	0.648	0.969	0.923	1.517	2.019	1.034	0.841	0.796	0.849	0.626	1.240	1.084
2011q1	1.019	1.030	0.879		1.120	1.157	1.350	2.404	1.430	1.071	0.952	0.977	0.639	1.308	0.990
2011q2	0.939	0.996	0.994		1.108	1.367	1.392	2.064	1.480	0.853	0.909	1.239	0.767	1.188	1.085
2011q3	1.065	0.785	1.091		1.080	1.449	1.419	2.236	1.377	0.869	0.982	1.128	0.885	1.054	0.869
2011q4	1.290	1.093	1.392		1.330	1.689	2.431	2.410	1.525	1.052	1.120	1.126	1.080	1.227	1.334
2012q1	2.002	2.252	1.520		1.453	2.515	2.437	3.072	2.170	1.472	1.643	1.922	1.126	2.018	2.254
2012q2	1.644	2.527	1.345		1.621	2.544	2.625	3.295	2.041	1.388	1.845	1.858	1.749	1.762	1.712
2012q3	1.821	1.805	1.530		2.036	2.168	2.371	3.457	2.114	1.041	1.924	1.864	2.044	1.675	1.516
2012q4	1.987	3.366	2.128		1.807	2.257	2.817	3.377	2.847	1.289	2.666	2.478	2.837	2.463	1.721
2013q1	1.730	3.903	2.485		3.684	2.685	3.101	2.954	2.342	2.515	3.495	3.255	3.193	3.001	1.774

Notes: The RPHI has been estimated in area 01: Ann Arbor, MI; 02: Boulder, CO; 03: Durham, NC; 04: Fairfax, VA; 05: Honolulu, HI; 06: Las Vegas, NV; 07: Medford, OR; 08: Miami, FL; 09: New Orleans; 10: Olympia, WA; 11: San Diego, CA; 12: San Luis Obispo, CA; 13: Santa Barbara, CA; 14: Toledo, OH; and in area 15: Youngtown, OH. The index measures the (quality adjusted) shift in the baseline hazard relative to the base period (2010q1).

Table 3
Repeat Median TOM Index (RMI) in Selected US MSAs

	AREA														
Period	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15
2002q1				0.278											
2002q2				0.417											
2002q3				0.827											
2002q4				0.904											
2003q1				0.444											
2003q2				0.409											
2003q3				0.496											
2003q4				0.404											
2004q1	0.565	0.942	0.841	0.212	0.500		0.572			0.666	0.089	0.318	0.275	0.476	0.893
2004q2	0.565	1.292	0.801	0.374	0.516		0.616			0.519	0.220	0.261	0.301	0.458	0.751
2004q3	0.804	1.403	0.867	0.488	0.551		0.511			0.605	0.450	0.478	0.447	0.724	0.905
2004q4	0.311	1.141	1.083	0.381	0.493		0.712			0.450	0.521	0.452	0.455	0.800	0.814
2005q1	1.139	0.982	0.772	0.228	0.396		0.453	0.893		0.504	0.347	0.413	0.466	0.582	0.806
2005q2	0.766	1.100	0.712	0.503	0.362		0.525	0.872		0.469	0.564	0.404	0.501	0.496	0.897
2005q3	1.097	1.180	0.918	1.553	0.469		0.644	0.602		0.454	0.856	0.549	0.669	0.582	1.001
2005q4	1.380	1.243	0.946	2.415	0.607		0.884	0.473		0.657	0.955	0.850	0.754	0.677	0.868
2006q1	1.093	1.026	0.767	2.697	0.586		0.793	0.333		0.561	1.031	0.859	1.040	0.722	0.869
2006q2	1.038	1.096	0.705	5.079	0.638		0.942	0.436		0.630	1.414	1.073	1.293	0.868	0.844
2006q3	1.367	1.346	0.885	5.336	0.926	0.933	1.168	0.556		0.624	1.561	1.104	0.908	0.738	1.084
2006q4	1.314	1.265	0.767	4.093	0.752	1.490	1.126	0.584		0.665	1.555	1.214	2.013	1.170	0.828
2007q1	1.271	0.915	0.694	3.429	0.698	2.866	0.980	0.857		0.634	1.633	0.842	1.411	1.414	0.986
2007q2	1.295	1.054	0.610	6.453	0.791	3.329	0.965	0.932		0.943	1.993	1.001	1.195	1.439	0.962
2007q3	1.390	0.982	0.768	7.973	0.988	3.705	0.914	1.279	0.815	0.700	2.672	1.389	1.589	0.991	1.048
2007q4	1.531	1.437	0.779	6.575	0.911	3.524	1.084	1.212	1.003	1.065	2.202	1.348	2.738	1.649	0.995
2008q1	1.507	1.027	0.867	6.252	1.057	3.337	0.811	1.285	1.025	0.806	2.060	1.125	1.720	0.844	1.104
2008q2	1.128	0.976	0.607	5.371	1.096	2.654	0.901	1.145	0.977	0.858	1.715	1.254	1.188	0.958	1.019
2008q3	1.599	1.156	1.374	4.501	1.422	2.548	1.462	1.092	1.210	0.831	1.500	1.220	1.005	1.072	0.964
2008q4	0.762	1.217	0.928	3.545	1.191	2.030	1.911	1.049	1.223	0.802	1.143	0.954	1.095	1.066	1.026
2009q1	2.270	1.241	0.976	1.838	1.144	1.532	1.504	0.842	1.212	1.142	1.397	1.143	1.088	1.123	0.926
2009q2	1.220	1.035	1.011	1.228	1.124	0.935	1.112	0.981	1.207	0.937	1.010	1.063	1.013	1.010	0.919
2009q3	1.155	1.259	0.994	1.153	0.968	0.845	1.109	0.987	1.102	1.075	0.939	0.859	0.889	0.991	0.886
2009q4	1.952	1.267	1.255	1.202	0.889	0.979	1.037	0.931	1.214	1.044	1.049	0.807	1.679	1.001	1.206
2010q1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2010q2	1.324	0.887	1.044	1.427	1.061	1.192	1.167	0.995	1.169	0.832	1.343	1.084	1.291	0.923	1.107
2010q3	1.077	2.083	1.179	1.745	0.976	1.326	1.096	0.963	1.206	1.415	1.521	1.176	1.797	1.210	1.168
2010q4	2.074	1.082	1.179	1.414	0.746	1.086	1.064	0.678	0.871	1.054	1.343	1.463	1.432	0.983	1.015
2011q1	1.271	1.401	1.343		1.061	0.905	1.261	0.589	0.948	1.289	1.086	0.841	1.510	0.959	1.221
2011q2	1.154	1.240	1.121		1.012	0.806	1.170	0.587	0.974	1.273	1.177	0.764	1.311	1.004	1.044
2011q3	1.453	1.230	1.194		0.896	0.648	1.001	0.594	0.994	1.378	1.121	0.945	1.203	1.073	1.126
2011q4	1.120	1.510	1.137		0.796	0.533	0.952	0.507	0.812	1.293	0.882	1.166	1.105	1.028	1.116
2012q1	1.151	0.958	1.013		0.766	0.294	0.802	0.408	0.685	1.077	0.658	0.750	1.207	0.946	0.925
2012q2	0.931	0.724	1.031		0.772	0.289	0.732	0.354	0.739	0.861	0.497	0.545	0.646	0.950	0.911
2012q3	0.784	0.722	0.964		0.687	0.372	0.780	0.322	0.679	1.111	0.507	0.513	0.585	0.955	0.778
2012q4	0.970	0.928	1.174		0.685	0.363	0.623	0.314	0.574	1.283	0.335	0.553	0.502	0.809	0.914
2013q1	0.909	0.551	0.656		0.412	0.232	0.512	0.237	0.390	0.728	0.203	0.345	0.251	0.598	0.558

Notes: The RMI has been estimated in area 01: Ann Arbor, MI; 02: Boulder, CO; 03: Durham, NC; 04: Fairfax, VA; 05: Honolulu, HI; 06: Las Vegas, NV; 07: Medford, OR; 08: Miami, FL; 09: New Orleans; 10: Olympia, WA; 11: San Diego, CA; 12: San Luis Obispo, CA; 13: Santa Barbara, CA; 14: Toledo, OH; and in area 15: Youngtown, OH. The index measures the shift in the (quality adjusted) median TOM relative to the base period (2010q1).