DNB Working Paper

No. 637 / May 2019

Local Constant-Quality Housing Market Liquidity Indices

Dorinth van Dijk

DeNederlandscheBank

EUROSYSTEEM

Local Constant-Quality Housing Market Liquidity Indices

Dorinth van Dijk *

* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

Working Paper No. 637

De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

May 2019

Local Constant-Quality Housing Market Liquidity Indices*

Dorinth Willem van Dijk[a,b]

[a] *De Nederlandsche Bank, Economics & Research Division, The Netherlands*
[b] *MIT Center for Real Estate, Cambridge, MA, USA*

May 2019

Abstract
The average time on market (TOM) of sold properties is frequently used by practitioners and policymakers as a market liquidity indicator. This figure might be misleading as the average TOM only considers properties that have been sold. Furthermore, traded properties are heterogeneous. Since these features differ over the cycle, the average TOM could provide wrong signals about market liquidity. These problems are more severe in markets where properties trade infrequently. In this paper, a methodology is provided that allows for the construction of constant-quality housing market liquidity indices in thin markets that can be estimated up to the end of the sample. The latter is particularly important since market watchers are generally interested in the most recent information regarding market liquidity and less in historical information. Using individual transactions data on three different types of Dutch municipalities (small, medium, and large) it is shown that the average TOM overestimates market liquidity in bad times and underestimates market liquidity in good times. The option to withdraw is the most important reason why the average TOM is misleading. Furthermore, constant-quality liquidity leads the average TOM and price changes. The indices not only show that illiquidity is higher during busts, but also that liquidity risk is higher. Additional results suggest that setting a high list price relative to the estimated value results in a higher TOM, but this effect differs over time. Both the list price premium and the effect on sale probability are higher during busts. Differences in housing quality over the cycle, however, also play a significant role. Finally, the method allows for the construction of indices that are more robust to revisions, especially in thinner markets.

Keywords: Liquidity, Housing, Quality, Index, Thin markets
JEL classifications: R30, C11, C41.

* E-mail addresses: d.w.van.dijk@dnb.nl / dvandijk@mit.edu (Dorinth van Dijk), Acknowledgments: I thank seminar participants at the AREUEA 2017 International conference, the Real Capital Analytics Index Seminar 2017, ReCapNet 2018, and the University of Amsterdam Seminar. In particular thanks to John Clapp, Martijn Dröes, Peter van Els, Jakob de Haan, Larisa Fleishman, Marc Francke, David Geltner, Oliver Lerbs, Alex van de Minne, and Hans van Ophem for insightful comments and feedback. Finally, thanks to the NVM for supplying the data. Views expressed do not necessarily reflect those of De Nederlandsche Bank.

1. Introduction and motivation

Market liquidity is frequently used by researchers, policymakers, and practitioners to assess current market conditions. In research, for example, there is ample evidence that developments of market liquidity foreshadow price developments (De Wit et al., 2013; Carrillo et al., 2015; Van Dijk and Francke, 2018). Policymakers look at market liquidity to identify hot markets (DNB, 2016; Hekwolter of Hekhuis et al., 2017) and brokers use liquidity to assess the market situation (NVM, 2016).

The definition of market liquidity stems from the financial economics literature and refers to the ease at which assets can be traded (Brunnermeier and Pedersen, 2009). Frequently, the average time on market (TOM) of sold houses is used as market liquidity indicator of the probability of sale. The TOM is very much related to market liquidity since a longer TOM is more costly to the holder of the asset. A quicker sale would imply that it is easier to trade the asset, at least from a holders' perspective. There are many examples of TOM analyses in the housing market literature, including Belkin et al. (1976); Haurin (1988), and more recently Genesove and Han (2012) who examine both the seller and buyer TOM. The average (seller) TOM of sold houses, however, might provide a misleading view regarding market liquidity.

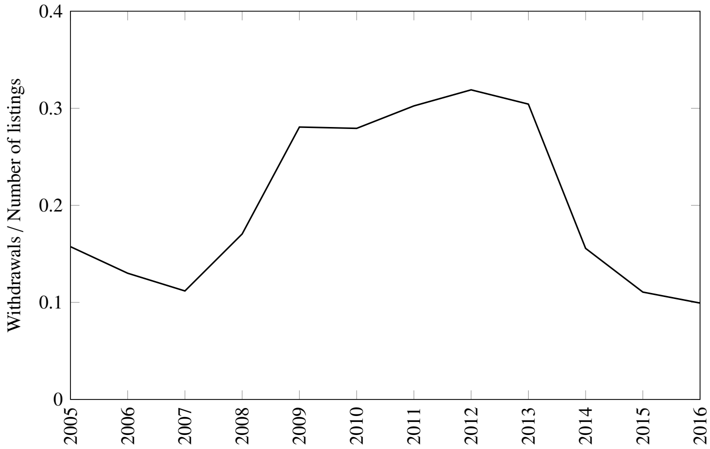
To illustrate, consider two houses with equal listing prices. House (1) is put on the market in January and sold in March, while house (2) enters the market in June and is sold in July. Hence, the TOM for house (1) is 2 months and the TOM for house (2) is 1 month. What can we infer from this? Did market liquidity improve between the sales of the two houses? It might as well be the case that house (1) was a very well-maintained property traded in a homogeneous market, whereas house (2) was a very badly maintained property traded in a heterogeneous market. Furthermore, the listing prices of one of the properties might be set "strategically" to ensure either a higher selling price or lower TOM.

This example is a drastically simplified view of reality and in calculating the mean some of these problems might cancel out. However, some of these problems may still exist when considering multiple properties in determining the market situation, especially in thin markets (markets with few transactions). But perhaps even more importantly, there is a censoring problem as only actually sold listings are included when using the mean TOM of sold properties as measure for the probability of sale. There could be a third house that is withdrawn and is not considered in the mean TOM of sold properties. Disregarding withdrawn properties is problematic, since not all information regarding the ease at which assets can be traded is used. Additionally, the time that a house was listed before it is withdrawn, i.e. the TOM of withdrawn properties, can provide useful information.

If these features differ over the cycle, these problems will be amplified. The number of withdrawals with respect to the number of listings in the Amsterdam region between 2005 and 2016 is presented in Figure 1. Before the bust, starting in 2007, the percentage of houses that are withdrawn was about 10 – 15 %. During the the bust (the through of the Dutch housing market was between 2011 and 2013) the percentage of properties that are withdrawn was much higher, about 30%. In recent years, starting in the second half of 2013, the market started recovering. This was accompanied by a significant decrease in the number of withdrawals. The fact that the probability of withdrawal is not constant over the cycle, has implications for estimating liquidity indices based on the probability of sale. Another feature that might differ over the cycle is quality. This is examined in earlier work by Clapp et al. (2017). These issues, among others, will be discussed in this paper.

Analogous to existing regional constant-quality house price indices, this paper proposes to

Figure 1: Fraction of houses withdrawn over the cycle in the Amsterdam region, 2005-2016.



create regional constant-quality liquidity indices. The method creates a measure for the probability of sale that takes withdrawals and quality differences into account. There are other papers that propose such corrections (Carrillo and Pope, 2012; De Wit and Van der Klaauw, 2013). I propose a method that allows for the construction of regional constant-quality market liquidity indices and add to the literature in three ways. Firstly, the indices can be constructed reliably up to the end of the sample (i.e. until the most recent data comes in). This is quite an important aspect since policymakers and other market watchers are interested in current market liquidity (and not only in the historical situation). Secondly, a novel feature of the method is that it allows to construct indices for markets in which transactions and withdrawals occur infrequently. Previous papers that create constant-quality liquidity indices do not attempt to tackle the data sparsity issue explicitly. By replacing fixed effects with a stochastic trend, it is possible to generate liquidity indices for small markets. This innovation has a positive side effect, namely that the indices become more robust to revisions (i.e. the change of the index in the past due to the addition of new data). Thirdly, the method allows for the examination of calendar time-varying effects of housing characteristics on sale probability. Examining these time-varying effects is interesting, as these could also give an indication about the market situation (besides the indices themselves).[1]

The article closest to the current research is Carrillo and Pope (2012), in which for a large suburb of Washington D.C. annual and quality-adjusted TOM distributions and hazard functions are created and analyzed. This has been subsequently extended by Carrillo (2013) with other heat measures for the housing market. Although the methodology of Carrillo and Pope (2012) theoretically allows for the creation of quarterly or monthly indices at a local scale, it is not possible to create indices at the end of the sample. The main reason is that Carrillo and Pope (2012) look at the *ex ante* distribution of the TOM, hence at the expected market time when the house is listed. Close to the end of the sample, only houses that are sold quickly are included in the sample and this will result in biased index estimates. Therefore, the proposition here is to create an index based on the realized TOM of sold and withdrawn houses, rather than on the

[1]This should not be confused with time-varying effects related to the duration of market time (i.e. duration dependence). This is examined for the Dutch housing market in De Wit and Van der Klaauw (2013).

expected TOM.

The downside is that the presented method is not able to correct for right-censoring (i.e. correct for the number of properties that are still on the market at the end of the sample). In stable times, right-censoring is exogenous and should not bias the indices. In some periods, however, this could result in a loss of information.[2]

Another issue that is tackled in this paper is related to the sparsity of data. Issues regarding data sparsity arise when creating quarterly indices for somewhat larger markets or when creating annual indices for the smallest markets. Another paper close to the current research is that of Carrillo and Williams (2015), who create quarterly "Repeat-Time-On-The-Market" indices for 15 MSAs in the US. The "smallest" region in this paper (Medford, OR) still includes around 707 listings per quarter on average. The smallest market in the current research contains 37 listings per quarter on average. As the repeat listings method discards single sales, this also poses difficulties for estimating the indices for small markets, as there is less information available to estimate the indices.

This paper also looks briefly at the determinants of the TOM (Haurin, 1988), the relationship between liquidity and list prices (Knight, 2002), and the relationship between liquidity and transaction prices (Fisher et al., 2003; Krainer, 2001; Goetzmann and Peng, 2006; Dubé and Legros, 2016; Van Dijk et al., 2018).

The results show that the mean TOM of sold properties overestimates market liquidity in bad times and underestimates market liquidity in good times with respect to the constant-quality indices. Perhaps even more importantly, the mean TOM lags behind the constant-quality indices. This indicates that it is better to use constant-quality market liquidity as leading indicator compared to the mean of the TOM of sold properties. While it is not the main subject of study of this paper, market liquidity is also shown to have a large commonality with transaction prices. When liquidity increases, prices increase as well and vice versa. Consistent with existing literature, changes in market liquidity Granger cause price changes. Furthermore, it is shown that not only illiquidity increases in down markets, but that the uncertainty regarding liquidity, i.e. *liquidity risk* as measured by the standard deviation, increases as well. This notion is consistent with the evidence from other markets such as the bond and stock markets.

The examination of the determinants of the probability of sale suggests that setting a relatively high list price compared to the estimated value results in a higher TOM. However, the effect is not constant over time. Not only is the list price premium higher during busts, but the total effect is also larger. In very hot markets, the average list price premium becomes a list price discount and the effect becomes positive. Most likely, the reason is that sellers change their behavior in this market, a phenomenon documented for the markets that are examined in this study. The most important factor explaining the difference between the average TOM and constant-quality liquidity indices is the possibility to withdraw. Quality differences, however, also play a significant role. Finally, the results show that the magnitude of revisions substantially decreases when replacing fixed effects with a stochastic trend. The added value of the stochastic trend becomes larger as the market becomes thinner.

The remainder of the paper is structured as follows. The next section presents the model and the data discussion. Section 3 presents the indices and a discussion on the commonality with transaction prices and liquidity risk. Section 4 offers additional analyses regarding the

[2]For example, in a crisis the market time of properties still on the market might also increase, and this could also give a useful indication regarding liquidity.

determinants of the TOM, a decomposition analysis, and the robustness with respect to revisions and correlated unobserved heterogeneity. Finally, section 5 concludes.

2. Model and data

When a house is on the market, it can either be sold or withdrawn. The decision to sell or withdraw can therefore be characterized as competing risks. The hazard function is then defined as the probability of a sale or withdrawal, conditional on survival up to that moment. The dependent variable is the time it takes for a house to be sold or withdrawn (TOM). The TOM is modeled in a hazard framework.

Besides conditioning on survival time, it is also desirable to condition on other covariates, in this case housing characteristics. This is usually done in a proportional hazard framework. Part of these covariates are, for example, calendar-time dummy variables that indicate in which period (i.e. annual, quarterly, or monthly dummies) a sale or withdrawal took place. These dummy-variables account for (time) fixed effects.

Intuitively, the coefficient on the dummy variable indicates the shift in the hazard rate. The size of the shift in the hazard rate indicates the magnitude of change in the probability of sale in this period. The dummy coefficients subsequently form an index of how the probability of sale has evolved of time. Note that these coefficients are conditioned on housing characteristics. By modeling the TOM in a competing risks hazard framework, the hazard rate of sale and the dummy coefficients also take withdrawals and the time that the house has already been on the market into account.

2.1. Model

The conditional (on current TOM and property characteristics) probability of sale or withdrawal are given by their respective hazard functions. Let t be the time the house is on the market, the proportional hazards of sales ($j = s$) and withdrawals ($j = w$) are given by:

$$\lambda_j(t_i, \mathbf{x_i}, \mathbf{z_i}, \nu_j) = \lambda_{0,j}(t_i)\exp(\mu_{i,j}), \tag{1}$$

$$\mu_{i,j} = \exp(\mathbf{x_i}\boldsymbol{\beta_j} + \mathbf{z_i}\boldsymbol{\alpha_j} + \nu_j). \tag{2}$$

Here, subscript i for $i = 1, ..., N$ denotes the property and subscript j for $j = s, w$ denote the competing risks, sales and withdrawals. Further, $\lambda_{0,}(t_i)$ are the baseline hazard functions, $\mathbf{x_i}$ is a row vector of size K of observed housing and other characteristics including a constant, and $\boldsymbol{\beta}$ is a vector of corresponding coefficients of size K. Next, $\mathbf{z_i}$ is a $(T-1)$ row vector of calendar time dummy variables in which the house was sold or withdrawn, and $\boldsymbol{\alpha}$ is the corresponding $(T-1)$ coefficient vector. Note that the coefficient vectors of the time dummy variables and covariates are risk-specific. Finally, ν_j denotes the hazard-specific unobserved heterogeneity term that is allowed to be correlated across hazards.

Theoretically, besides a sale or withdrawal, a third option option is possible: The house can still be on the market at the end of the sample (i.e. right-censoring). Practically, however, it is not feasible to include these observations as right-censored observations (see the discussion at the end of this section). For now, however, assume that right-censoring is also a possibility. In this case, the likelihood contribution of the competing risk model consists of three types (Jenkins, 2005):

$$\mathcal{L}_s = f_s S_w : \text{exit the market through a sale,}$$
$$\mathcal{L}_w = f_w S_s : \text{exit the market through a withdrawal,}$$
$$\mathcal{L}_c = S_s S_w : \text{still on the market at the end of the sample,}$$

where f and S are the density and survivor functions, respectively. Next, let δ be a variable that indicates whether the observed property is sold ($\delta_s = 1$), withdrawn ($\delta_w = 1$) or right-censored ($\delta_s = \delta_w = 0$). The individual likelihood contribution can in this case be written as:

$$\mathcal{L} = (\mathcal{L}_s)^{\delta_s}(\mathcal{L}_w)^{\delta_w}(\mathcal{L}_c)^{1-\delta_s-\delta_w}, \tag{3}$$

which can be written as (see Jenkins, 2005):

$$\begin{aligned} \ln \mathcal{L} = \ell &= [\delta_s \ln \lambda_s + \ln S_s] + [\delta_w \ln \lambda_w + \ln S_w], && (4)\\ &= \ell_A + \ell_B. && (5) \end{aligned}$$

Assuming that the correlation between the unobserved heterogeneity of the two competing risks is zero (i.e. $Cov(\nu_s, \nu_w) = 0$), the likelihood factorizes into two parts (A and B) and can be maximized separately. This is done by maximizing the partial likelihood of each competing risk and treating the other risk as censored (Cameron and Trivedi, 2005). Note that part A only depends on parameters from the sale hazard rate and survivor function and part B only on parameters from the withdrawal functions. Assuming the relatively flexible (2-parameter) Weibull distribution as baseline hazard function with shape parameters $\rho_j \in (0, \infty)$, scale parameters $\mu_j \in (0, \infty)$, the log of the hazard function is given by:

$$\ln[\lambda_j(t_i, \mathbf{x_i}, \mathbf{z_i}, \nu_j)] = \ln[\mu_{i,j}\rho_j t_i^{\rho_j - 1}]. \tag{6}$$

The log of the survivor function is given by:

$$\ln[S_j(t_i, \mathbf{x_i}, \mathbf{z_i}, \nu_j)] = \ln[\exp(-\mu_{i,j} t^{\rho_j})] = -\mu_{i,j} t_i^{\rho_j}. \tag{7}$$

The loglikelihood is given by:

$$\begin{aligned} \ell(t_i, \mathbf{x_i}, \mathbf{z_i}, \nu_s, \nu_w) &= \sum_i^N \left\{\delta_s \ln(\mu_{i,s}\rho_s t_i^{\rho_s - 1}) + \ln(-\mu_{i,s} t_i^{\rho_s})\right\} \\ &+ \sum_i^N \left\{\delta_w \ln(\mu_{i,w}\rho_w t_i^{\rho_w - 1}) + \ln(-\mu_{i,w} t_i^{\rho_w})\right\} \\ &= \ell_A + \ell_B. \end{aligned} \tag{8}$$

In the case of uncorrelated unobserved heterogeneity, the heterogeneity gets absorbed in the risk-specific constants, which are included in $\beta_{\mathbf{s}}$ and $\beta_{\mathbf{w}}$ (part of $\mu_{i,s}$ and $\mu_{i,w}$). The assumption of no correlated unobserved heterogeneity is made since the focus in the present study is on smaller markets and the problem of correlated unobserved heterogeneity is expected not to play a major role. Also, with correlated unobserved heterogeneity, convergence is much more difficult to achieve and the estimation takes substantially longer. Section 4.6 includes a robustness check and provides indices corrected for correlated unobserved heterogeneity. The unobserved heterogeneity is assumed to be normally distributed.

Note that even though ℓ_A and ℓ_B are maximized separately, the sale (withdraw) likelihood does take withdrawals (sales) into account. For example, when withdrawals would not be taken into account in ℓ_A, the last part of the likelihood, $\ln(-\mu_{i,s}t_i^{\rho_s})$ would be different as this does not only depend on observations where $\delta_s = 1$. This impacts the estimated coefficients which are included in $\mu_{i,s}$.

In order for the methodology to work in thin markets, the calendar time-fixed effects are replaced by a stochastic structure. More specifically, these are modeled as a random walk. The latter is similar to real estate price applications in Francke and De Vos (2000), Francke (2010), and Geltner et al. (2017) who allow for a local linear trend, which also includes the random walk specification. The random walk specification is given by:

$$\alpha_{\tau,j} = \alpha_{\tau-1,j} + \varepsilon_{\tau,j}, \tag{9}$$

where $\varepsilon_{\tau,j} \sim N(0, \sigma^2_{\varepsilon,j})$ for $\tau = 1, ..., T$ for $j = s, w$, and with $\alpha_1 = 0$. Note that t represents the duration to sale/withdraw and τ represents the calendar time period. At this point, it might be useful to point out that when the random walk structure on $\boldsymbol{\alpha}$ is left out (equivalent to setting $\sigma^2_{\varepsilon,j}$ to a very large number), the model is a regular survival model with calendar time fixed effects.

The coefficients that need to be estimated in this procedure are $\boldsymbol{\alpha_j}$ (calendar time effects), $\boldsymbol{\beta_j}$ (coefficients on property characteristics), ρ_j (shape parameters), and $\sigma_{\varepsilon,j}$ (signals of α_j).

Taking into account withdrawals partly corrects for a censoring problem that occurs. However, right-censored observations (houses that are still for sale at the end of the sample period) are removed in the current setup. The reason is that the period in which the sale of withdrawal will take place is not known yet. An alternative would be to include dummy variables for the period the house has been listed (a setup more similar to Carrillo and Pope, 2012). This, however, causes a downward bias in the coefficients on the dummy variables of the final time periods. The reason is that only houses that are sold or withdrawn quickly are included in the sample which drives the estimated TOM for that period down (see Appendix A). Another alternative is to follow De Wit and Van der Klaauw (2013) and assume that the time of exit is equal to the time the house was at the market at the end of the sample. The downside of this alternative is that the "observed" TOMs of these observations will be artificially low, so that this will result in an upward bias in the calendar-time effects of sold properties at the end of the sample.[3]

If the problem at hand is to merely control for these fixed effects, this will not pose an issue. However, in the present study, the interest is on the estimated values of these coefficients ($\alpha_{t,s}$) as these form the liquidity index. The downside, however, is that some information is disregarded. For example, in periods of crisis, an increasing number of houses that remain on the market also might give a useful indication regarding the market situation. In stable markets, however, right-censoring should be largely exogenous and therefore should not play a large role.

[3]The average TOM of the withdrawn observations will be lower at the end of the sample, resulting in a higher index value of sold observations.

2.2. Estimation

In order to estimate the model, the parametric Bayesian Proportional Hazard Model of Dellaportas and Smith (1993) is extended with a stochastic calendar time trend.[4] In the estimation procedure uninformative priors are used: $\beta_j \sim$ N(0, 10), $\rho_j \sim$ Log-Normal(0, 1), and $\sigma_{\varepsilon,j} \sim$ Inverse Gamma (3, 1).

Markov Chain Monte Carlo (MCMC) techniques are used to evaluate the posterior density. More specifically, the RStan package is employed that uses the No-U-Turn-Sampler (NUTS) (Hoffman and Gelman, 2014; Carpenter et al., 2016).[5] To determine the mixing and convergence of the models the $\hat{R}$ and Neff statistics are used (Francke et al., 2017). Additionally, the Monte Carlo error, the Heidelberger-Welch stationarity and half-width statistics are examined. To compare the model fit, the Watanabe Akaike information criterion (WAIC; Watanabe 2010) and leave-one-out cross-validation statistic (LOO; Vehtari et al. 2017) are considered.

The variables are non-centered reparameterized for estimation purposes (i.e. Matts' trick; Betancourt and Girolami, 2015). This implies that instead of sampling α_j directly, the innovations in α_j are sampled with the prior N(0, 1), these innovations are then multiplied with $\sigma_{\varepsilon,j}$ to obtain α_j. This drastically improves the computational time and convergence is more easily achieved. The estimation time depends on the number of observations. On a modern computer with 4 cores and 32 GB RAM-memory, the estimation time (without correlated unobserved heterogeneity) ranges from 2 hours (small market, 2,175 observations) to 24 hours (large market, 113,005 observations).

2.3. Data

The main source of data originates from the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM). The data contain a large share of housing transactions within the Netherlands from 2005–2016 including many property characteristics. However, not all houses transacted or withdrawn are included in this database. Earlier articles that use the NVM database report a market share of around 75%, (De Wit et al., 2013; Van Dijk and Francke, 2018).

The focus in this paper is on three different types of markets: small, medium and large markets. The small market is *Aalsmeer*, representing a situation in which the problem of data sparsity is large. The medium market is *Amstelveen*, in which there might be data sparsity problems during some periods (e.g. in busts). The large market is *Amsterdam*, in which there are no data sparsity problems. Although these markets are relatively close in terms of geographical distance, they can be characterized as different markets. Amsterdam is the largest city in the Netherlands. Amstelveen is a medium-sized suburban municipality at the southern border of Amsterdam, whereas Aalsmeer is a small suburban municipality at the southern border of Amsterdam. Table 1 includes descriptive statistics of the markets. The small market contains, on

[4] Although there are non-parametric methods to estimate the hazard function corrected for covariates, it is not clear how to apply a random walk structure on the coefficients in this case. Moreover, the thinness of the market poses additional difficulties to estimate the model non-parametrically. Therefore, in this paper parametric methods are applied. Carrillo and Pope (2012) have looked at the *ex ante* distribution of the sale probability, conditional on housing characteristics, in a non-parametric fashion. The analogy in this case would be to include calendar-time dummies that indicate in which period the house was listed. A more detailed empirical comparison between the presented methodology and the methodology by Carrillo and Pope (2012) is offered in Appendix A.

[5] Four parallel chains with different initial values and 2,000 (including 1000 warm-up) iterations per chain are used. Therefore, the maximum effective sample size is 4,000. In the small market, convergence was more difficult to achieve, therefore the total number of samples per chain is set to 5,000 (including 2,500 warm-up). The chains are not thinned.

average per quarter, around 37 sales, the medium market around 187 sales, and the large market around 1,883 sales. The small market contains approximately 13,000 houses in 2016, of which around 8,100 (62%) are owner-occupied. The medium market contains 43,000 houses, of which 19,500 (45%) are owner-occupied. Finally, the large market contains 425,000 houses of which 126,000 (30%) are owner-occupied (Statistics Netherlands, 2017).

The data base includes the date the house was put on the market and the date the house was sold or withdrawn, hence it is possible to infer the TOM. Some houses are withdrawn and almost immediately relisted. These observations can cause a bias in the indices as the TOM seems shorter than the true one. Therefore, if a house is relisted within 90 days, the original date of when the house was put on the market is used to calculate the TOM. When a house is still on the market at the end of the sample, the property is removed. As mentioned before, this throws away some information and could give some problems at the end of the sample. For example, in the beginning of the bust the amount of not yet sold or withdrawn properties might increase. However, at the end of the sample there are only 16 (small market), 57 (medium market) and 534 (large market) properties not yet sold or withdrawn in the three markets. This is less than 1% of the total sample size in each market and therefore should not pose a big problem.

The property characteristics for which the liquidity indices are controlled for are log size, squared log size, dummies for gardens, parking places, landleases, maintenance (bad, normal and well-maintained), construction period (before 1905, 1906-1944, 1945-1990, 1991-2000, after 2001), and property type (terraced, back-to-back, corner, semi-detached, detached, ground floor split level apartment, upper floor split level, other apartment).[6]

Besides these property characteristics, the list price premium is expected to influence the TOM. Following Genesove and Mayer (2001), Bokhari and Geltner (2011), and Clapp et al. (2017), the list price premium is defined as the difference between the list price and the estimated market value of the property at the time of entry.[7] The estimated value at the time of entry is determined by a hedonic price model, which is included in Appendix B. In case a house is relisted and the list price has been revised, the first known list price is used.[8]

The average percentage of houses that are withdrawn from the market is fairly similar in the three markets, around 18%. Over time, however, there are substantial differences in the fraction of houses withdrawn, ranging from 32% in 2012 to 10% in 2016. The average TOM of both sold and withdrawn houses is shorter in larger markets. This also holds for the standard deviation. Interestingly, the standard deviation is also lower when the TOM is shorter for both sold and withdrawn properties. This indicates that the observed TOMs are more dispersed and possibly less informative in times of crisis.

Finally, the liquidity indices will be compared to transaction price indices. The transaction price indices are constructed by estimating a Hierarchical Trend Model (Francke and De Vos, 2000; Francke and Vos, 2004). This method allows to construct price indices in thin markets. Appendix C includes a more elaborate discussion on the price index estimation procedure.

[6] Some properties are freehold whereas others and leasehold, this is corrected for by including a dummy-variable in case the property is leasehold.

[7] Clapp et al. (2017) actually use the residual of list price on estimated transaction value, controlling for anchoring. However, this requires a repeat sales framework, which is problematic in the context of thin markets. Furthermore, the residual would get rid of cyclical variation in the list price premium, which is also a topic of interest in the case of this study.

[8] List price reductions might also influence the TOM. See, for example, Merlo and Ortalo-Magne (2004); De Wit and Van der Klaauw (2013). This issue is outside the scope of this paper and will not be pursued here.

Table 1: Description of the three markets between 2005 and 2016.

Year	N	S	W	$\overline{TOM}$ S	SD TOM S	$\overline{TOM}$ W	SD TOM W
2005	9624	8109	1515	120.9	130.1	213.7	200.6
2006	10143	8824	1319	99.1	117.9	197.2	187.2
2007	10234	9090	1144	78.5	101.6	161.2	173.3
2008	10287	8533	1754	76.0	94.4	138.6	147.4
2009	10425	7499	2926	112.9	113.3	185.3	144.4
2010	10311	7431	2880	141.4	155.8	248.0	200.7
2011	9929	6926	3003	144.3	157.9	271.6	219.6
2012	10041	6838	3203	171.4	174.9	304.8	228.4
2013	9589	6671	2918	189.7	211.5	368.8	264.6
2014	11532	9737	1795	158.1	219.5	349.9	295.6
2015	12358	10991	1367	96.2	159.0	262.0	282.2
2016	11610	10457	1153	58.6	103.3	169.7	222.5
Market	N	S	W	$\overline{TOM}$ S	SD TOM S	$\overline{TOM}$ W	SD TOM W
Small	2175	1758	417	201.7	208.2	331.4	257.6
Medium	10903	8961	1942	144.1	175.0	292.1	245.9
Large	113005	90387	22618	111.9	149.7	248.1	227.5

Notes: N(Number of observations)=S(Sold)+W(Withdrawn), $\overline{TOM}$ = mean TOM, SD = Standard Deviation.

3. Market liquidity and risk

3.1. Liquidity indices

Three different quarterly liquidity indices are presented for these markets between 2005 and 2016: (i) an index based on the mean TOM of sold properties, (ii) a constant-quality index that does not contain the random walk structure (i.e. a regular parametric survival model), and (iii) a constant-quality index that contains the random walk structure. The indices for the three markets are shown in Figure 2. Notice that a higher index indicates a higher TOM/lower probability of sale and thus a more illiquid market.

First of all, note the large differences between the indices based on the mean of sold properties and the two constant-quality indices. Generally, in times when the TOM is increasing, the constant-quality indices are above the mean indices. This indicates that the mean of sold properties underestimates market illiquidity during crises. Conversely, when market liquidity is increasing, the constant-quality indices are below the mean of sold properties. In other words, not only does it take longer for houses to be sold, the quality of the houses that are sold is different and/or the withdrawal probability is different. This shows the importance to correct for property characteristics and withdrawals.

Moreover, the mean TOM indices lag behind the constant-quality indices. The start of the bust is visible earlier in the constant-quality indices than in the mean TOM of sold properties. Furthermore, the recovery is earlier visible. This phenomenon is most clear in the medium and large market, but it also holds for the small market. More formally, a Granger causality analysis shows that the constant-quality random walk index Granger causes the mean TOM of sold properties at the 1% level.[9] This suggests that the leading indicator role that the TOM generally has for policymakers and brokers may even be stronger if the TOM is corrected for quality and withdrawals.

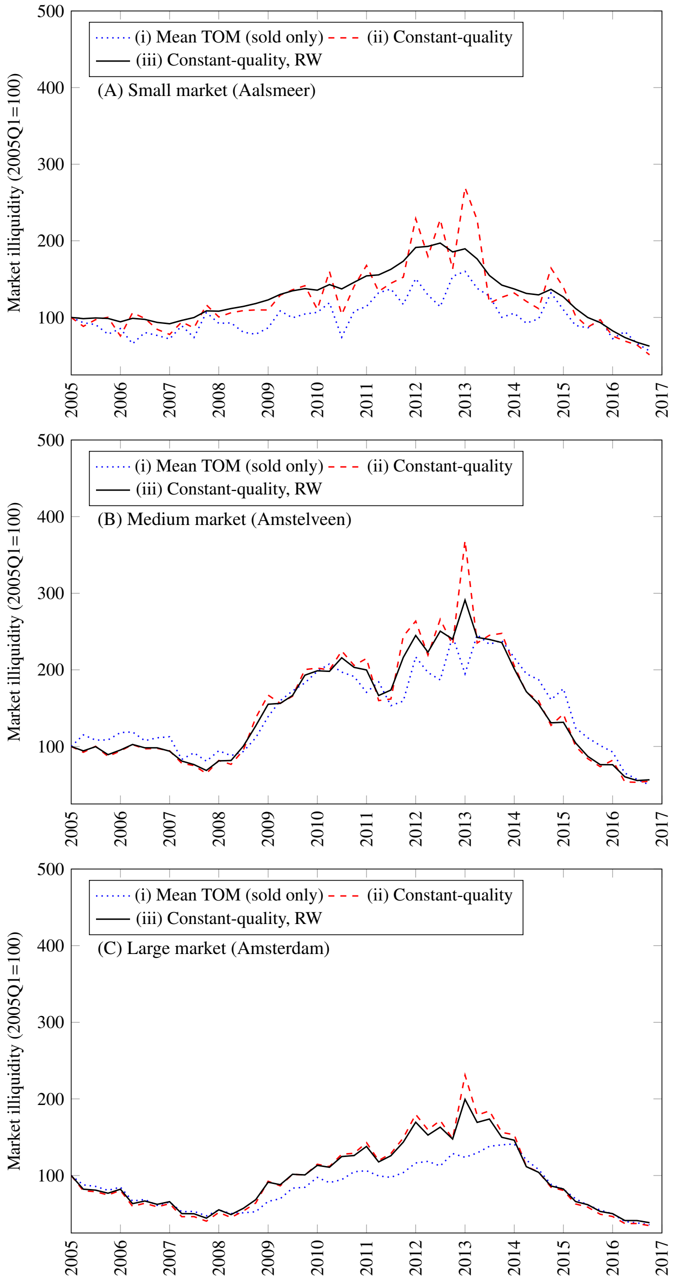
There are differences between the index without and with random walk structure. Especially in the small market, the random walk index contains significantly less noise. Comparing between the different markets, the results suggest that the difference between the indices becomes smaller as the markets become larger. Also, when the data contain less noise and are more informative about market liquidity (i.e. during calm times and in larger markets) the presented methodology offers similar results to more conventional methods. However, when there is more noise and the data are less informative (i.e. during crises and in smaller markets), the differences are much smaller. However, when there is more noise and the data are less informative (i.e. during crises and in smaller markets), the random walk structure adds substantial value.

Note that since the indices are indexed at 100 in the first time period, this makes it difficult to compare between the municipalities. By indexing the indices at the unconditional mean (i.e. the average TOM of sold properties over the whole sample, see Table 1) in the first time period, the comparison becomes easier. In every quarter, liquidity was highest in the large market, and, for most of the time, liquidity was lowest in the small market. In all markets, there is an upward trend in the TOM during the bust, starting in 2008 and lasting until 2013 (Figure 3). The Dutch housing market started recovering in late 2013, resulting in a higher sale probability and lower TOM. At the end of the sample, market liquidity surpassed pre-crisis levels. The decrease in the sale probability during the crisis (2007Q4–2013Q1) was the largest in the large market: the

[9]The Granger causality analysis is based on a Panel VAR with 2 lags, but the results are robust for lag lengths of 1 to 4 quarters. The Panel VAR is estimated by OLS with heteroscedastic robust standard errors. As the time-dimension is sufficiently large (48 quarters), the Nickel bias is expected to be negligible and a GMM approach is not necessary.

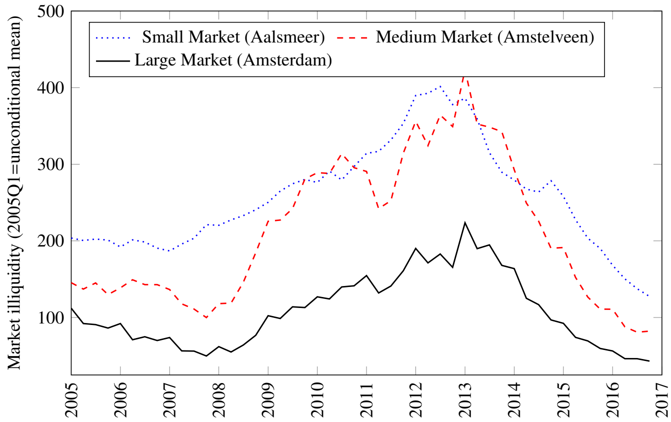
sale probability was roughly 5 times smaller 2013Q1 than in 2007Q4. The recovery (2013Q1–2016Q4), however, was also strongest: the sale probability was more than 6 times larger in 2016Q4 than in 2013Q1.

Figure 2: Two constant-quality illiquidity indices and an index of the mean TOM of sold properties, 2005-2016.



Note: a higher index indicates a higher TOM/lower probability of sale and a more illiquid market.

Figure 3: Comparison of market illiquidity (random walk indices) between the three markets, 2005-2016.



3.2. Commonality with transaction prices

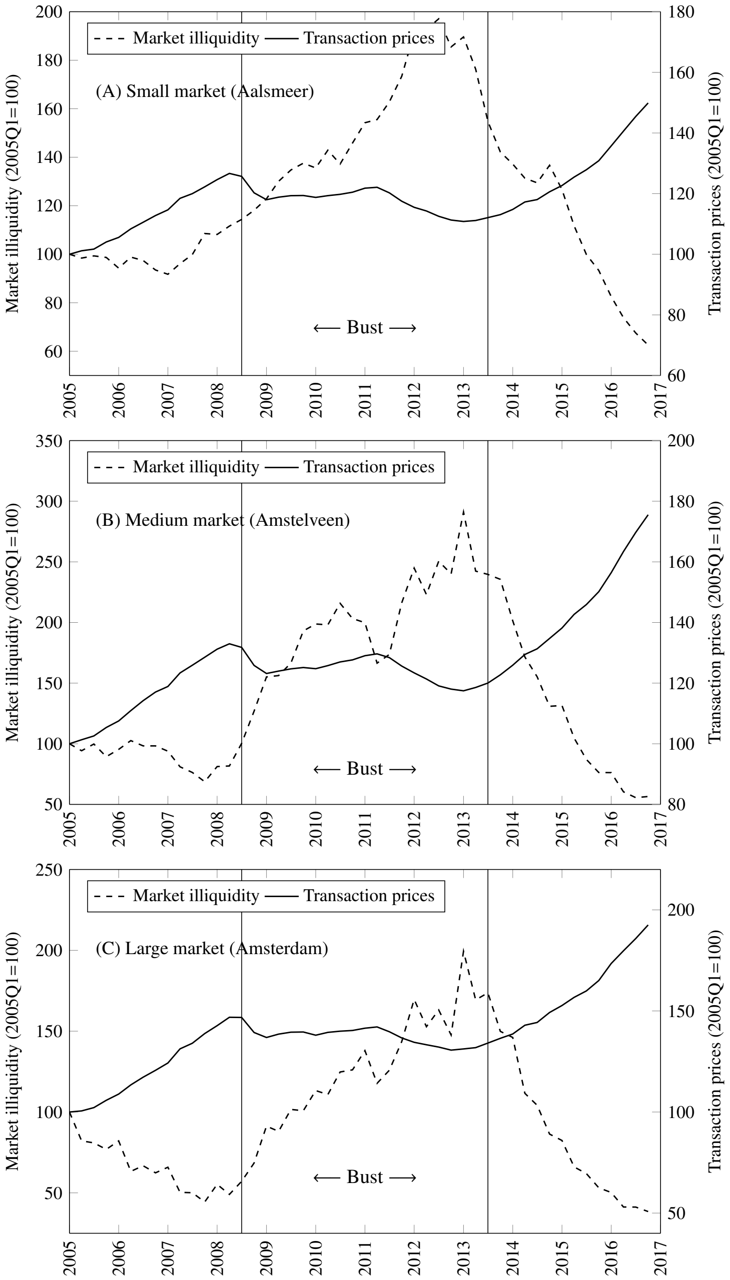
The link between transaction prices and market liquidity is omnipresent in the literature. For example, Fisher et al. (2003, 2007) provide a methodology for controlling for varying liquidity in price indices and it is generally accepted that market liquidity leads transaction price changes (De Wit et al., 2013; Carrillo et al., 2015; Van Dijk and Francke, 2018). Whereas it is outside the scope of this paper to create constant-liquidity price indices, this section explores the commonality of liquidity and transaction prices (see Van Dijk et al., 2018, for a method to create constant-liquidity price indices). First, quarterly constant-quality transaction price indices for the three markets are estimated using a Hierarchical Trend Model (Francke and De Vos, 2000; Francke and Vos, 2004). These price indices are also constant-quality and are controlled for by the same property characteristics as the liquidity indices. A more detailed discussion on the transaction price index estimation is included in Appendix C.

Figure 4 presents the estimated transaction price and liquidity indices for the three markets. Note the similarity between the development of transaction prices and liquidity. As expected, illiquidity is higher when prices are low. The contemporaneous correlation between the level of illiquidity and prices is -0.41. The contemporaneous correlation between the first differences is -0.55. Furthermore, developments in liquidity foreshadow price developments. The turning point from boom to bust is around 3 quarters earlier in the liquidity indices compared to the price indices.[10] Moreover, a Granger causality analysis shows that changes in market liquidity Granger cause changes in prices at the 5% level.[11]

[10]The turning point from boom to bust is defined as the first quarter with negative price growth in all three municipalities (2008Q3) and the turning point from bust to boom is defined as the first quarter with positive price growth the three municipalities (2013Q2).

[11]The Granger causality analysis is based on a Panel VAR with 3 lags, but the results are robust for lag lengths 2 to 4 quarters. The Panel VAR is estimated by OLS with heteroscedastic robust standard errors. As the time-dimension is sufficiently large (48 quarters), the Nickel bias is expected to be negligible and a GMM approach is not necessary.

Figure 4: Illiquidity (constant-quality and random walk, left axis) and transaction price (right axis) indices, 2005-2017.

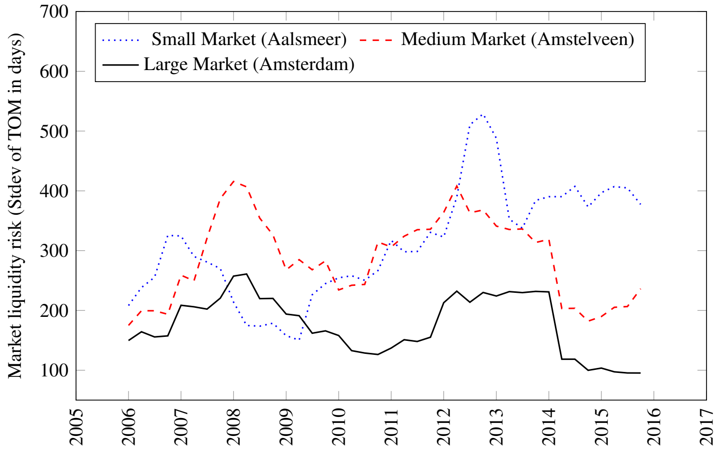


Note: a higher index indicates a higher TOM/lower probability of sale and a more illiquid market.

3.3. Liquidity risk

Another salient feature of the indices is that there is more variability in market liquidity in times of crisis. This is also visible in the summary statistics as the standard deviation of the TOM of all properties is higher during the bust (Table 1). Figure 5 shows indices based on the 9-quarters centered (-4 and +4 quarters) rolling standard deviations of the returns of the constant-quality random walk indices. These are indexed at the unconditional standard deviation of the TOM of sold properties over the whole sample (Table 1). The figure indicates that the standard deviation of the liquidity indices becomes higher in times of crisis as markets become thinner. In the small market, the increase in risk is visible somewhat earlier than in the other two markets and seems to recover somewhat more slowly after the crisis. The main picture, however, is that liquidty risk increases up to the through of 2013Q1 in all three markets. In other words, not only illiquidity is higher in bad times, but *liquidity risk* is also higher. These findings are consistent with the general asset pricing literature in which it is well documented that illiquid stocks and bonds also entail more liquidity risk (Acharya and Pedersen, 2005; Acharya et al., 2013).

Figure 5: Comparison of market illiquidity risk between the three markets, 2005-2016.



Note: illiquidity risk indices are based on 9-quarters centered rolling window standard deviation of growth rates of the random walk indices.

4. Determinants, decomposition, and robustness

This section looks at the (time-varying) determinants of the TOM. The effect on the indices of withdrawals and quality is disentangled to examine which is most important. Finally, the magnitude of revisions is examined. To what extent do the indices change when new data comes in? And are there differences in revisions between models that correct for quality and/or withdrawals and models that do not correct for these? Finally, some robustness checks are performed with respect to correlated unobserved heterogeneity between withdrawals and sales.

4.1. Determinants of the time on market

The estimated coefficients for the control variables β_s and shape parameter ρ_s are presented in Table 2. The coefficient estimates are almost equivalent across the estimations (with and without random walk). There is a substantial decrease in the WAIC and LOO statistics of the random walk models in the small and medium market, which indicates that the fit of the random walk models is better than that of the models without the random walk structure. In the large market, the index without the structure has a slightly better fit, but the difference is very small. Note that the coefficients contain the effects on the sale probability, so a positive (negative) coefficient indicates a positive (negative) effect on sale probability and market liquidity, and a negative (positive) effect on the TOM. There are substantial differences in the estimates across markets. It is difficult to attach a causal interpretation to the coefficients. Also, the credible intervals are quite large, especially in the smaller markets. For example, in the small market almost all credible intervals for the coefficients include 0. This, however, does not imply that controlling quality is not important for index construction (see later in section 4.3). In other words, even though that the individual effects are insignificant in the classical econometric sense, the joint effect is important for index construction.

Some general patterns on the effect of individual characteristics, consistent with the literature, seem to arise. For example, apartments, which are usually more homogeneous than other house types, sell quicker in the medium and large market. Therefore, this notion is consistent with the finding that the TOM of homogeneous houses is generally shorter than that of heterogeneous house types that are more atypical (Haurin, 1988).[12]

A higher list price premium (i.e. the list price is relatively high compared to the estimated market value at the time of listing), results in a lower probability of sale, hence a higher TOM. The effect of list price premia will be discussed in more detail in section 4.4.

The estimates of the shape parameter ρ are very similar across the models. For the small market, the estimate is not significantly different from 1, indicating that the TOM follows a (negative) exponential distribution in this market. In the medium and large markets, the estimated shape parameters are 0.96 and 0.90, respectively. This indicates that the probability of sale decreases as the property remains longer on the market. This finding is consistent with the results of from De Wit and Van der Klaauw (2013).

The model statistics indicate that the mixing went satisfactorily, the MCMC-error is close to 0 and the the $\hat{R}$ (not to be confused with the R^2) is close to 1. The effective sample size relative to the number of total samples (4000 in the medium and large market) is close to 1 in the two largest markets. It is smaller for the small market, but by setting a larger sample size (of 10,000) the remaining number of samples is large enough to produce reliable results. Both Heidelberger tests are passed in almost all cases, the value in Table 2 indicates the mean of all tests on all parameters and every tests gets the value 1 if the test is passed.

[12] Although atypicality is not explicitly controlled for, controlling for the separate characteristics per submarket has a similar effect.

Table 2: Estimates of the control variables for three different markets in two different models.

Variable	β_{cq}	$p_{2.5,cq}$	$p_{97.5,cq}$	β_{rwcq}	$p_{2.5,rwcq}$	$p_{97.5,rwcq}$
			Small Market			
Constant	0.755	-9.262	10.364	0.727	-9.898	10.430
Bad Maint.	(Omitted)			(Omitted)		
Normal Maint.	-0.359	-0.545	-0.168	-0.358	-0.544	-0.166
Good Maint.	-0.420	-0.661	-0.185	-0.419	-0.644	-0.171
< 1905	(Omitted)			(Omitted)		
1906 – 1944	-0.442	-1.096	0.228	-0.448	-1.102	0.284
1945 – 1990	-0.550	-1.201	0.117	-0.555	-1.186	0.150
1991 – 2000	-0.669	-1.340	-0.004	-0.678	-1.333	0.025
> 2001	-0.665	-1.304	0.019	-0.652	-1.341	0.016
HT Terraced	(Omitted)			(Omitted)		
HT Back-to-Back	-0.457	-0.844	-0.079	-0.450	-0.838	-0.082
HT Corner	0.064	-0.070	0.202	0.062	-0.073	0.201
HT Semi-Detached	-0.184	-0.356	-0.019	-0.191	-0.362	-0.030
HT Detached	-0.387	-0.605	-0.178	-0.401	-0.608	-0.187
AT Split-Level (Ground or multiple)	0.000	-0.283	0.297	0.015	-0.265	0.305
AT Split-Level (Upper floor)	-0.180	-0.472	0.113	-0.191	-0.469	0.093
AT Other	-0.049	-0.303	0.191	-0.039	-0.274	0.207
$\log(size)$	-1.144	-4.579	2.151	-1.061	-4.353	2.624
$\log(\text{size})^2$	0.040	-0.237	0.341	0.030	-0.279	0.317

Estimates of the control variables for three different markets in two different models (continued)

Variable	β_{cq}	$p_{2.5,cq}$	$p_{97.5,cq}$	β_{rwcq}	$p_{2.5,rwcq}$	$p_{97.5,rwcq}$
Garden	0.205	0.006	0.415	0.218	0.021	0.406
Parking	-0.103	-0.223	0.016	-0.094	-0.211	0.020
Landlease	0.857	-0.137	1.837	0.982	0.000	1.927
List Price Premium	-1.875	-2.217	-1.534	-1.850	-2.195	-1.523
ρ	1.001	0.963	1.036	1.005	0.968	1.041
Loglike	-11446.8			-11440.8		
MCMC-error	0.0027			0.0020		
Neff	3310.2			4094.2		
Heid. stationarity	1.0000			1.0000		
Heid. Halfwidth	0.9886			0.9864		
LOO	22952.8			22920.1		
WAIC	22952.2			22919.8		
$\hat{R}$	1.0008			1.0005		
Medium Market						
Constant	-11.601	-13.237	-10.076	-11.310	-12.929	-9.904
Bad Maint.	(Omitted)			(Omitted)		
Normal Maint.	-0.352	-0.414	-0.289	-0.352	-0.413	-0.291
Good Maint.	-0.352	-0.434	-0.273	-0.355	-0.440	-0.276
< 1905	(Omitted)			(Omitted)		
1906 – 1944	0.404	-0.022	0.817	0.384	-0.036	0.828
1945 – 1990	0.370	-0.052	0.790	0.348	-0.073	0.793
1991 – 2000	-0.081	-0.497	0.351	-0.102	-0.508	0.364
> 2001	-0.152	-0.580	0.300	-0.174	-0.609	0.279
HT Terraced	(Omitted)			(Omitted)		
HT Back-to-Back	-0.739	-0.942	-0.542	-0.741	-0.943	-0.544
HT Corner	-0.025	-0.091	0.045	-0.026	-0.096	0.036
HT Semi-Detached	-0.565	-0.680	-0.453	-0.560	-0.682	-0.450
HT Detached	-1.016	-1.183	-0.829	-1.006	-1.180	-0.828
AT Split-Level (Ground or multiple)	0.137	-0.003	0.282	0.126	-0.016	0.268
AT Split-Level (Upper floor)	0.134	-0.017	0.283	0.126	-0.014	0.279
AT Other	0.222	0.080	0.360	0.217	0.075	0.351
log(*size*)	1.811	1.387	2.277	1.779	1.366	2.216
$\log(\text{size})^2$	-0.108	-0.141	-0.077	-0.106	-0.138	-0.076
Garden	0.112	-0.015	0.233	0.111	-0.010	0.238
Parking	-0.273	-0.332	-0.210	-0.270	-0.330	-0.210
Landlease	1.397	0.813	2.074	1.377	0.729	1.962
List Price Premium	-1.793	-1.915	-1.656	-1.785	-1.911	-1.650

Estimates of the control variables for three different markets in two different models (continued)

Variable	β_{cq}	$p_{2.5,cq}$	$p_{97.5,cq}$	β_{rwcq}	$p_{2.5,rwcq}$	$p_{97.5,rwcq}$
ρ	0.960	0.944	0.975	0.960	0.945	0.975
Loglike	-54903.0			-54902.2		
MCMC-error	0.0012			0.0010		
Neff	3829.4			3956.4		
Heid. stationarity	1.0000			1.0000		
Heid. Halfwidth	0.9999			0.9985		
LOO	109891.0			109875.3		
WAIC	109890.3			109874.4		
$\hat{R}$	1.0001			0.9999		
Large Market						
Constant	-1.953	-2.167	-1.744	-1.971	-2.193	-1.750
Bad Maint.	(Omitted)			(Omitted)		
Normal Maint.	-0.302	-0.326	-0.278	-0.302	-0.325	-0.278
Good Maint.	-0.284	-0.311	-0.258	-0.284	-0.310	-0.258
< 1905	(Omitted)			(Omitted)		
1906 – 1944	0.102	0.083	0.122	0.102	0.082	0.123
1945 – 1990	-0.163	-0.187	-0.141	-0.163	-0.186	-0.137
1991 – 2000	-0.213	-0.242	-0.185	-0.212	-0.242	-0.183
> 2001	-0.320	-0.355	-0.288	-0.320	-0.355	-0.285
HT Terraced	(Omitted)			(Omitted)		
HT Back-to-Back	-0.105	-0.241	0.038	-0.106	-0.242	0.025
HT Corner	-0.038	-0.091	0.013	-0.040	-0.090	0.012
HT Semi-Detached	-0.117	-0.206	-0.030	-0.118	-0.203	-0.030
HT Detached	-0.382	-0.473	-0.293	-0.383	-0.477	-0.292
AT Split-Level (Ground or multiple)	0.154	0.124	0.185	0.154	0.124	0.186
AT Split-Level (Upper floor)	0.199	0.167	0.232	0.198	0.165	0.232
AT Other	0.138	0.101	0.171	0.137	0.102	0.172
log(*size*)	-0.656	-0.714	-0.595	-0.656	-0.719	-0.596
log(size)^2	0.035	0.031	0.040	0.035	0.031	0.040
Garden	0.126	0.102	0.148	0.126	0.104	0.151
Parking	-0.277	-0.303	-0.251	-0.277	-0.301	-0.252
Landlease	0.100	0.084	0.115	0.100	0.084	0.115
List Price Premium	-1.571	-1.611	-1.531	-1.571	-1.610	-1.532
ρ	0.901	0.897	0.906	0.901	0.897	0.906
Loglike	-537074.8			-537074.8		
MCMC-error	0.0003			0.0003		
Neff	3899.0			3980.7		

Estimates of the control variables for three different markets in two different models (continued)

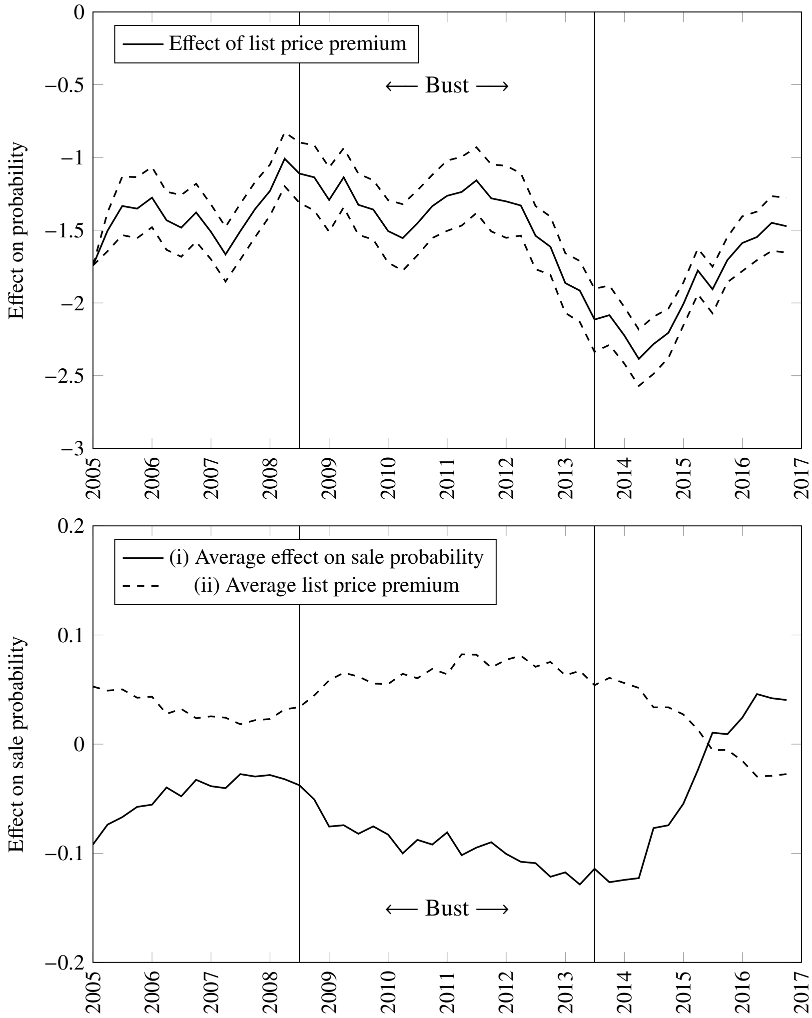
Variable	β_{cq}	$p_{2.5,cq}$	$p_{97.5,cq}$	β_{rwcq}	$p_{2.5,rwcq}$	$p_{97.5,rwcq}$
Heid. stationarity	0.9989			0.9934		
Heid. Halfwidth	1.0000			1.0000		
LOO	1074227.8			1074237.5		
WAIC	107228.4			1074238.0		
$\hat{R}$	0.9999			0.9999		

Dependent variable is the probability of sale, a positive coefficient indicates a positive effect on this probability. β_{cq} and $\beta_{cq,rw}$ are the coefficient estimates of the constant-quality model and constant-quality model with random walk, respectively. The 95% HPD intervals are given by $P_{2.5}$ and $P_{97.5}$. HT = House type, AT = Apartment type. Loglike is the log-likelihood, MC-error the mean of Monte Carlo standard error for all parameters, Neff the mean effective sample size (total number of samples = 4000 and 4000 warm-up) of all parameters, Heidelberger-Welch stationarity/Halfwidth is the mean of the test of all parameters (a parameter gets the value 1 (0) when the test is passed (failed) at the 5% level). The WAIC is the Watanabe Akaike information criterion and the LOO is leave-one-out cross-validation statistic. Finally, $\hat{R}$ is the mean *Rhat* statistic for all parameters.

4.2. Time-varying effect of list price premium

Theoretically, every coefficient on property characteristics can be made (calendar) time-varying. Practically, model identification becomes much more complicated and simulation and sampling becomes more time-consuming. Additionally, having more observations makes it easier to identify a time-varying effect. For illustration purposes, the coefficient on the list price premium, i.e. the premium of the original list price over the predicted list price (based on a hedonic regression), has been made time-varying in the large market (Amsterdam). A more detailed description of the definition of this variable is included in Appendix B. Similar to the time-fixed effects, the time-varying coefficient on the list price premium is structured to follow a random walk.

Figure 6: Time-varying effect of list price premium and 95% HPD intervals (top panel) and the marginal effect (bottom panel) in the large market (Amsterdam), 2005-2016.



Note: a higher positive (negative) value indicates a larger positive (negative) effect on the probability of sale.

The likelihood takes a similar form as that of Equation 8. The main difference is that the location parameters are now equal to: $\mu_{i,j} = \exp(\mathbf{x_i}\boldsymbol{\beta_j} + \mathbf{z_i}\boldsymbol{\alpha_j} + \mathbf{l_i}\boldsymbol{\gamma_j} + \nu_j) \in (0, \infty)$, for $j = s, w$. Besides the parameters as discussed in section 2.1, l_i is a $(T-1)$ row-vector containing the list price premium (scalar) multiplied with a $(T-1)$ selection row-vector (which is 1 at the quarter of withdrawal / sale and 0 otherwise). Next, $\boldsymbol{\gamma}$ is a $(T-1)$ vector containing the time-varying effects of the list price premium. The effect of the list price premium is also assumed to follow a random walk:

$$\gamma_{\tau,j} = \gamma_{\tau-1,j} + \eta_\tau, \eta \sim N(0, \sigma^2_{\eta,j}). \tag{10}$$

The additional coefficients that need to be estimated are the signals of γ_j ($\sigma_{\eta,j}$) and the innovations in γ_j. For the signal and innovations uninformative priors are used: $\sigma_{\eta,j} \sim$ Inverse Gamma$(3,1)$ and N$(0,1)$, respectively. The initial value ($\gamma_{1,j}$) is equal to the estimated effect of the model without time-variation in the parameters (i.e. the unconditional mean of the effect).

The estimated time-varying effect of the list price premium in the large market is shown in the top panel of Figure 6. Similar to Table 2, the list price premium has a negative effect in all time periods. This indicates that a higher list price premium leads to a lower probability of sale. The effect is somewhat smaller during the bust and starts increasing close to the end of the bust after which it starts increasing again. However, since the list price premium itself is also likely to exhibit cyclical behavior (see section 4.4), it is more informative to look at the effect multiplied with the average list price premium of sold properties per time period (bottom panel in Figure 6). This shows that the effect on sales probability becomes more negative during the bust since the list price premia are higher during this time.

Starting in 2014, the strong recovery of the Amsterdam market is clearly visible. Especially close to the end of the sample an interesting phenomenon is visible. The average list price premium decreases, whereas the effect on sales probability also decreases. The average list price premium actually turns into an average list price discount starting in 2015. The reason is the huge demand relative to supply. This results in a different behavior of sellers than usual. Koster and Rouwendal (2017) state that a better strategy in these times is to set a relatively low list price, as this results in both a quicker sale and higher transaction price. This strategy, however, only works in an extremely booming market. According to the Dutch Central Bank, the Amsterdam market was showing signs of overheating in 2015 and 2016 (Hekwolter of Hekhuis et al., 2017).

The result is an increase in the total (multiplied) effect (i.e. a less negative or even positive effect). Therefore, this time-varying coefficient on the list price premium, in combination with the average list price premium, could potentially be used as an indicator to spot overheating markets.

4.3. Decomposition of effects: the effect of quality and withdrawals

Apart from the fact that the mean TOM is noisy in thin markets, the proposed methodology corrects the mean TOM for two features: (i) quality and (ii) withdrawals. The aim of this section is to disentangle these effects and to determine their respective importance. To examine the effect of quality, an index (with random walk structure) is estimated without the control variables. To examine the effect of withdrawals, an index (with random walk structure) is estimated for sold properties only. In this case, ℓ_A of the likelihood in Equation 8 without the last part, $\ln(-\mu_{i,s} t_i^{\rho_s})$, is maximized. This index is subsequently compared to an index that controls for both withdrawals and housing quality.[13]

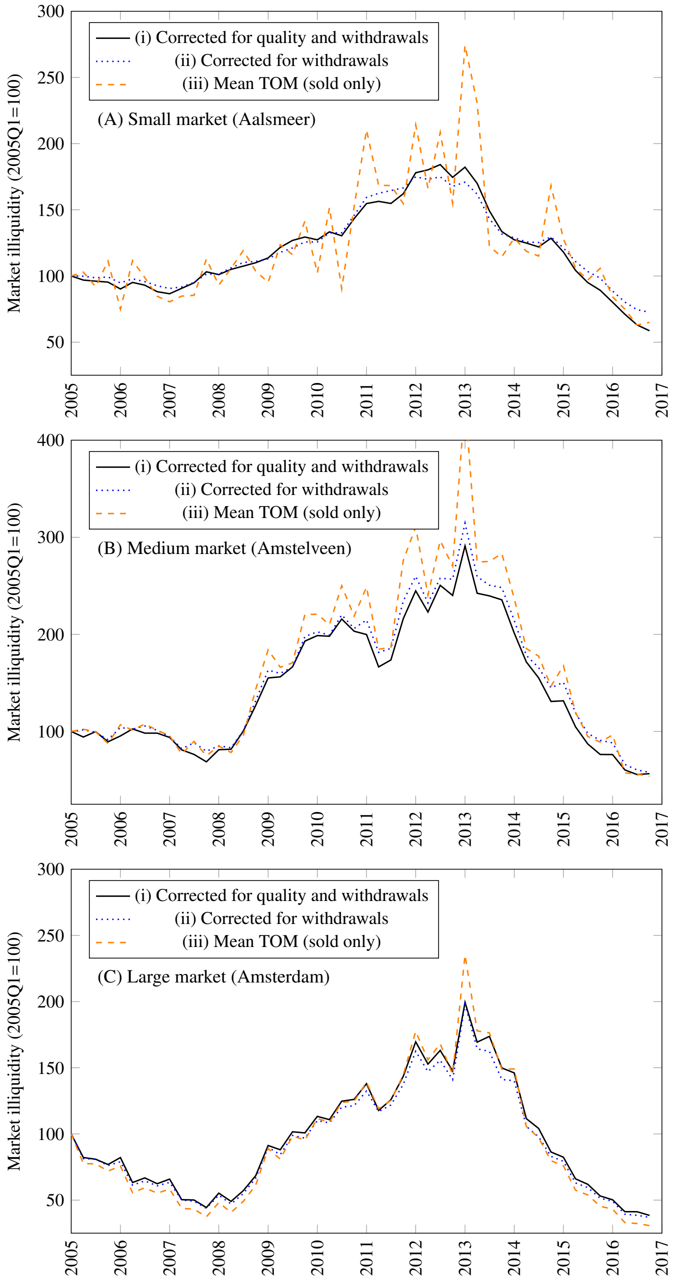
The results for the small, medium, and large market are shown in Figure 7. In all three markets the constant-quality indices are more similar to the indices corrected for withdrawals only than the indices corrected for quality only. Hence, withdrawals seem to be the major driver of differences. This is in line with the findings of Carrillo and Pope (2012).

Although the effect of quality is smaller than the effect of withdrawals, the effect of quality is still substantial. Furthermore, the influence of quality differs over the cycle. The percentage differences between the constant-quality indices and withdrawal-only controlled indices in levels are plotted in Figure 8. The largest difference is 17% (in 2016Q4 in the small market). The results further indicate that the indices controlled for withdrawals and quality predict a more illiquid market during busts than indices controlled for withdrawals only. More formally, a regression of the dummies for the three depicted periods in Figure 8 on the difference between the indices yields statistically significant (at 1%) coefficients on the bust dummy compared to the two other periods. The average difference between boom (either the first or second) and bust ranges from 3.5% to 7.1%. This indicates that illiquidity according to the constant-quality indicator was actually worse than illiquidity according to the indicator not corrected for quality. This in turn implies that housing quality differs over the cycle: in busts different quality properties sell than during booms. The conjecture that quality is different in busts and booms has also been put forward in Clapp et al. (2017).

Although differences in quality play a role, a very large part of the difference between the mean TOM and the constant-quality indices can be accounted for by only correcting for withdrawals. A big advantage of not controlling for property characteristics is that it simplifies the estimation and that the the computational time decreases by about 60%. For some applications this might be an interesting alternative.

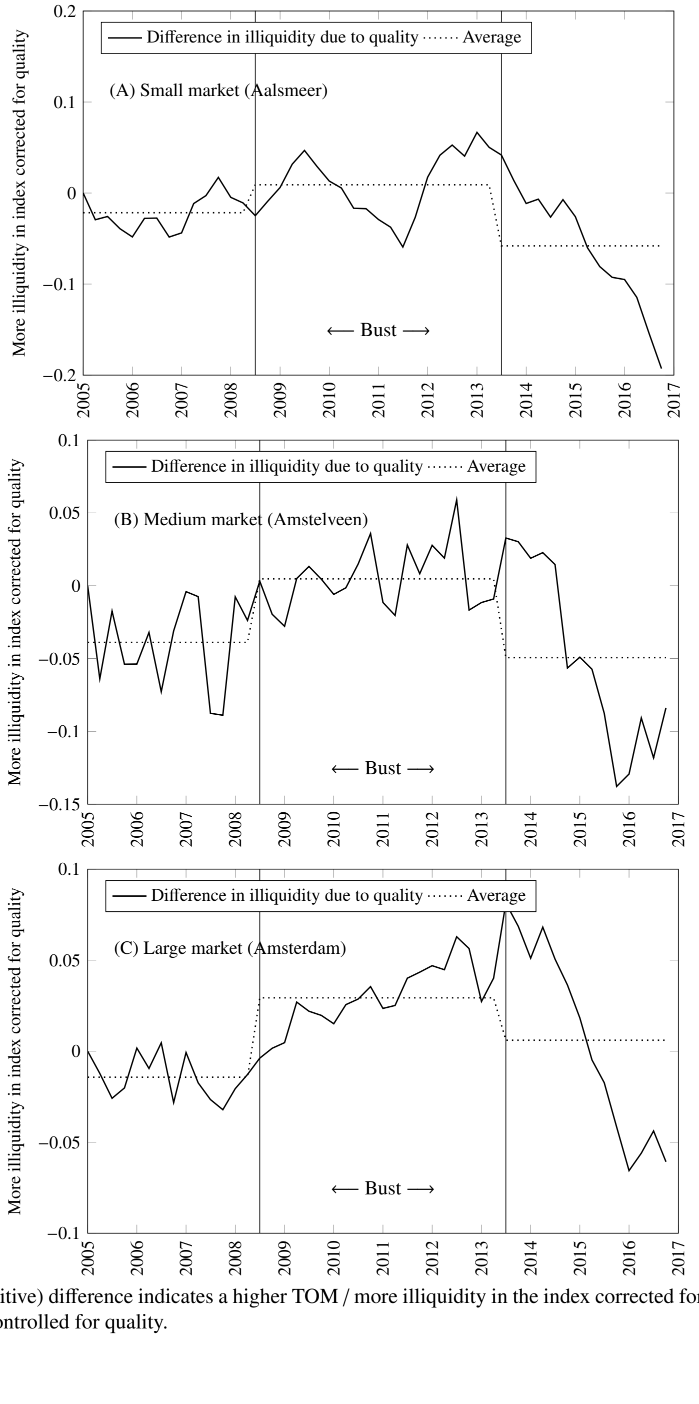
[13] But not for the list price premium to isolate the effect of quality.

Figure 7: Decomposition of effects.



Note: a higher index indicates a higher TOM/lower probability of sale and a more illiquid market.

Figure 8: Difference in illiquidity due to quality.



Note: a bigger (positive) difference indicates a higher TOM / more illiquidity in the index corrected for quality compared the the index not controlled for quality.

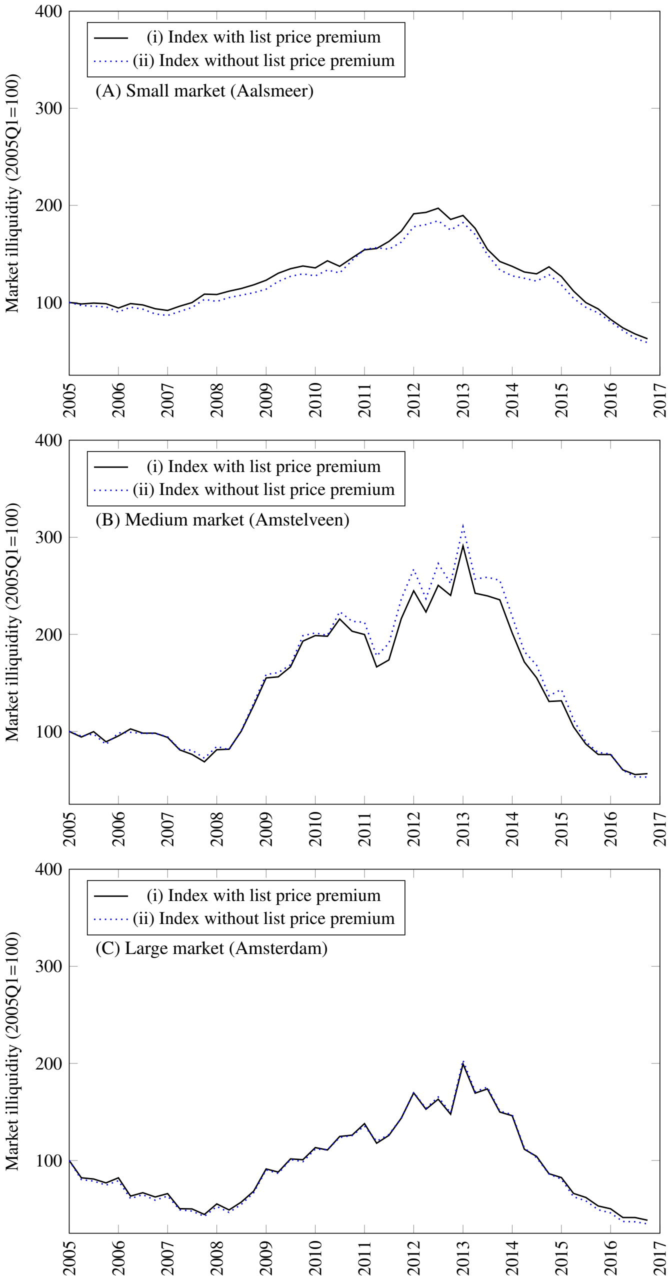
4.4. Decomposition of effects: the effect of list price premium

Although the list price premium is based on the estimated market value at the time of entry, there might be concerns that the list price itself is endogenous to the TOM. Therefore, this subsection is devoted to indices that do not contain the list price premium as independent variable. Indices controlled for and not controlled for the list price premium are shown in Figure 9, while the differences between the indices are depicted in Figure 10.

In the small market, the differences between the indices are not structural over the cycle (Figure 10). A regression of the difference on the boom dummy variables and bust dummy yields insignificant coefficients. However, in both the medium and large market the differences are significant and follow a similar pattern over the cycle. In busts, the illiquidity is lower in the indices that are corrected for the list price premium, than in booms. This indicates that indices corrected for the list price premium are less cyclical than the uncorrected indices. This reflects that list price behavior of sellers is cyclical as well (see bottom panel of Figure 6). Obviously, for the large market, there is a strong similarity between the index differences and the time-varying effect of the list price premium as shown in Figure 6 in section 4.2.

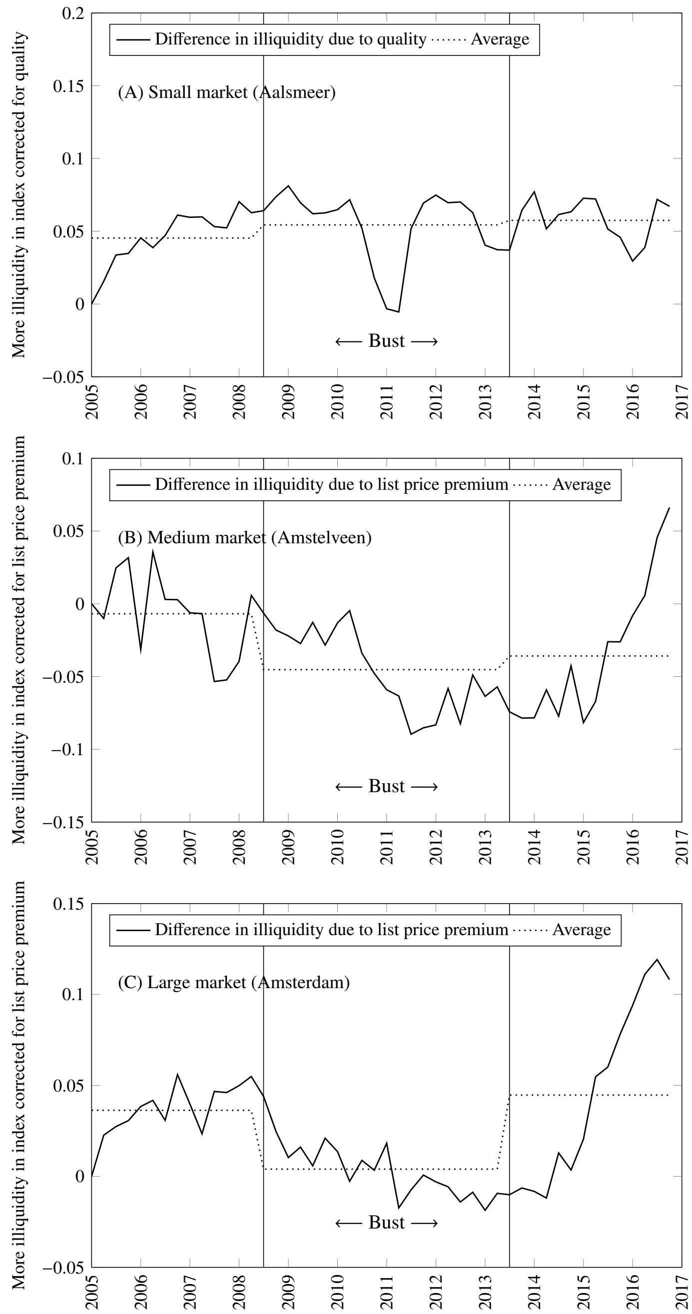
Setting the list price too high during busts is more likely to occur if homeowners are loss averse (Genesove and Mayer, 2001; Clapp et al., 2017). This has also been documented for the Dutch market (Van der Cruijsen et al., 2018). In other words, by not controlling for the list price premium, the indices are more cyclical as these will pick up some of the cyclicality of the list price behavior. The question of whether to control for the list price premium depends on the problem at hand. For example, a policymaker who wants to identify boom and bust cycles might want to use the indices not controlled for the list price premium as the identification of these cycles becomes easier.

Figure 9: Illiquidity indices with and without list price premium, 2005-2016.



Note: a higher index indicates a higher TOM/lower probability of sale and a more illiquid market.

Figure 10: Difference in illiquidity due to list price premium, 2005-2016.



Note: a bigger (positive) difference indicates a higher TOM / more illiquidity in the index corrected for the list price premium compared the the index not controlled for the list price premium.

4.5. Revisions

Revisions are changes that occur to previous values of an index when new data comes in. The magnitude of revisions is a useful measure for the quality of an index. This reflects both the precision of an index as well as the practical usefulness for businesses and policy purposes (Francke et al., 2017).[14] The expectation is that the magnitudes of the revisions are larger for thinner markets, as new data will be relatively more influential in these markets. By introducing the random walk structure, the expectation is that the magnitude of the revisions will be smaller.

I use a similar measure for the maginitude of revisions as Francke et al. (2017). More specifically, indices without data on the last year (2016) are estimated and these are compared to the baseline indices that are estimated on all data. Next, the absolute difference between both the levels (in percentage difference) and returns (in percentage points) are examined for the whole sample. Statistics for the magnitude of revisions is shown in Table 3.

In general, the absolute average revisions (|Mean|) are substantially smaller for the indices estimated with a random walk structure. In levels, the magnitude of revisions is almost 4 times smaller for the RWCQ model compared to the model without random walk. This holds for all three markets. In returns, the magnitude is 3 times smaller in the small market, 2 times smaller in the medium market and roughly the same in the large market. Also, the maximum size of the revision is much smaller in the random walk indices than in the indices without the random walk assumption. Another feature is that the size of the revisions becomes larger as the market becomes smaller. This holds for both levels and returns. The reason is most likely that new data will be relatively more influential in these markets.[15]

Finally, in the two largest markets, there are no substantial differences in the degree of revisions between the three models that contain a random walk structure. The random walk indices not corrected for quality (but for withdrawals) seem to exhibit somewhat fewer revisions in the small and medium markets, but the difference is very small. In other words, controlling for quality or withdrawals does not result in extra revisions.

[14] Francke et al. (2017) examine revisions in a repeat sales framework, in which revisions play a larger role than in a hedonic framework. The presented liquidity indices in the current study are estimated in a hedonic-like framework, but there still might be substantial revisions due to the thinness of some markets.

[15] In fact, even if the number of new observations is small in a thin market, these new observations will affect the signal more than the noise, so that the indices are more prone to change. See Francke et al. (2017) for a more detailed discussion and simulations of revisions with respect to the signal-to-noise ratio.

Table 3: Summary statistics of revisions.

	CQ	RWCQ	RW	RWCQNC
Small Market				
Levels				
Mean	-0.055	0.008	0.011	-0.080
Std. Dev.	0.045	0.027	0.021	0.057
|Mean|	0.061	0.016	0.014	0.084
|Max|	0.141	0.133	0.106	0.183
Returns				
Mean	-0.006	0.002	0.002	0.001
Std. Dev.	0.045	0.014	0.010	0.034
|Mean|	0.034	0.011	0.007	0.028
|Max|	0.113	0.045	0.044	0.095
Medium Market				
Levels				
Mean	-0.038	0.010	0.005	0.004
Std. Dev.	0.009	0.008	0.005	0.007
|Mean|	0.038	0.010	0.005	0.006
|Max|	0.052	0.024	0.019	0.027
Returns				
Mean	-0.001	0.000	0.000	0.000
Std. Dev.	0.011	0.005	0.004	0.004
|Mean|	0.007	0.004	0.003	0.003
|Max|	0.037	0.012	0.012	0.011
Large Market				
Levels				
Mean	-0.009	-0.001	-0.002	-0.001
Std. Dev.	0.002	0.002	0.002	0.002
|Mean|	0.009	0.002	0.002	0.002
|Max|	0.013	0.005	0.006	0.005
Returns				
Mean	0.000	0.000	0.000	0.000
Std. Dev.	0.002	0.003	0.003	0.002
|Mean|	0.002	0.002	0.002	0.002
|Max|	0.008	0.009	0.011	0.005

Revisions over 2005Q1–2015Q4 w.r.t. an extra year of data (2016Q1–2016Q4). A revision in levels is defined as the percentage difference between the two index levels, in returns it is the percentage point difference in returns. CQ constant-quality model without random walk structure, RWCQ a constant-quality model with random walk structure, RW is a model with random walk structure and not controlled for quality differences, and RWCQNW is constant-quality model with random walk structure but not controlled for withdrawals.

4.6. Correlated unobserved heterogeneity

A parametric specification is used for the unobserved heterogeneity term (ν_j, which is part of μ_j in equation 8). More specifically, a similar specification as in Cameron and Trivedi (2005) is used:

$$\nu_1 = \varepsilon_1 + \omega_{1,2}\varepsilon_2, \tag{11}$$

$$\nu_2 = \omega_{2,1}\varepsilon_1 + \varepsilon_2, \tag{12}$$

$$\varepsilon_j \sim \mathrm{N}(0, \sigma_j^2), j = s, w. \tag{13}$$

Here subscript j denotes sale ($j = 1$) and withdrawal ($j = 2$) . The factor loadings $\omega_{1,2}$ and $\omega_{2,1}$ and the variances σ_1^2 and σ_2^2 are estimated. The factor loadings are sampled with prior N(0,1) and the standard deviations with Inverse Gamma(3, 1) priors. If the factor loadings $\omega_{1,2}$ and $\omega_{2,1}$ are non-zero, the unobserved heterogeneity terms are correlated. The posterior estimates of the factor loadings and standard deviations are included in Table 4.

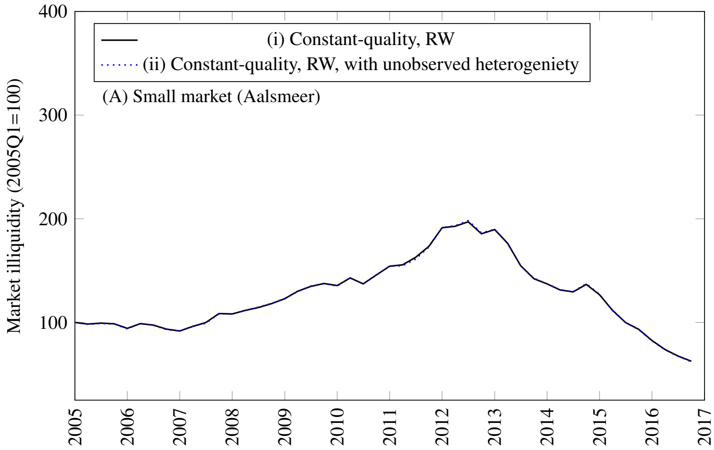
Since the credible intervals are quite large, there is little evidence of correlated unobserved heterogeneity. Consequently, the indices estimated with correlated unobserved heterogeneity are very similar to those estimated without correlated unobserved heterogeneity (Figure 11). The reason is probably that the markets are relatively small and homogeneous (even the large market is quite homogeneous), thus the unobserved heterogeneity component should be small. Therefore, practically, it is more convenient to estimate the model without correlated unobserved heterogeneity (i.e assume $\omega_{1,2}$=$\omega_{2,1}$=0) as only the partial likelihood has to be evaluated. As discussed in section section 2.2, this substantially reduces computation time.

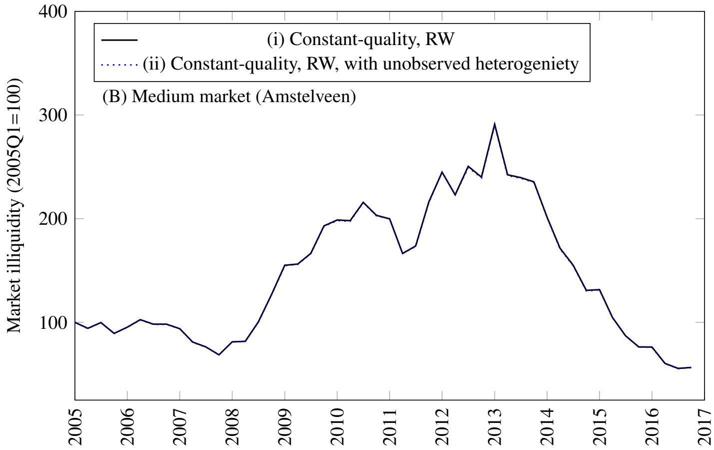
Table 4: Posterior means and 95% HPD intervals for the factor loadings and standard deviations of the unobserved heterogeneity components.

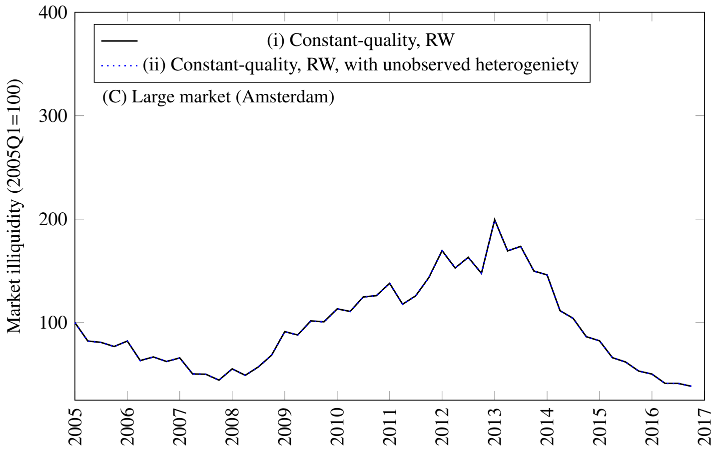
	Small market			Medium market			Large market		
	Mean	$p_{2.5}$	$p_{97.5}$	Mean	$p_{2.5}$	$p_{97.5}$	Mean	$p_{2.5}$	$p_{97.5}$
$\omega_{1,2}$	0.013	-3.894	3.868	0.013	-3.878	4.068	0.028	-3.831	3.780
$\omega_{2,1}$	-0.063	-3.834	3.816	0.012	-3.863	3.804	-0.117	-3.999	3.895
σ_1	0.481	0.139	1.488	0.489	0.137	1.513	0.483	0.137	1.522
σ_2	0.515	0.138	1.864	0.475	0.136	1.389	0.466	0.138	1.327

Mean denotes the posterior mean. $p_2.5$ and $p_97.5$ denote the lower (2.5%) and upper bound (97%) of the 95% credible intervals, respectively.

Figure 11: Illiquidity indices with and without correlated unobserved heterogeneity, 2005-2016.







Note: a higher index indicates a higher TOM/lower probability of sale and a more illiquid market.

5. Conclusion

In this paper a methodology is presented that allows for the construction of constant-quality liquidity indices when transaction data is sparse. These indices can be useful for policymakers, brokers, and other market participants. The presented methodology addresses the problem that heterogeneous properties are traded in different periods. Furthermore, in some periods more properties are withdrawn than in others. The latter issue is treated as a censoring problem and is explicitly taken into account in the methodology.

The results show that simply taking the mean of the TOM of sold properties underestimates (overestimates) market liquidity in good (bad) times. In other words, the quality of the properties that are sold is higher and/or the probability of withdrawal is different. Moreover, the constant-quality indices lead the mean TOM of sold properties. This indicates that the leading indicator properties of constant-quality liquidity indices are better than those of indicators currently used.

One of the main advantages of the presented method is that it can also be used in thin markets or in times of high uncertainty. In more dense markets or during "normal" times, the method is similar to more conventional methods. In times of high uncertainty, indices produced by conventional methods are unreliable. The proposed methodology induces a structure that allows to also create reliable indices in these times. Also, the method provides indices that are less sensitive for revisions than more conventional techniques. The magnitude of revisions is substantially smaller when a random walk structure is introduced. Revisions are larger for thinner markets, but the added value of the random walk structure is also larger.

It is shown that during busts the TOM is high and market liquidity is low. Furthermore, it is shown that the constructed liquidity indices and transaction price indices move similarly over the cycle. Consistent with the literature, liquidity changes lead price changes. A novel finding, consistent with the general asset pricing literature, is that liquidity risk is also higher in busts. A suggestion for future research is to delve further in this issue. Liquidity risk, for example, can potentially be modeled in a more sophisticated way. The volatility of the dummy variables can be modeled as a stochastic process itself (i.e. stochastic volatility). This could give more accurate insights in liquidity risk. However, this might result in additional difficulties in the identification of the model.

The methodology also allows for an examination of the determinants of market liquidity. The effects of housing characteristics are in general not equal across different regions. More homogeneous housing types like apartments generally sell quicker. A higher list price premium (i.e. a higher list price compared to the predicted list price) is related to a lower sale probability. The effect is shown to be varying over time; in busts both the average list price premium and the total effect on sale probability increase. Since 2015, the list price premium turns, on average, into a list price discount. The reason is that sellers change their behavior due to the extreme tightness of the market.

The presented methodology corrects for both quality and withdrawals. The results suggest that withdrawals are the main driver of the difference between the average TOM of sold properties. Quality, however, also plays a significant role. The results suggest that the quality of sold properties is different over the cycle. Nevertheless, correcting for withdrawals is the most important issue. By not controlling for quality, the estimation procedure is much quicker. Therefore, for some applications correcting only for the number of withdrawals might be enough.

References

Acharya, V. V., Y. Amihud, and S. T. Bharath (2013). Liquidity risk of corporate bond returns: conditional approach. *Journal of Financial Economics 110*(2), 358–386.

Acharya, V. V. and L. H. Pedersen (2005). Asset pricing with liquidity risk. *Journal of Financial Economics 77*(2), 375–410.

Belkin, J., D. J. Hempel, and D. W. McLeavey (1976). An empirical study of time on market using multidimensional segmentation of housing markets. *Real Estate Economics 4*(2), 57–75.

Betancourt, M. and M. Girolami (2015). Hamiltonian Monte Carlo for hierarchical models. *Current trends in Bayesian methodology with applications 79*, 30.

Bokhari, S. and D. Geltner (2011). Loss aversion and anchoring in commercial real estate pricing: Empirical evidence and price index implications. *Real Estate Economics 39*(4), 635–670.

Brunnermeier, M. and L. Pedersen (2009). Market liquidity and funding liquidity. *Review of Financial Studies 22*(6), 2201–2238.

Cameron, A. C. and P. K. Trivedi (2005). *Microeconometrics: Methods and Applications*. Cambridge University Press.

Carpenter, B., A. Gelman, M. Hoffman, D. Lee, B. Goodrich, M. Betancourt, M. A. Brubaker, J. Guo, P. Li, and A. Riddell (2016). Stan: A probabilistic programming language. *Journal of Statistical Software 20*, 1–43.

Carrillo, P., E. De Wit, and W. Larson (2015). Can tightness in the housing market help predict subsequent home price appreciation? *Real Estate Economics 43*(3), 609–651.

Carrillo, P. and B. Williams (2015). The repeat time-on-the-market index. *SSRN Working Paper 2584558*.

Carrillo, P. E. (2013). To sell or not to sell: Measuring the heat of the housing market. *Real Estate Economics 41*(2), 310–346.

Carrillo, P. E. and J. C. Pope (2012). Are homes hot or cold potatoes? the distribution of marketing time in the housing market. *Regional Science and Urban Economics 42*(1), 189–197.

Clapp, J. M., R. Lu-Andrews, and T. Zhou (2017). Is the behavior of sellers with expected gains and losses relevant to cycles in house prices? *SSRN Working paper 2877546*.

De Wit, E., P. Englund, and M. Francke (2013). Price and transaction volume in the Dutch housing market. *Regional Science and Urban Economics 43*(2), 220–241.

De Wit, E. R. and B. Van der Klaauw (2013). Asymmetric information and list-price reductions in the housing market. *Regional Science and Urban Economics 43*(3), 507–520.

Dellaportas, P. and A. F. Smith (1993). Bayesian inference for generalized linear and proportional hazards models via Gibbs sampling. *Applied Statistics 42*(3), 443–459.

DiNardo, J., N. M. Fortin, and T. Lemieux (1996). Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach. *Econometrica 64*(5), 1001–1044.

DNB (2016). Overzicht Financiële Stabiliteit Herfst 2016 [In Dutch].

Dubé, J. and D. Legros (2016). A spatiotemporal solution for the simultaneous sale price and time-on-the-market problem. *Real Estate Economics 44*(4), 846–877.

Fisher, J., D. Gatzlaff, D. Geltner, and D. Haurin (2003). Controlling for the impact of variable liquidity in commercial real estate price indices. *Real Estate Economics 31*(2), 269–303.

Fisher, J., D. Geltner, and H. Pollakowski (2007). A quarterly transactions-based index of institutional real estate investment performance and movements in supply and demand. *The Journal of Real Estate Finance and Economics 34*(1), 5–33.

Francke, Marc Geltner, D., A. Van de Minne, and B. White (2017). Revisions in granular repeat sales indices. *SSRN Working paper 3016563*.

Francke, M. and A. De Vos (2000). Efficient computation of hierarchical trends. *Journal of Business & Economic Statistics 18*(1), 51–57.

Francke, M. and G. Vos (2004). The hierarchical trend model for property valuation and local price indices. *The Journal of Real Estate Finance and Economics 28*(2), 179–208.

Francke, M. K. (2010). Repeat sales index for thin markets. *The Journal of Real Estate Finance and Economics 41*(1), 24–52.

Geltner, D., A. Kumar, and A. van de Minne (2017). Riskiness of real estate development: A perspective from urban economics & option value theory. *SSRN Working paper 2907036*.

Genesove, D. and L. Han (2012). Search and matching in the housing market. *Journal of Urban Economics 72*(1), 31–45.

Genesove, D. and C. Mayer (2001). Loss aversion and seller behavior: Evidence from the housing market. *The Quarterly Journal of Economics 116*(4), 1233–1260.

Goetzmann, W. and L. Peng (2006). Estimating house price indexes in the presence of seller reservation prices. *Review of Economics and Statistics 88*(1), 100–112.

Haurin, D. (1988). The duration of marketing time of residential housing. *Real Estate Economics 16*(4), 396–410.

Hekwolter of Hekhuis, M., R. Nijskens, and W. Heeringa (2017). De woningmarkt in de grote steden [In Dutch]. *DNB Occasional Studies 15*(1).

Hoffman, M. D. and A. Gelman (2014). The No-U-turn sampler: Adaptively setting path lengths in Hamiltonian Monte Carlo. *Journal of Machine Learning Research 15*(1), 1593–1623.

Jenkins, S. P. (2005). Survival analysis. *Unpublished manuscript, Institute for Social and Economic Research, University of Essex, Colchester, UK 42*, 54–56.

Kaplan, E. L. and P. Meier (1958). Nonparametric estimation from incomplete observations. *Journal of the American Statistical Association 53*(282), 457–481.

Knight, J. (2002). Listing price, time on market, and ultimate selling price: Causes and effects of listing price changes. *Real Estate Economics 30*(2), 213–237.

Koster, H. and J. Rouwendal (2017). Verkopen boven de vraagprijs-buitensporig of nieuwe werkelijkheid? [In Dutch]. *ASRE Research Papers 2017*(05).

Krainer, J. (2001). A theory of liquidity in residential real estate markets. *Journal of Urban Economics 49*(1), 32–53.

Merlo, A. and F. Ortalo-Magne (2004). Bargaining over residential real estate: evidence from england. *Journal of Urban Economics 56*(2), 192–216.

NVM (2016). Analyse Woningmarkt Q1 2016 [In Dutch].

Van der Cruijsen, C., D.-J. Jansen, and M. van Rooij (2018). The rose-tinted spectacles of homeowners. *Journal of Consumer Affairs 52*(1), 61–87.

Van Dijk, D., D. Geltner, and A. van de Minne (2018). Revisiting supply and demand indexes in real estate. *DNB Working paper 583*.

Van Dijk, D. W. and M. K. Francke (2018). Internet search behavior, liquidity and prices in the housing market. *Real Estate Economics 46*(2), 368–403.

Vehtari, A., A. Gelman, and J. Gabry (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing 27*(5), 1413–1432.

Watanabe, S. (2010). Asymptotic equivalence of Bayes cross validation and widely applicable information criterion in singular learning theory. *Journal of Machine Learning Research 11*(Dec), 3571–3594.

Appendix A Comparison with Carillo and Pope (2012)

This appendix offers a comparison of the presented methodology with indices produced by applying the non-parametric methodology of Carrillo and Pope (2012) (henceforth CP). The CP-method is very useful for large markets and can be estimated quickly. However, in smaller markets the method provides somewhat noisy estimates.

The methodology takes the Kaplan-Meier estimator as basis to estimate the (empirical) cumulative distribution functions and survivor functions for each time-period (Kaplan and Meier, 1958). Properties that are sold are treated as "failure" in Kaplan-Meier terminology and properties that are withdrawn from the market or those that are still on the market are treated as "censored".

In order to create an index, quantiles of these distributions are linked. It might be illuminating to consider an example with two years. First, TOM distributions of listed properties for both years are estimated using the Kaplan-Meier estimator. Next, the median TOM of each distribution is taken. The line between these medians represents a liquidity index. The index can in principle be estimated for each point in the distribution. Note that the Kaplan-Meier estimate of the distribution does not take individual property characteristics into account. Therefore, the distributions are also estimated using a weighted Kaplan-Meier estimate. These will subsequently result in constant-quality liquidity indices. CP propose an extenstion to the methodology of DiNardo et al. (1996) (DFL), in which the DFL-decomposition is combined with the Kaplan-Meier estimator to allow it to work with censored variables. The weights of the weighted Kaplan-Meier estimator are based on the degree of similarity between the property in question and properties in the reference year. Intuitively speaking, more (less) weight is attached to properties that are more (less) similar to properties in the reference quarter. The weights are estimated by estimating a logit on the properties sold or withdrawn in the reference quarter and the properties sold or withdrawn in the quarter in question. The dependent variable in this logit takes 1 if the property is sold or withdrawn in the reference quarter. The independent variables are housing characteristics.[16] Therefore, the predicted probabilities of this logit provide a measure of how similar a property in a given quarter is to properties from the reference quarter (a higher predicted value indicates more similarity).

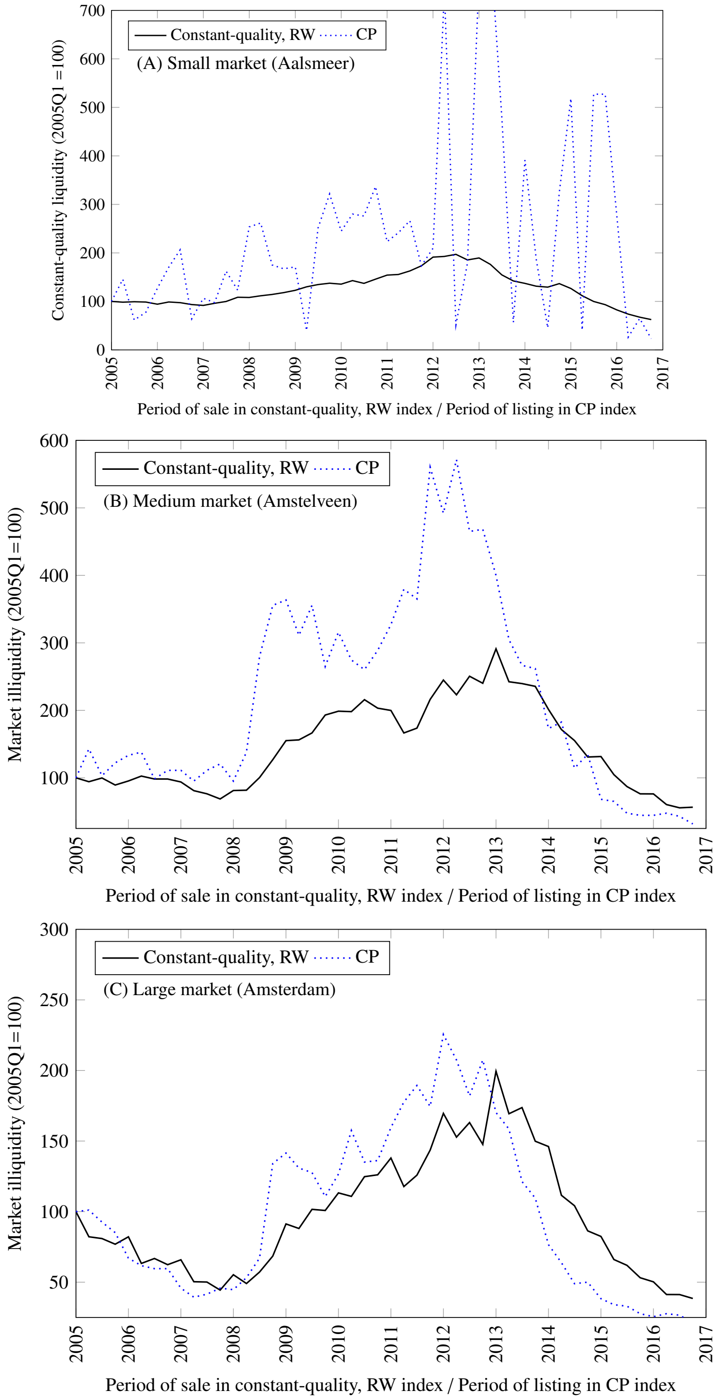
When the reference quarter and the comparison quarter consists of many observations, the estimated logit will provide sensible results. However, when there are few transactions, the logit is based on too few observations and the coefficients become unstable. Another difference with the presented methodology is that the methodology of CP looks at the *ex ante* distribution of the TOM. In other words, the average TOM of the quarter when the house was *listed* is calculated. This obviously results in indices that are leading compared to indices based on the average TOM of the quarter when the house was sold. However, this also means that close the end of the sample, the data will only include properties that are sold or withdrawn quickly. In quarter N-1 there will only be properties that are sold or withdrawn in quarter N-1 or N. Hence, the indices will be biased downwards if these are estimated in the final years of the sample.

A comparison between the indices based on the CP methodology and the presented methodology in this study with random walk structure is included in Figure 12. Note that the CP indices indicate the *ex ante* sale probability, hence the the expected TOM of a house in the period the house was listed. The indices based on the methodology from this study are based on the realized sale probability, or the TOM of the period in which the house was sold or withdrawn. The obvious consequence is that the CP indices seem to lead to indices based on the presented methodology for most of the sample, but the x-axes are not the same.

In the small market it proves to be rather problematic to estimate constant-quality liquidity indices with the CP methodology. However, in the medium, and especially in the large market, the results are much more comparable (Figure 12).

[16]The control variables are the same as in the presented Bayesian methodology: log size, log size squared, dummies for gardens, parking places, landleases, maintenance (bad, normal and well-maintained), construction period (before 1905, 1906-1944, 1945-1990, 1991-2000 after 2001), and property type (terraced, back-to-back, corner, semi-detached, detached, ground floor split level apartment, upper floor split level, other apartment), and list price premium.

Figure 12: Comparison between constant-quality random walk illiquidity indices and Carillo and Pope (2012).



Appendix B Estimated transaction price at time of entry

To determine the expected transaction price at time of entry, a hedonic price model is estimated. Transaction prices are modeled as a function of housing characteristics that are also included as controls in the liquidity indices. The model is estimated separately for each municipality and includes dummies for the quarter of sale. The predicted values of this model (with the dummy for quarter of sale replaced by the value it entered the market) represent the estimated transaction price. Note that it is also possible to estimate the expected transaction price of houses that are eventually withdrawn.

The estimated coefficients for each market are included in Table 5. As the model is used for the calculation of one control variable only (list price premium), the coefficients are not discussed in detail. Most coefficients have the expected sign and are significant. Although the analysis of this study focuses on houses sold or withdrawn between 2005 and 2016, it might be the case the house was listed before this period. Therefore, in order to determine the market value at time of entry, the hedonic model is estimated using all observations some of which are also sold prior to the period of interest. Therefore the recorded number of observations per municipality in this Appendix are somewhat different than those reported in Table 1.

Table 5: Hedonic estimation of the coefficients on log transaction price.

	Small Market		*Medium Market*		*Large Market*	
Variable	β	t	β	t	β	t
Constant	4.29	21.9	9.94	114.3	3.2	110.9
Bad Maint.	(Omitted)		(Omitted)		(Omitted)	
Normal Maint.	0.10	10.0	0.11	28.2	0.1	73.4
Good Maint.	0.18	15.1	0.24	46.9	0.2	117.1
< 1905	(Omitted)		(Omitted)		(Omitted)	
1906 – 1944	-0.07	-1.5	0.22	4.8	0.0	-27.5
1945 – 1990	-0.05	-1.2	-0.07	-1.6	-0.1	-44.0
1991 – 2000	0.07	1.4	0.26	5.5	0.0	0.0
> 2001	0.10	2.2	0.34	7.2	0.0	-7.2
HT Terraced	(Omitted)		(Omitted)		(Omitted)	
HT Back-to-Back	0.19	6.4	0.27	15.0	0.1	7.1
HT Corner	0.05	8.1	0.06	12.8	0.0	9.0
HT Semi-Detached	0.19	19.0	0.39	39.6	0.2	27.0
HT Detached	0.36	27.0	0.72	47.3	0.3	33.0
AT Split (GF)	0.05	3.4	-0.39	-41.5	-0.1	-49.1
AT Split (UF)	0.00	-0.1	-0.41	-45.2	-0.1	-39.3
AT Other	-0.03	-1.8	-0.44	-57.9	-0.1	-51.6
log(*size*)	1.76	33.7	0.31	17.0	2.0	412.9
log(size)^2	-0.10	-32.2	-0.02	-16.7	-0.1	-383.8
Garden	0.01	0.9	0.00	0.6	0.1	51.5
Parking	0.10	13.6	0.16	35.1	0.1	46.2
Landlease	-0.04	-1.0	-0.58	-11.0	0.0	-9.3
Market conditions	Quarter of sale dummies					
Location	ZIP-code dummies					
Observations	3,667		21,405		143,299	
R^2	0.9143		0.9096		0.9243	
RMSE	0.1477		0.1943		0.1816	

HT = House type, AT = Apartment type, GF = Ground floor, UF, Upper floor.

Appendix C Transaction prices indices

The transaction price indices are estimated using a hedonic model. More specifically, the indices are estimated using a Hierarchical Trend Model (HTM) (Francke and De Vos, 2000; Francke and Vos, 2004). This model is well-suited to estimate constant-quality price indices in thin markets and is also used in Van Dijk and Francke (2018) to estimate quarterly transaction price indices in the Netherlands. The hedonic regression is performed for the COROP-region in which the three municipalities are located.[17] The common COROP-trend is modeled as local linear trend and the municipal trends are modeled as a random walk. The HTM is defined as (Francke and Vos, 2004):

$$y_t = i\mu_t + D_{\vartheta,t}\theta_t + X_t\beta + \varepsilon_t, \varepsilon_t \sim N(0, \sigma^2_\varepsilon I), \tag{14a}$$

$$\mu_{t+1} = \mu_t + \kappa_t + \eta_t, \eta_t \sim N(0, \sigma^2_\eta), \tag{14b}$$

$$\kappa_{t+1} = \kappa_t + \zeta_t, \zeta_t \sim N(0, \sigma^2_\zeta), \tag{14c}$$

$$\theta_{t+1} = \theta_t + \varpi_t, \varpi_t \sim N(0, \sigma^2_\varpi I). \tag{14d}$$

Here y_t is a vector of log selling prices. Next, μ_t is the common trend of the COROP-region, vector θ_t contains the municipal-specific trends, and matrix D is a selection matrix of the municipality. Finally, X_t is a vector with house characteristics with coefficients β.

Results of coefficient estimates of the housing characteristics are shown in first two columns of Table 6. As this estimation is only performed to calculate the price indices that are used in one subsection, the coefficients are not discussed in detail. All coefficients, however, have the expected signs and the fit is satisfactory. The transaction price indices for the three municipalities are the sum of the common trend (of the COROP-region) and the municipal trend. These indices are presented in Figure 4.

[17] A COROP-region is the Dutch equivalent of an MSA, it is however much smaller in geographical and population size.

Table 6: Hedonic (HTM) estimation of the coefficients on log transaction price.

	Transaction price	
Variable	β	t
Bad Maint.	(Omitted)	
Normal Maint.	0.097	45.0
Good Maint.	0.194	77.5
< 1905	(Omitted)	
1906 – 1944	-0.117	52.8
1945 – 1990	-0.388	155.7
1991 – 2000	-0.235	81.2
> 2001	-0.252	79.9
HT Terraced	(Omitted)	
HT Back-to-Back	0.130	17.5
HT Corner	0.022	7.6
HT Semi-Detached	0.132	33.8
HT Detached	0.231	46.1
AT Split-Level (Ground or multiple)	0.113	40.7
AT Split-Level (Upper floor)	0.117	37.1
AT Other	0.025	7.9
log(*size*)	2.148	298.1
$\log(\text{size})^2$	-0.120	215.2
Garden	0.067	26.4
Parking	0.067	33.4
Landlease	-0.110	64.8
Market conditions	Common trend (Local Linear Trend)	
Location	Muncipal trends (Random Walk)	
Observations	132243	
R^2	0.7871	
RMSE	0.2239	

HT = House type, AT = Apartment type

Previous DNB Working Papers in 2019

No. 622 **David-Jan Jansen,** Did Spillovers From Europe Indeed Contribute to the 2010 U.S. Flash Crash?
No. 623 **Wilko Bolt, Kostas Mavromatis and Sweder van Wijnbergen,** The Global Macroeconomics of a trade war: the EAGLE model on the US-China trade conflict
No. 624 **Ronald Heijmans and Chen Zhou,** Outlier detection in TARGET2 risk indicators
No. 625 **Robert Vermeulen, Edo Schets, Melanie Lohuis, Barbara Kölbl, David-Jan Jansen and Willem Heeringa,** The Heat is on: A framework measuring financial stress under disruptive energy transition scenarios
No. 626 **Anna Samarina and Anh D.M. Nguyen,** Does monetary policy affect income inequality in the euro area?
No. 627 **Stephanie Titzck and Jan Willem van den End,** The impact of size, composition and duration of the central bank balance sheet on inflation expectations and market prices
No. 628 **Andrea Colciago, Volker Lindenthal and Antonella Trigari,** Who Creates and Destroys Jobs over the Business Cycle?
No. 629 **Stan Olijslagers, Annelie Petersen, Nander de Vette and Sweder van Wijnbergen,** What option prices tell us about the ECB's unconventional monetary policies
No. 630 **Ilja Boelaars and Dirk Broeders,** Fair pensions
No. 631 **Joost Bats and Tom Hudepohl,** Impact of targeted credit easing by the ECB: bank-level evidence
No. 632 **Mehdi El Herradi and Aurélien Leroy,** Monetary policy and the top one percent: Evidence from a century of modern economic history
No. 633 **Arina Wischnewsky, David-Jan Jansen and Matthias Neuenkirch,** Financial Stability and the Fed: Evidence from Congressional Hearings
No. 634 **Bram Gootjes, Jakob de Haan and Richard Jong-A-Pin,** Do fiscal rules constrain political budget cycles?
No. 635 **Jasper de Jong and Emmanuel de Veirman,** Heterogeneity and Asymmetric Macroeconomic effects of changes in Loan-to-Value limits
No. 636 **Niels Gilbert,** Euro area sovereign risk spillovers before and after the ECB's OMT

DeNederlandscheBank

EUROSYSTEEM

De Nederlandsche Bank N.V.
Postbus 98, 1000 AB Amsterdam
020 524 91 11
dnb.nl