Residential real estate market liquidity in Amsterdam

Introduction

Real estate is an inherent illiquid asset class compared to, for example, stocks and bonds. Especially during the Global Financial Crisis (GFC) the importance of (the lack of) market liquidity became clear. Prices fell tremendously, but maybe even more importantly, investors and households were not able to sell their assets as quickly as desired. For investors, lower liquidity of their investment portfolio means that it is more difficult to rebalance their portfolio. For households, lower liquidity implies that they are not able to move if desired, which has consequences for labor mobility as well.

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In the financial economics literature, market liquidity is usually defined as the ease at which an asset can be traded (Brunnermeier & Pedersen, 2009). Ametefe et al. (2016) identify five dimensions of real estate market liquidity: tightness, depth, resilience, breadth, and immediacy. Market tightness refers to the costs related to taking a 'round-trip' (i.e. simultaneously buy and sell or sell and buy). Market depth measures the extent to which trading can occur without affecting prices. After a while, more trading will affect prices more, the magnitude by which this happens is called resilience. The breadth refers to the overall size of all trades. Finally, immediacy relates to the discount or premium related to selling or buying quickly.

This article estimates two different empirical liquidity measures for the residential real estate market in Amsterdam. One measure focuses on the first dimension of liquidity (market tightness) and one measure focuses on the fifth dimension (immediacy). The results further include a discussion on the commonality between these measures and the co-movement with prices. The results indicate that the two measures – based on different data – are very similar and both show a strong decrease in market liquidity during the GFC. In the recent years, market liquidity recovered to pre-crisis levels.

The next section starts with two views on the concept of real estate market. The econometric details and equations will not be discussed. For these I refer to the PhD thesis. The goal of this article is to present liquidity indices for Amsterdam, intuitively explain the models, and to provide some stylized empirical facts.

Two measures for market illiquidity

First measure: Difference between reservation prices

The first measure develops a model to estimate reservation prices of buyers and sellers to obtain a measure for market tightness. In this model, reservation price dynamics are the root of price and liquidity changes in the market. The model builds on the empirical fact that liquidity and prices are highly pro-cyclical in real estate. The model is an extension of the model of Fisher et al. (2003) in a repeat-sales structural time series framework. This makes it possible to estimate reliable, robust investor supply and demand indices for granular markets. The difference between the central tendencies of these reservation prices can be used as a measure for market tightness. This measure can be viewed as an analogue to the bid-ask spread, which is commonly used as a market liquidity measure in the stock market.

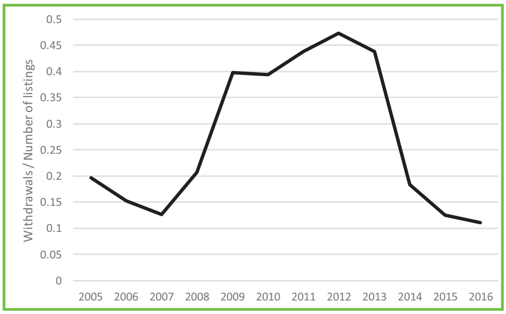
The model to estimate the reservation price indices of buyers and sellers is based on the three-step approach of Fisher et al. (2003), which in turn is based on the two-step Heckman selection model for censored regressions.[1] The *midpoint price* is the transaction price observed in real estate markets and is, by definition, in-between the buyers' and sellers' reservation prices. An important assumption of the model is that the transaction price is *exactly* in-between the buyers' and sellers' reservation price. By making this assumption, the midpoint price is known. Additionally, following Fisher et al. (2003), the reservation prices of buyers and sellers are assumed to be normally distributed. Moreover, the transaction volume can be readily observed from the data and is known. In turn, a reasonable model – consistent with pro-cyclical liquidity – for the buyers' and sellers' reservation prices can be backed out (for more details see Van Dijk, Geltner & Van de Minne, 2018).

The estimation procedure is as follows. In the first step, a probit regression is estimated to determine the probability of sale. Here, a property is 'tracked' over time: the dependent variable takes the value 1 if the property is sold and 0 if it is not sold. Included as right-hand-side variables in this probit regression are calendar time dummy variables that indicate the shift in the probability of sale in this period. After running the probit, the *inverse Mills ratio* is calculated which serves as an input for the second step: the estimation of the repeat sales model.[2] In this repeat sales model, the *difference* of the inverse Mills ratio is included (i.e. the difference between the value at the time of the second sale and the first sale). Finally, in the third step, the repeat sales index estimates are combined with the probit results and the residuals of the repeat sales regression. This step yields two reservation price indices: one for the sellers and one for the buyers. Tracking the difference between these indices over time indicates how market tightness evolves (a bigger difference indicates that buyers' and sellers' reservation prices are further apart, which implies a less liquid market).

Second measure: A (correct) TOM

The second measure focuses on the TOM (Time-on-the-Market). From an investors' perspective, a lower expected TOM is related to more immediacy (lower costs of selling quickly). Practitioners and policymakers frequently use the average TOM of sold properties as a market liquidity indicator. The average TOM can be misleading, mainly due to two reasons. Firstly, in calculating the average TOM, only properties that are sold are considered. However, a seller might choose to withdraw the property. If many sellers choose to do so, this is an indication of an illiquid market. If, for example, the probability of a withdrawal increases during some periods, the average TOM might give a wrong signal about liquidity. Empirically, the percentage of withdrawn houses differs over the cycle (Figure 1). Secondly, houses are heterogeneous assets. Some houses, usually more homogeneous properties like apartments, transact quicker. The constructed measure for market liquidity corrects for these features. Novel features of the presented method include that the liquidity indices can be created reliably up to the end of the sample (*until the most recent data comes in*) and that indices can be constructed in markets where transactions or withdrawals occur infrequently.

FIGURE 1 ▸ FRACTION OF HOUSES WITHDRAWN OVER THE CYCLE IN AMSTERDAM, 2005 - 2016



When a house is on the market, it can be either sold or withdrawn. The decision to sell or withdraw can therefore be characterized as competing risks. The TOM is modeled in a hazard framework. 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). By estimating the model in a competing risks framework, the probability of sale is estimated conditionally on the probability of withdrawal. If, for example, during a crisis the probability of withdrawal increase this will affect the probability of sale as well (usually the latter probability will become lower).

Besides conditioning on survival time, it is also desirable to condition on other covariates, in this case housing characteristics and the list price premium.[3] 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 a 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. In order for the methodology to work in thin markets, the calendar time-fixed effects are replaced by a stochastic structure.[4] More specifically, these are modeled as a random walk. The intuition behind the random walk assumption is that the level of the liquidity in previous period contains information regarding the level of liquidity of today.

Constructing empirical liquidity measures for Amsterdam

Data

Transactions data between 2005-Q1 and 2016-Q4 of the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM) are used. The data contain the sale price, date of sale, date of listing, (original) list price, unique identifying property id, and several housing characteristics.

For the first measure, only the sale price, date of sale, and the unique property id are strictly necessary, as the model is an adapted repeat sales model. Hence the (fixed) housing characteristics are canceled out. However, some housing characteristics may be included in the first-step (the probit regression). In this case, the size (in m^3), property type dummy variables (terraced, back-to-back, corner, semi-detached, detached, apartment), and building period dummy variables (<1905, 1905-1944, 1945-1990, >1990) are included. The results are robust to including additional property characteristics. The reason not to include too many characteristics is mainly a practical one. Since properties are 'tracked' over time, the probit takes roughly N*T observations, where N is the total (sold and not sold) number of properties and T the number of periods. When estimating quarterly indices for Amsterdam, the total amount of observations in the probit amounts to almost 3.8 million.[5] When including more property characteristics, the estimation time will increase tremendously.

The main input for the second measure is the time the house is on the market (TOM) and whether the property is sold or withdrawn. For the second measure, somewhat more housing characteristics are included: size (in m^3), property type dummy variables (terraced, back-to-back, corner, semi-detached, detached, ground level apartment, upper floor apartment, and other apartment), building period dummy variables (<1905, 1905-1944, 1945-1990, 1991-2000, >2000), garden dummy, parking dummy, land lease dummy, and list price premium. The *list price premium* is frequently used in TOM analysis in the real estate literature (Genesove & Mayer, 2001; Bokhari & Geltner, 2011; Clapp & Lu-Andrews, 2017), and is defined as the difference between the list price and estimated market value of the property at the time of entry. The market value is estimated with a hedonic model, which will not be discussed here and is available in the thesis or upon request. The thesis additionally includes a discussion on the effect of the list price premium on the indices. This discussion shows that the indices become less cyclical when correcting for the premium, which reflects the fact that the list price premium is cyclical as well.

Results

The demand and supply reservation price indices for Amsterdam are shown in Figure 2. The lines represent indices that indicate the development of the respective reservation prices over time.[6] Similar to the findings for US commercial real estate, demand seems to lead supply (Van Dijk, Geltner & Van De Minne, 2018). Visually, the turning points in the demand index seem to be happening earlier in the demand indices than in the supply indices. The Granger causality running from the returns of the demand index to those of the supply index is stronger than vice versa.[7] This implies that the effect of demand on supply is stronger than the other way around.

FIGURE 2 ▸ DEMAND AND SUPPLY RESERVATION PRICE INDICES FOR AMSTERDAM, 2005Q1-2016Q4

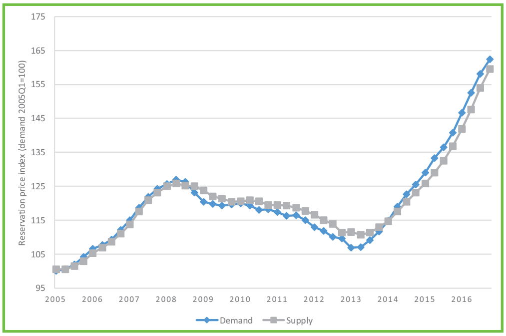
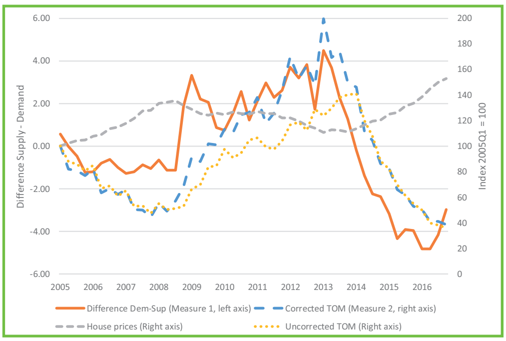


FIGURE 3 ▸ COMPARISON BETWEEN THE TWO MEASURES FOR LIQUIDITY AND HOUSE PRICES IN AMSTERDAM, 2005Q1-2016Q4



A measure for *illiquidity* can be obtained by calculating the difference between sellers' and buyers' reservation prices. The development of the difference between supply and demand reservation prices is shown in Figure 3. Note that this difference is based on the indices, so the level of the difference has no interpretation, only the evolution over time can be interpreted. If the difference between supply and demand becomes bigger (or more positive), the reservation prices of sellers and buyers are, on average, further apart. This implies that there will be, on average, less matches (transactions) and that the market is less liquid. If the difference becomes smaller (or more negative), the reservation prices are closer together, and the market is said to be more liquid. Notice that there is a significant increase in illiquidity in 2008-Q3, which is generally seen as the start of the GFC. Illiquidity, according to measure 1, remains low until 2013-Q1, after which it starts decreasing again.

The illiquidity indices based on the second measure, the 'Corrected TOM', are also presented in Figure 3. Note that a higher TOM indicates a less liquid market, and thus is expected to be high (low) in a bust (boom). The measure indicates that there is a general increase in illiquidity since 2008-Q2 until 2013-Q1. After 2013-Q1, the corrected TOM decreases steadily until 2016-Q4. Figure 3 further shows an 'Uncorrected TOM' index, which is simply an index based on the average TOM of sold properties. Hence, this index is not corrected for withdrawals and differences in quality. The average, uncorrected, TOM is frequently used by practitioners and policymakers as a market indicator. The index clearly picks up less cyclicality and lags behind the corrected TOM index. In other words, it is better to use a corrected TOM index to monitor the market situation. However, estimating a corrected TOM index requires more data and is more cumbersome to estimate compared to taking the average TOM of sold properties.[8]

Visually, the contemporaneous commonality between the two measures for illiquidity is striking. The correlation between the measures in levels is indeed very high: 0.79. In differences, the correlation is somewhat lower, but still high: 0.58. The correlation between the first measure and the uncorrected TOM is much lower: 0.63 in levels and 0.10 in differences.

The turning points in the two measures occur in roughly the same quarter. The start of the GFC is visible one quarter earlier in the second measure (2008-Q2 vs 2008-Q3) and according to both measures, the recovery starts in 2013-Q1. The start of the GFC is visible somewhat later in the uncorrected TOM measure (2008-Q4). Especially the recovery starts later: in 2014-Q1.

Figure 3 additionally includes the house price index for Amsterdam from Statistics Netherlands (CBS). The peak before the GFC was in 2008-Q3 and the trough was in 2013-Q1. In general, when prices were decreasing during the GFC, both measures indicate a decrease in liquidity. Furthermore, the recovery in prices is accompanied by an increase in liquidity. The contemporaneous correlation between the first (second) measure and prices in levels is -0.39 (-0.46). This confirms the notion of pro-cyclical liquidity for the Amsterdam market. For more details on the relationship between prices and liquidity, see De Wit et al. (2013) and Van Dijk & Francke (2018).

Conclusion

In real estate, prices and liquidity famously move together. This article discusses two ways to empirically measure liquidity. The methods are estimated for the Amsterdam housing market. The relationship between the measures is surprisingly strong, given the fact that the measures use different information sets. The first measure uses prices, transaction dates, and housing characteristics whereas the second measure uses transaction dates, listing dates (or the TOM), withdrawals, and housing characteristics. In some sense, the result that the empirical measures are very similar is rather reassuring since both measures will result in a comparable conclusion regarding the market situation. Moreover, both measures show a commonality with the transaction price index for Amsterdam. This confirms the pro-cyclical behavior of prices and liquidity for the Amsterdam market.

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NOTES

1 Originally, the Heckman selection model corrects for the fact that the data on which a model is estimated is not random and may not be representative of the population. Intuitively, for this application, the correction is based on the fact that transaction volume is not the same over time. The model corrects for this and estimates indices as if transaction volume were constant.

2 The inverse Mills ratio is defined as the ratio of the estimated probability of sale to the estimated cumulative probability. By including this variable in the second step, a correction is made for the possible correlation between the decision to sell and the sales price equation.

3 The list price premium is defined as the premium of the list price relative to the expected sale price at the time of listing.

4 Amsterdam is a relatively large market, but the thesis also discusses results for smaller markets like Aalsmeer and Amstelveen.

5 After cleaning, the data contain roughly 80,000 properties (sold and unsold) * 48 quarters = 3.84 MLN.

6 The level of the buyers' and sellers' reservation prices is not estimated, only the difference over time. This is also the reason why the index of sellers' reservation prices can be higher than the index of buyers' reservation prices.

7 Granger causality investigates causality between time series to examine whether one series leads to other. Based on a VAR model in first differences with 2 lags, number of lags are chosen according to the AIC and HQIC information criteria. Chi^2 Demand > Supply 38.9, Chi^2 Supply > Demand 26.8, both are statistically significant at the 1% level.

8 The thesis additionally shows an index that is solely corrected for withdrawals (and not for quality), which is easier to estimate than the fully corrected index. Empirically, the results are very similar.

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