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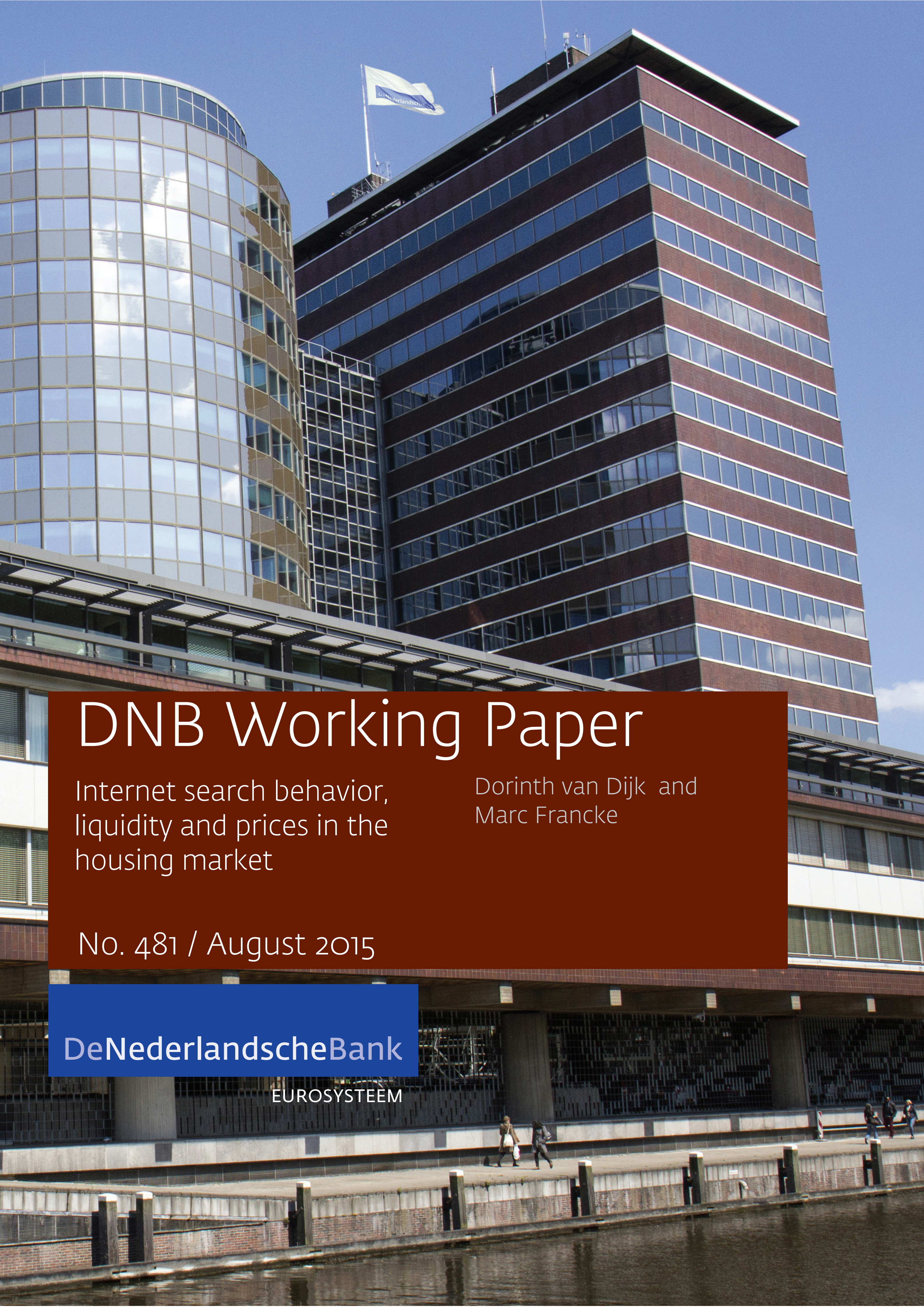
DOI
10.2139/ssrn.2654170

Publication date
2015

Document Version
Submitted manuscript



DNB Working Paper

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No. 481 / August 2015

DeNederlandscheBank

EUROSYSTEEM

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

Working Paper No. 481

August 2015

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Internet search behavior, liquidity and prices in the housing market

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August 2015

Abstract

In this article we employ detailed internet search data to examine price and liquidity dynamics of the Dutch housing market. The article shows that the number of clicks on online listed properties proxies demand and the amount of listed properties proxies supply. The created market tightness indicator Granger causes both changes in prices and market liquidity. The results of the panel VAR suggest a demand shock results in a temporary increase in liquidity and a permanent increase in prices. This is in accordance with search and matching models. This paper also provides evidence for loss aversion for current homeowners as prices generally declined during the sample period (2011 - 2013).

Keywords: House prices, Liquidity, Internet search data, Funda,Panel VAR.
JEL classification: R21, R31, C81.

Introduction

The internet proves to be a valuable source of information that foreshadows economic developments (Lohr, 2012). The basic idea is that future consumption is preceded by information gathering. Askitas and Zimmerman (2009) call this behavior preparatory steps to spend. In line with Wu and Brynjolfsson (2014) this paper employs internet search data to examine the effects for the housing market. We argue that potential home buyers start their search for a house by browsing the internet. The availability of detailed data in the Netherlands allows to examine the relationship between online search behavior and housing market developments on a local scale. The largest housing website in the Netherlands is *Funda.nl*, which has a stable market share of around 60% of all housing websites (Kerste, Baarsma, Roosenboom, & Risseeuw, 2012). Furthermore 83% of potential buyers uses Funda to find a suitable home (Conclusr, 2014). Therefore, the activity on this website, more specifically search behavior, could give a useful indication about (future) demand. Moreover, the number of listed properties could be a useful supply indicator. By combining these, we develop a demand versus supply or market tightness indicator. The advantage of these data is that it can be determined on a detailed scale, both over time (quarterly) and over the cross-section (municipalities).

A large share of the literature that examines the relationship between house prices and market liquidity, uses shocks in, for example, the labor market (Clayton, Miller, & Peng, 2010) or the mortgage rate (Hort, 2000; De Wit, Englund, & Francke, 2013) to determine the price-volume correlation. Although some articles examine the effects on a regional or local scale, these shocks usually occur on a national scale. By including the internet search data, the shocks can be linked more closely to local housing market developments. The main aim of this paper is to gain insights in the dynamics between market liquidity and house prices by using internet search query data.

The number of times watched per month of each individually online listed house is received from Funda. Due to privacy issues, the lowest level at which the internet search data can be linked to transaction data is on ZIP code level. Unfortunately, this level is too low in order to generate reliable times watched per house series, liquidity series or price indexes for all areas in the Netherlands. Therefore, we aggregate the data at the municipal and quarterly level. The result is a quarterly panel of all 403 Dutch municipalities that contains the number of houses which are for sale on Funda and how many times these houses have been clicked upon in the corresponding quarter. By dividing the times watched by the number of online listed houses, we generate a demand versus supply variable (*i.e.* market tightness indicator). This variable is subsequently included into a panel VAR in order to test whether it foreshadows developments on the housing market in the short run. We find that the market tightness indicator significantly Granger causes both house price changes and changes in liquidity.

Booming markets are typically characterized by more liquidity, while bust markets with declining prices usually show less liquidity (Stein, 1995; Clayton et al., 2010; De Wit et al., 2013). We consider three (not mutually exclusive) theories: (i) search and matching models, (ii) downpayment constraints and (iii) behavioral explanations. Following Genesove and Mayer (2001), De Wit et al. (2013), among others, we employ the rate of sales (*i.e.* sales in a given period divided by the number of houses for sale at the beginning of the period) as market liquidity measure.

To determine the liquidity-price relation, we estimate the impulse response functions of the market tightness indicator in a panel VAR framework. The cumulative effect on house prices is positive. Furthermore, we find that liquidity increases temporary, but reverts back to its original level after house prices have adjusted to the new level. This is in line with the search and matching framework in which buyers respond more quickly to a demand shock than sellers (Genesove & Han, 2012). Moreover, as the sample period is generally characterized by decreasing house prices, the paper provides empirical evidence for loss aversion for current homeowners (Genesove & Mayer, 2001).

The next section will discuss some of the literature on the relationship between prices and liquidity in the housing market and on the usage of internet data in economic research. Next the used data and the econometric model are described, followed by a discussion of the results with respect to price and liquidity dynamics in the property market.

Literature review

Prices and liquidity in the housing market

Since housing markets are not perfectly efficient (Case & Shiller, 1990) and no central housing exchange exists, the housing market can be characterized as a search market, in which buyers and sellers look for each other until they are matched (Genesove & Han, 2012). If there is a match, a trade will occur which means a house will be transacted. This search and matching principle is important in house price dynamics. Buyers and sellers set their reservation prices for which they are willing to buy or sell (Yavas & Yang, 1995; Knight, 2002). A transaction occurs if the reservation price of the buyer equals or exceeds the reservation price of the seller. Because of information asymmetry, buyers and sellers react differently to a shock. Genesove and Han (2012) show that sellers react to a demand shock with a lag. In other words sellers gradually adjust their reservation prices upwards (downwards) when demand increases (decreases). If demand increases, the group of buyers willing to pay the sellers' reservation prices increases. Hence, the probability that a transaction occurs increases.

Besides this search and matching approach De Wit et al. (2013) identify two other groups of theories in the literature: (i) the interaction between downpayment constraints, mobility and house prices and (ii) behavioral explanations. The authors stress however that the three approaches are not mutually exclusive. The fundamentals of the group of downpayment constraints lie within the work of Stein (1995), who introduces the *downpayment hypothesis*. This hypothesis states that homeowners who would like to buy a house are constrained by a downpayment that they have to make in order to buy the new house. We expect that the downpayment hypothesis is not very applicable to the Dutch situation as the current LTV-limit is relatively high[1].

Finally, there are behavioral explanations for the relationship between prices and liquidity. The behavioral bias of loss aversion is generally thought to hold in commercial (Bokhari & Geltner, 2011) and residential (Genesove & Mayer, 2001) markets. As prices go down, homeowners don't like to sell their houses for less than what they paid. Van der Cruijsen, Jansen, and

[1] Although the LTV-limit will be decreased to 100% by 2018, it is still high compared to other countries (Almeida, Campello, & Liu, 2006). An exception might be current homeowners who are *underwater* and are constrained by negative equity in buying their next home.

Van Rooij (2014) show that this principle of loss aversion combined with an endowment effect leads to an overestimation of the value of the house by the homeowner. The result is that reservation prices of sellers, hence asking prices, remain too high in bad times. Consequently, market liquidity will dry up during these times.

The financial economics literature generally distinguishes between market liquidity and funding liquidity (Brunnermeier & Pedersen, 2009). Market liquidity is defined as the ease at which assets can be traded while funding liquidity refers to the ease they can be financed. In the housing market literature examples of market liquidity include the rate of sales (Genesove & Mayer, 2001; Hort, 2000; De Wit et al., 2013), (seller) time on market (Jud, Seaks, & Winkler, 1996; Kang & Gardner, 1989; Glower, Haurin, & Hendershott, 1998) and the number of transactions (Wu & Brynjolfsson, 2014). An example of funding liquidity is the ease to obtain a mortgage (*i.e.* credit constraints, see Duca, Muellbauer, & Murphy, 2011; Mian & Sufi, 2009; Francke, Van de Minne, & Verbruggen, 2014). In this paper we are interested in market liquidity and employ the rate of sales as measure. The rate of sales is defined as the number of transactions in a period divided by the number of houses on the market at the begin of the period.

The relationship between market tightness (i.e. the ratio of buyers to sellers) and subsequent price appreciation is set out by Carrillo, De Wit, and Larson (2015). They use *ex ante* sale probability (based on the time on market) and sellers' bargaining power (based on list price, sale price and time on market) to measure market tightness. We relate to this paper by combining market tightness and price changes in one model. However, we propose a different measure for market tightness based on internet search data.

Internet as a new source for data

Recently, the use of alternative data has received some attention in the literature, or as the New York Times puts it: "Welcome to the Age of Big Data" (Lohr, 2012). Most articles use data that measure the gathering of information. The authors argue that information which consumers gather today, can say something about actions taken in the future. Hence, they provide a measure of preparatory steps to spend (Askitas & Zimmerman, 2009).

Askitas and Zimmerman (2009) find that Google Trends[2] is useful for employment forecasts in Germany. They construct an index based on Google search queries like "unemployment office", "unemployment rate", "personnel consultant" and the names of German job search agencies. They argue that a search query like "unemployment office" is associated with a *flow into unemployment* as this internet search behavior is linked to contacting the unemployment office. Conversely, searches for the names of German job search agencies are related to a *flow out of unemployment*. The findings suggest that the former has a significant positive impact on unemployment figures in both the short and long run and the latter has a significant negative impact on employment figures in the short run.

Similarly, Vosen and Schmidt (2011) also use data from Google Trends to forecast economic data. They create an indicator of private consumption based on Google Trends. They compare this Google Trends indicator with two survey-based private consumption indicators (*i.e.* MSCI and CCI). Google groups several search queries into aggregated search indexes regarding a certain topic, like "Real Estate". They find that using the indicator

[2]Back then known as Google Insights.

improves the out-of-sample one-month ahead forecasts. But more interestingly, the Google trends indicator significantly outperforms the MSCI and CCI indicators.

Recently, internet data is also applied in real estate research to predict future trends (Wu & Deng, 2015; Lee & Mori, 2014; Wu & Brynjolfsson, 2014). Wu and Brynjolfsson (2014) use data from Google Trends to forecast transactions and price developments in the housing market. They use quarterly search query data from Google for 51 states in the United States. They use two different predefined search query indexes: (i) Real Estate Listing and (ii) Real Estate Agencies. Category (i) reflects all search queries related to real estate listings and category (ii) approximates for home buying activities. They add Google search variables based on these categories to their baseline model and find that the coefficient on the Google variable is significantly related to contemporaneous home sales, but the lagged coefficient is insignificant. They find that their model with Google search variables beats the predictions published by the National Association of Realtors for future home sales.

Finally, Wu and Deng (2015) also use internet search data from Google to detect information flows regarding price discovery from larger cities to smaller cities. They use this data to construct an information flow indicator of the Chinese housing market. Although, Wu and Deng (2015) also examine price discovery in the housing market with internet search data, they seek to find a lead-lag relationship between larger and smaller cities (*i.e.* intercity price discovery). In this paper we specifically look at changes in liquidity and price discovery after a demand shock measured by internet search data.

Table 1: Overview of variables.

Variable	Description	Period	Frequency	Level	Source
pr	House price index	2000 - 2014	Quarterly	Municipality	NVM*
ros	Rate of sales	2000 - 2014	Quarterly	Municipality	NVM*
fw	Times watched	2011 - 2014	Quarterly	Municipality	Funda
fh	Number of listed houses	2011 - 2014	Quarterly	Municipality	Funda
wph	Times watched per house	2011 - 2014	Quarterly	Municipality	Funda*

*Own calculations. The price index and rate of sales are based on individual transaction data of the Dutch Brokerage Association (NVM), see Appendix for the index estimation. All variables except rate of sales in logs.

Data

This paper combines internet search data, price changes and changes in market liquidity in a single panel VAR model. Both transaction data and click data are available on the individual level, but due to privacy issues the lowest scale at which the data can be matched is on ZIP[3] code level. Unfortunately, we have to aggregate the data further to municipal and quarterly levels because ZIP code level is too detailed to generate reliable price, liquidity and internet search indexes. Hence we estimate a price index and the rate of sales from individual transaction data and a times watched per house series from individual click data for each municipality in each quarter (Table 1).

Transaction data

We use detailed data from the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM) to construct the quarterly house price index at the municipal level. The data include the sale price, date of sale and several house-specific characteristics (see Appendix). In total there are over 1.6 million transactions[4] included between 2000 and 2014.

[3] 4 digit level.

[4] A transaction is denoted as "transaction" in the NVM database at the time of the signing of the buyers' contract. Other Dutch databases like the Kadaster (Dutch Land Registry) a transaction is included when the legal transfer takes place. Therefore it is generally found that NVM transaction data leads other data sources.

Although a relatively large share of all transactions in the Netherlands is included, the data used in this research are not fully representative of the Dutch housing market. The used data set includes approximately 69%[5] of all transactions over the sample period (2011 - 2013). Kerste et al. (2012) and De Wit et al. (2013) report percentages of 75% in 2010 and 55-60% in 2007.

The house price index is estimated using a Hierarchical Trend Model (HTM) as proposed by Francke and De Vos (2000) and Francke and Vos (2004). A HTM is a hedonic price model that specifically addresses the spatial and temporal dependence of selling prices and is well suited to construct constant quality price indexes in thin markets. The model and price indexes of the municipalities within one COROP-region[6] (Amsterdam region) are presented in the Appendix.

Figure 1 contains a map with the values of a standardized home in each municipality between 2011 and 2013. The map shows that central areas in the *Randstad* or areas close to the *Randstad* and cities are more expensive. Furthermore, the constant quality prices are the lowest in the Northern provinces of *Friesland*, *Groningen* and *Drenthe*.

The rate of sales per municipality per quarter is determined by dividing the number of sales by the number of houses for sale at the beginning of the quarter. The series are seasonally adjusted and smoothed by estimating an unobserved components model (local level[7], see Equations 3a - 3c in the

[5]The used NVM data set of consists of roughly 1.6 million transactions between 2000 and 2013. The Dutch National Bureau of Statistics (CBS, they regard all transactions) reports little under 2.4 million transactions in this same period.

[6]The Dutch equivalent of a NUTS-3 region and comparable to the MSA classification in the US.

[7]We also experimented with a local linear trend model, but the trend component proves to be insignificant for most municipalities.

Appendix). Figure 5 in the Appendix includes rate of sales estimates of municipalities within one COROP-region.

During the sample period, house prices generally declined (Table 2). During 2013 some areas started recovering, but on average house prices declined. The rate of sales declined in 2011 and 2012, but started increasing in 2013.

The results of Fisher's combing p-values test (Maddala & Wu, 1999), in which separate ADF regressions are run for each municipality are shown in Table 3. House prices are I(1): the series are non-stationary in levels but stationary in first-differences. The rate of sales series are I(0).

Figure 1: Map that depicts the value of a standardized home within each municipality between 2011 and 2013.

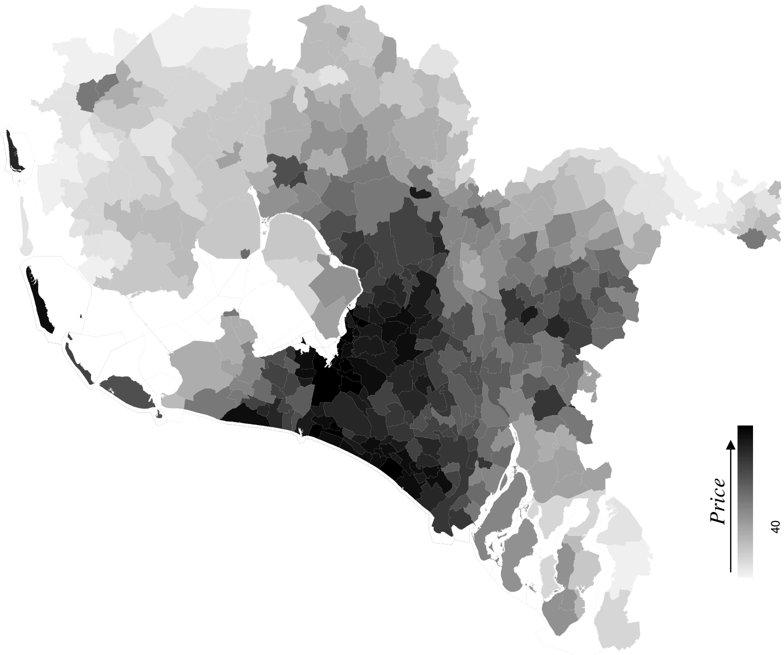


Figure 2: Map that depicts the average times watched per house of each municipality between 2011 and 2013.

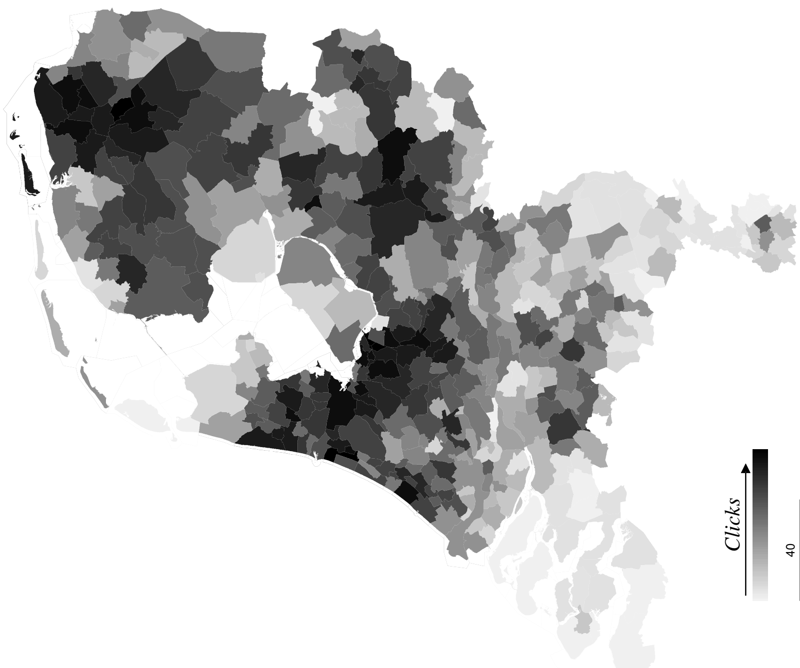


Table 2: Descriptive statistics 2011 - 2013 per year.

Year	Variable	Average	σ	Min	Max
2011	pr	8.4786	0.4572	7.1014	9.6625
	ros	0.0421	0.0135	0.0103	0.1158
	WPH	248.91	92.98	39.47	679.36
	wph	5.4379	0.3788	3.8421	6.3550
	Δpr	-0.0123	0.0059	-0.0367	0.0080
	Δros	-0.0026	0.0048	-0.0282	0.0212
	Δwph	-0.0471	0.0652	-0.3382	0.2145
2012	pr	8.4127	0.4577	7.0827	9.6298
	ros	0.0372	0.0109	0.0147	0.0903
	WPH	238.72	80.51	29.67	621.41
	wph	5.4043	0.3733	3.5568	6.1941
	Δpr	-0.0174	0.0052	-0.0407	0.0027
	Δros	-0.0004	0.0040	-0.0255	0.0184
	Δwph	0.0012	0.0501	-0.2347	0.2693
2013	pr	8.3667	0.4568	7.0768	9.5625
	ros	0.0423	0.0148	0.0161	0.1242
	WPH	262.20	78.33	38.29	536.67
	wph	5.5137	0.3465	3.4934	6.2972
	Δpr	-0.0062	0.0070	-0.0331	0.0164
	Δros	0.0024	0.0048	-0.0162	0.0616
	Δwph	0.0556	0.0628	-0.2136	0.3889
2011-2013	pr	8.4193	0.4594	7.0768	9.6625
	ros	0.0405	0.0134	0.0103	0.1242
	WPH	249.95	84.72	29.67	679.36
	wph	5.4519	0.3692	3.4934	6.3550
	Δpr	-0.0120	0.0076	-0.0407	0.0164
	Δros	-0.0002	0.0050	-0.0282	0.0616
	Δwph	0.0078	0.0719	-0.3382	0.3889

Average and σ depict the mean and standard deviation of the respective variable per year of all municipalities. Min and Max describe the minimum and maximum value of the variable of any municipality in the corresponding year. WPH and wph denote the regular and log-transformed version of the watched per house variable respectively. Δ denotes the average quarterly change of the given year.

Table 3: Results of the combining p-value tests to test for a unit root in the specified variables.

Variable	1 lag in ADF		3 lags in ADF	
	p-statistic	p-value	p-statistic	p-value
pr	488.08	1.0000	617.80	1.0000
ros	926.72	0.0020***	1584.88	0.0000***
wph	1118.20	0.0000***	1102.11	0.0000***
Δpr	976.14	0.0000***	1732.69	0.0000***
Δros	1927.74	0.0000***	3707.65	0.0000***
Δwph	1178.62	0.0000***	6341.29	0.0000***

The regression include a time trend and cross-sectional specific intercepts between 2011 and 2013. H_0: All panels contain unit roots, H_a: At least one panel is stationary. There has been experimented with different lag-lengths in the separate ADF equations, lags 1 and 3 are shown. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Internet search data

Internet search popularity is based on data of the housing website *Funda*. In a survey executed by Conclusr (2014), 93% of the respondents mention "Funda" when they are asked to name a housing website. Additionally, 81% prefers Funda if they would sell their home online. In 2013 there were 4.2 million unique visitors per month on the website. Kerste et al. (2012) show that Funda is by far the most popular housing website in the Netherlands. According to this research, Funda has a stable market share of around 60% of all Dutch housing websites[8]. The owner of Funda is NVM from which the transaction data originates. Kerste et al. (2012) point out that most of the brokers that are active on Funda are NVM brokers. Hence the online listed properties are mostly properties that are brokered by these NVM brokers.

The data describes the *times watched* per *listed house* per month. Next, listings of which the number of clicks is in the top percentile of each year are removed. These outliers are likely to be houses of celebrities or other irregular properties and may be not representative for the "normal" number of clicks. For example, in 2011 the house at the 99th percentile is watched almost 3,600 times, while the house that is watched most often is watched almost 315,000 times. After aggregation to quarterly data, the mean number of times watched per quarter in 2011 is 249 after the removal of these outliers. The listed houses are subsequently linked to a municipality. In the next step the totals per municipality and per quarter are calculated. The results are (i) *times watched* and (ii) *number of houses* per municipality per quarter.

To measure *internet search popularity* we generate an additional variable:

[8] The websites that have the second and third largest market share are *Jaap.nl* and *Huizenzoeker.nl* with market shares of 9% and 8% respectively.

times watched per house. This variable measures how many times listed properties have been watched on average per quarter per municipality. This variable has an intuitive interpretation: a higher value for this variable could indicate a more popular area. The concept behind this interpretation is as follows. More clicks on a listed property could imply the property is relatively popular. Therefore, more clicks on houses (relative to the total number of listed houses) in a certain area could be evidence for a more popular area. The number of times watched can therefore be characterized as a demand variable. The number of listed houses per area can proxy for supply in a certain area, as these are roughly equal to the number of houses for sale in this area. The generated variable can therefore approximate market tightness.

With respect to the popularity of the municipalities on Funda, the map in Figure 2 provides a clear-cut overview. More popular areas are the areas in or close to larger cities. The comparison between the maps regarding prices and times watched per house is striking. For example, houses in the *Randstad* are watched relatively more often and are also more expensive. Likewise, houses in municipalities which are located in or near larger cities are watched more often and are more expensive.

Although this pattern is visible for most of the country, some areas in the North (*e.g. Groningen*) show a somewhat different pattern. A possible explanation for this phenomenon could be that in the years over which the sample was taken (2011 - 2013), this area was hit by several induced[9] earthquakes. During these times questions were raised whether these earth-

[9] The earthquakes in the area are caused by natural gas extraction, for more information see http://www.rijksoverheid.nl/onderwerpen/aardbevingen-in-groningen/aardbevingen-door-gaswinning-in-groningen.

quakes had an impact on house prices. Although research by Francke and Lee (2013) has shown that prices changes in *Groningen* did not differ significantly from a comparison area, news regarding house prices in *Groningen* may have triggered internet search behavior. This simultaneous causality is explicitly taken into account as internet search behavior is also included as dependent variable. Furthermore, we perform an additional robustness check that excludes this area.

To cope with seasonal effects and noise, the times watched per house series have been seasonally adjusted and smoothed by estimating an unobserved components model. For this local level model, see the description and Equations (2d) - (3c) in the Appendix.

Over the sample period, the times watched per house variable decreased in 2011, remained relatively stable in 2012 and started increasing in 2013 (Table 2). A graph showing the development of the time watched per house in the Amsterdam region is included in Figure 5 in the Appendix.

Finally, the unit root tests in Table 3 indicate the times watched per house variable is I(0).

Model

In order to examine the relationship between house prices and liquidity and how these respond to changes in the time watched per house variable we define a panel Vector Autoregression (VAR) in (1). Table 1 describes the used variables. All variables except the rate of sales are modeled in logs. We take the first difference of these variables in the panel VAR.

$$\Delta y_{i,t} = \begin{bmatrix} \Delta pr_{i,t} \\ \Delta ros_{i,t} \\ \Delta wph_{i,t} \end{bmatrix} = \sum_{q=1}^{Q} \mathbf{\Gamma}_q \Delta y_{i,t-q} + \lambda_t + \varepsilon_{i,t}, \varepsilon_{i,t} \sim N(0, \Sigma_\varepsilon). \tag{1}$$

Here y is a vector of dependent variables which contains changes in log house prices (pr), changes in liquidity (ros) and changes in log number of clicks per property (wph). This vector depends on lagged values of these variables up to quarter Q and the estimated coefficients are included in matrix $\mathbf{\Gamma}$. Subscripts i and t denote the municipality and quarter respectively. Time fixed effects are included in the models and are denoted by λ_t. By transforming the variables, which in this case is done by taking first differences, the unobserved heterogeneity between the municipalities cancels out. Finally ε is the error term.

In this model price changes, changes in liquidity and changes in clicks are modeled simultaneously. The simultaneous causality is explicitly taken into account by the impulse responses generated by the VAR model and are therefore able to provide insights in this relationship.

It is generally accepted that house price changes exhibit positive serial correlation in the short run (Capozza, Hendershott, & Mack, 2004). This suggests that lags of the dependent variable should be included in the models. Hence, modeling the data as a dynamic panel seems most natural. A problem that arises when including lags of the dependent variable in the regression is that these lags are correlated with the error term and therefore will result in biased results (*i.e.* Nickell's bias, see Nickell, 1981; Roodman, 2009). In order to cope with these issues, the parameters of interest are estimated using system Generalized Method of Moments (GMM).

Results

Estimation results

Table 4 presents the results of the quarterly panel VAR of the house price index, rate of sales and times watched per house for Dutch municipalities between 2011 and 2013. In column (i) the change in house prices is the dependent variable, in column (ii) the change in the rate of sales is the dependent variable and in column (iii) the change in in times watched per house is the dependent variable. The optimal number of lags as indicated by the information criteria[10] is two quarters.

The results indicate that the one-quarter lagged times watched per house variable is positive and significant in the house price equation (at 5%) and positive and marginally significant (at 10%) in the rate of sales equation. This indicates that if there is a growth in clicks in the previous quarter, this results in a growth in house prices and the rate of sales in this quarter. The Granger causality tests confirm these findings. These indicate that a change in the times watched per house Granger causes both changes in house prices and the rate of sales. This confirms the findings of Carrillo et al. (2015), who find that market tightness is positively related to future price appreciation. Although, it might seem that a one-quarter lag seems too short (*i.e.* the time between browsing the internet and the sale might be longer). The date of transaction is the date of the signing of the buyers' contract, the actual

[10]MMSC-Bayesian information criterion (MBIC), MMSC-Akaike's information criterion (MAIC), and MMSC-Hannan and Quinn information criterion (MQIC), see Andrews and Lu (2001).

Table 4: Panel VAR regression results.

	Δpr	Δros	Δwph
Δpr_{t-1}	0.4860***	0.0091	-0.0342
	(14.8)	(0.4)	(-0.1)
Δpr_{t-2}	0.0455**	-0.0285	-0.0173
	(2.1)	(-1.2)	(-0.1)
Δros_{t-1}	0.0466*	-0.0597*	-0.7902***
	(1.8)	(-1.6)	(-3.4)
Δros_{t-2}	0.0120	-0.0024	-0.4074**
	(0.7)	(-0.1)	(-2.2)
Δwph_{t-1}	0.0036***	0.0031*	0.1445***
	(2.6)	(1.9)	(6.6)
Δwph_{t-2}	0.0003	-0.0020	0.0268
	(0.2)	(-1.4)	(1.6)
Granger causality tests:			
Δpr	N/A	1.814	0.033
Δros	3.449	N/A	12.175***
Δwph	7.096**	6.187**	N/A
All variables	10.974**	9.766**	12.343**
Fixed effects	Quarterly and municipal		
N	3224		
Number of panels	403		
Sample period	2011Q1 - 2013Q4		
Eigenvalue stability condition	Yes, panel VAR is stable		

In (i) changes in log house prices are regressed on lagged changes in log house prices, lagged changes in the rate of sales and changes in log times watched per house, in (ii) changes in the rate of sales are regressed on lagged changes in rate of sales, lagged changes in log house prices and changes in log times watched per house. Column (iii) includes the times watched per house as dependent variable. The time and cross-sectional dimensions are 12 quarters between 2011 and 2013 and 403 municipalities respectively. Coefficients are estimated using system GMM and standard errors are robust to hetereoskedasticity and autocorrelation and are clustered by municipality. Optimal number of lags based on information criteria. The table further depicts Granger causality tests of the variables in each equation. T-statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

legal transfer is approximately three months later[11].

The model also provides evidence regarding the price-volume correlation. Changes in the lagged rate of sales has a positive effect on price changes today, although it is only marginally significant. This confirms the findings of, for example, Miller and Sklarz (1986), who find that the changes in the rate of sales is a leading indicator of price changes. The Granger causality test, however, cannot be interpreted as significant. There seems to be no relationship running from price changes to changes in liquidity. The lack of significance in these findings might be attributed to the relative short

[11]For example, De Wit et al. (2013) use a lag of 3 months, see also http://www.kadaster.nl/web/Themas/Themapaginas/dossier/Toelichting-op-de-cijfers-in-het-Vastgoed-Dashboard.htm.

sample (*i.e.* 3 years).

Interestingly, the change in the times watched per house responds (besides on its own lag) also significantly to changes in the rate of sales but not to changes in prices. There seems to be a negative relationship between changes in the rate of sales and changes in times watched per house. The underlying mechanism might be the following. If more houses are sold in the previous quarter in a municipality, there are fewer potential buyers left who are still looking to buy a house in this municipality, hence the reduction in clicks. The Granger causality test confirms that changes in the rate of sales Granger causes changes in the times watched per house.

Impulse responses

To interpret the results economically, this section looks at the impulse responses generated by the model in Table 4. The main advantage of interpreting the results through studying the impulse responses is that these capture the full dynamics of the model. If, for example, the times watched per house increases, the one-quarter lagged coefficient indicates a direct effect on prices. There is, however, an additional effect running through liquidity. Furthermore, the autoregressive components amplify the effects. This is also clearly visible in Figure 3, which depicts the impulse responses. The dashed lines represent the 95% confidence bounds and are obtained by Monte Carlo simulation. The size of a shock amounts to one standard deviation of the impulse variable.

In the bottom left panel of Figure 3 a shock has been given to the growth in the times watched per house and the function depicts the response of change in house prices. The graph shows that the largest growth in house prices is in the quarter after the shock, but that the shock only dies out after roughly one year. The shock also has a positive impact on the change in the rate of sales in the first quarter. The shock has a negative impact (although only marginally significant) on the rate of sales in the second quarter.

The cumulative impulse responses as presented in Figure 4 depict the cumulative growth of the response variable after a shock in the impulse variable. Hence, these can be interpreted as the level change of the response variable. This graph indicates that a change in the number of clicks has a permanent effect on prices, but only a temporary effect on liquidity as measured by the rate of sales. An increase in one standard deviation (37%) in the times watched per house leads to a permanent price increase of roughly 0.4%. The rate of sales increases by approximately 0.1%-point after 1 quarter. After 2 quarters, the rate of sales decreases to the pre-shock level.

The slow adjustment process of prices during a period in which prices generally decreased (Table 2) are also supportive of the principle of loss aversion as documented by Genesove and Mayer (2001). To illustrate this, consider the case of a negative demand shock. Because sellers keep their listing prices too high during these bad times, fewer transactions occur. After sellers realize the market has gone down, they lower their listing prices resulting in further price decreases.

To summarize the main findings, liquidity responds fairly quickly to a positive demand shock, its effect is short-lived. Prices respond much more gradual and there seems to be a permanent increase in prices. This is in line with the search and matching models as proposed by Genesove and Han (2012). Finally, the findings are also in line with the principle of loss aversion as documented by Genesove and Mayer (2001).

Figure 3: Impulse-response functions, impulse variable → response variable.

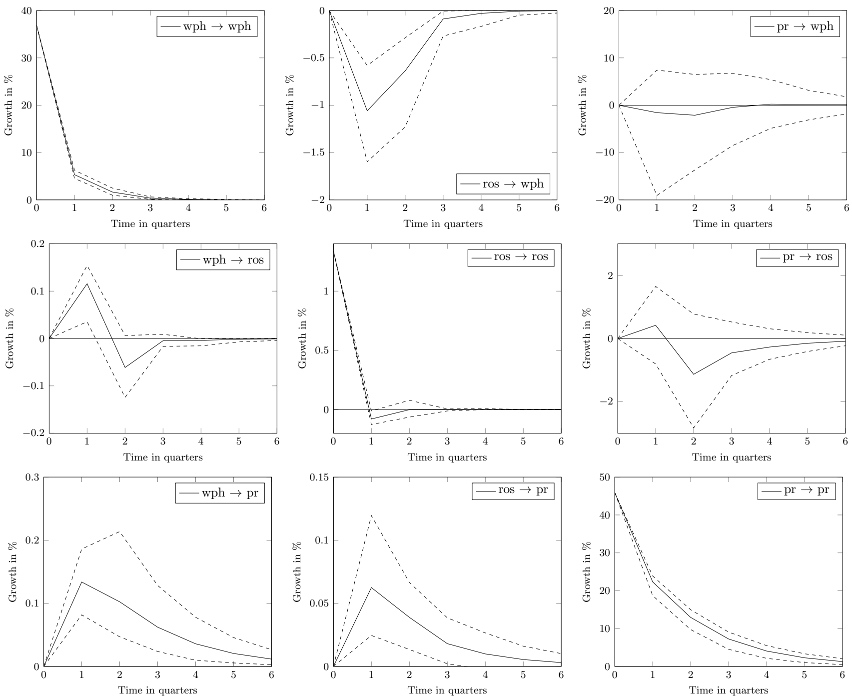
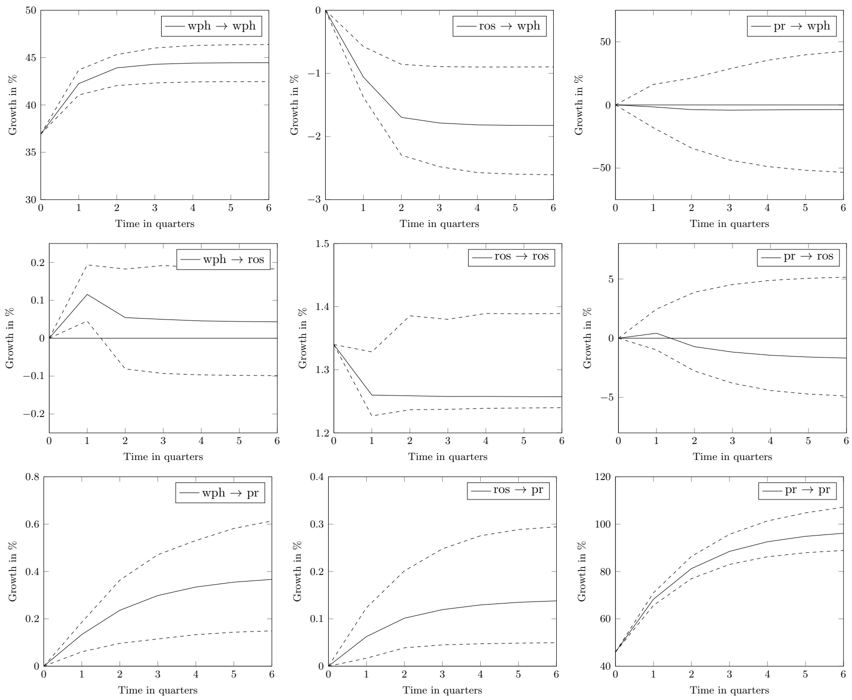


Figure 4: Cumulative impulse-response functions, impulse variable → response variable.



Robustness checks

The earthquakes in the Northeastern part of the Netherlands (*Groningen*) might have resulted in search behavior, while people were not actually interested in buying in the area. This might be a cause for bias in the estimated coefficients. We did a robustness check on the model that excludes the municipalities within the earthquake area[12]. The results of the Panel VAR model excluding the earthquake area are in Table 5. All coefficients and their significance are very similar to those presented in Table 4, hence the coefficients are not biased due to the inclusion of the region.

Table 5: Robustness check: Panel VAR regression results without earthquake areas.

	Δpr	Δros	Δwph
Δpr_{t-1}	0.4744***	0.1024	0.0054
	(14.2)	(0.4)	(0.0)
Δpr_{t-2}	0.0404*	-0.0293	0.0153
	(1.8)	(-1.2)	(0.1)
Δros_{t-1}	0.0497*	-0.0590*	-0.7665***
	(1.9)	(-1.7)	(-3.2)
Δros_{t-2}	0.0120	-0.0024	-0.4074**
	(0.7)	(-0.1)	(-2.2)
Δwph_{t-1}	0.0037***	0.0032*	0.1425***
	(2.6)	(1.9)	(6.3)
Δwph_{t-2}	0.0004	-0.0016	0.0361**
	(0.3)	(-1.1)	(2.1)
Granger causality tests:			
Δpr	N/A	1.912	0.008
Δros	3.537	N/A	10.709***
Δwph	7.274**	5.211*	N/A
All variables	11.335**	8.970*	10.864**
Fixed effects	Quarterly and municipal		
N	3040		
Number of panels	380		
Sample period	2011Q1 - 2013Q4		
Eigenvalue stability condition	Yes, panel VAR is stable		

In (i) changes in log house prices are regressed on lagged changes in log house prices, lagged changes in the rate of sales and changes in log times watched per house, in (ii) changes in the rate of sales are regressed on lagged changes in rate of sales, lagged changes in log house prices and changes in log times watched per house. Column(iii) includes the times watched per house as dependent variable. The time and cross-sectional dimensions are 12 quarters between 2011 and 2013 and 380 municipalities respectively. The municipalities within the earthquake area have been left out. Coefficients are estimated using system GMM and standard errors are robust to hetereoskedasticity and autocorrelation and are clustered by municipality. Optimal number of lags based on information criteria. The table further depicts Granger causality tests of the variables in each equation. T-statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[12] These are the municipalities that are located within the COROP regions *Oost-Groningen*, *Delfzijl en Omgeving* and *Overig Groningen*.

Conclusion

This paper has shown that the internet search data variable *times watched per house* Granger causes both house price changes and changes in market liquidity. Furthermore, the inclusion of this variable in a panel VAR model allows to gain useful insights in housing market dynamics thereby empirically confirming the theoretical findings of Genesove and Han (2012). The findings suggest a demand shock gets temporarily absorbed in market liquidity as measured by the rate of sales. Prices adapt more gradually and the effect is permanent. Following this price adjustment, liquidity reverts back closely to its original level.

Moreover, internet search behavior does not seem to respond to price changes, but only to changes in liquidity. The relationship between changes in liquidity and time watched per house is found to be negative. Possibly, because more houses sold in the previous quarter indicates there are fewer potential buyers left who are still looking to buy in a particular municipality.

Finally, as the sample period is characterized by declining house prices, it might be the case that homeowners kept their listing prices too high. Hence, the slow adjustment process of prices found in this paper, is supportive of loss aversion in the housing market (Genesove & Mayer, 2001).

In the internet era vast amounts of data are produced which can be incorporated into economic models. We have shown that the housing market proves to be no different than, for example, the labor market or the stock market when it comes to the added value of internet data. Although vast amounts of data are received, it is only possible to use Funda data from 2011 onward, hence the sample period is only three years. In these three years prices generally decreased, therefore it would be interesting to repeat the research in price increasing markets to see whether the dynamics are different. Furthermore, although the data is available at house level it cannot be linked to the address due to privacy issues. If the Funda data could be linked to a specific address, it can be merged with the database from which the house price and liquidity indexes originate. This would allow to do the research on an individual house level rather than on an aggregated scale.

Acknowledgments

The authors would like to thank both Funda and the NVM for supplying the data. Special thanks go out to Ruben Scholten for collecting and organizing the Funda data. We are also grateful to seminar participants of the 2015 Global Real Estate Summit, NVM research department and De Nederlandsche Bank and for providing useful comments. Finally, we would like to thank Martijn Dröes, Jakob de Haan, Alex van de Minne, Simon Stevenson and Patrick Tuijp for providing many helpful suggestions.

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

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Appendix

House price index and rate of sales estimation

The house price index is estimated using a Hierarchical Trend Model (HTM). The HTM is estimated recursively over 40 COROP-regions in the Netherlands to allow for different effects of house characteristics on prices in each region. To estimate a quarterly price index on municipal level, each COROP-region is subdivided into municipalities each containing their own trend which is modeled as a random walk. The COROP-region trend is modeled as a local linear trend. By summing the municipal trend and the COROP-region trend, the quarterly price index of 403 municipalities is estimated. The HTM is defined in Equations (2a) - (2d) (Francke & Vos, 2004):

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

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

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

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

Here y_t is a vector of log selling prices within a COROP-region, μ_t is the COROP-trend, and vector θ_t contains the municipal-specific trends. Furthermore, matrix D is a selection matrix to select the municipality in which the transaction has taken place. Finally, X_t is a vector containing house characteristics with the estimated coefficients β.

Table 6 includes a table with summary statistics of the regressions of all COROP-regions. Additionally results for one COROP region (COROP region 23 *Amsterdam region*) are presented. Table 7 presents the estimated coefficients for this region and the top left panel of Figure 5 presents the estimated price index for six municipalities within this COROP region.

Finally, the rate of sales is estimated by dividing the number of transactions by the houses for sale at the beginning of the quarter. The estimated rate of sales for the municipalities within the Amsterdam region are depicted in in the top right panel of Figure 5.

The rate of sales and times watched per house series have been seasonally adjusted and smoothed by estimating an unobserved components model (Local Level). This process is depicted in Equations (3a) - (3c) in which y_t is the observation vector, μ_t is the trend component (i.e. smoothed series) and γ_t is a stochastic seasonal component. Moreover, dummies for 2012Q4 and 2013Q1 are included in these unobserved component models as there was a sudden increase and subsequent drop in these quarters due to the abolishment of the deductibility of interest-only mortgages.

$$y_t = \mu_t + \gamma_t + \varepsilon_t, \varepsilon_t \sim N(0, \sigma_\varepsilon^2 I), \tag{3a}$$

$$\mu_{t+1} = \mu_t + \eta_t, \eta_t \sim N(0, \sigma_\eta^2), \tag{3b}$$

$$\gamma_t = -\sum_{j=1}^{s-3} \gamma_{t-j} + \zeta_t, \zeta_t \sim N(0, \sigma_\zeta^2). \tag{3c}$$

Table 6: Summary statistics of HTM estimations of the price index.

COROP	R^2	RMSE	N
1	0.818	0.177	11,097
2	0.813	0.176	4,561
3	0.834	0.178	31,410
4	0.844	0.172	23,844
5	0.845	0.177	11,585
6	0.875	0.147	16,840
7	0.852	0.157	20,808
8	0.826	0.167	15,979
9	0.847	0.146	12,064
10	0.850	0.140	28,960
11	0.854	0.150	13,480
12	0.859	0.152	42,322
13	0.855	0.149	54,033
14	0.868	0.149	27,552
15	0.846	0.160	55,828
16	0.877	0.138	18,130
17	0.861	0.160	107,482
18	0.839	0.166	21,771
19	0.888	0.143	25,255
20	0.857	0.150	15,871
21	0.882	0.191	22,019
22	0.848	0.134	13,350
23	0.842	0.175	61,618
24	0.900	0.177	26,194
25	0.878	0.145	30,551
26	0.882	0.197	43,689
27	0.860	0.137	12,618
28	0.883	0.136	25,486
29	0.841	0.169	72,992
30	0.869	0.143	25,472
31	0.860	0.190	7,157
32	0.864	0.170	14,645
33	0.848	0.160	45,383
34	0.876	0.144	37,388
35	0.867	0.140	43,744
36	0.876	0.141	50,907
37	0.864	0.143	8,171
38	0.830	0.152	12,145
39	0.833	0.181	18,502
40	0.869	0.123	37,110
Average	0.857	0.158	29,200

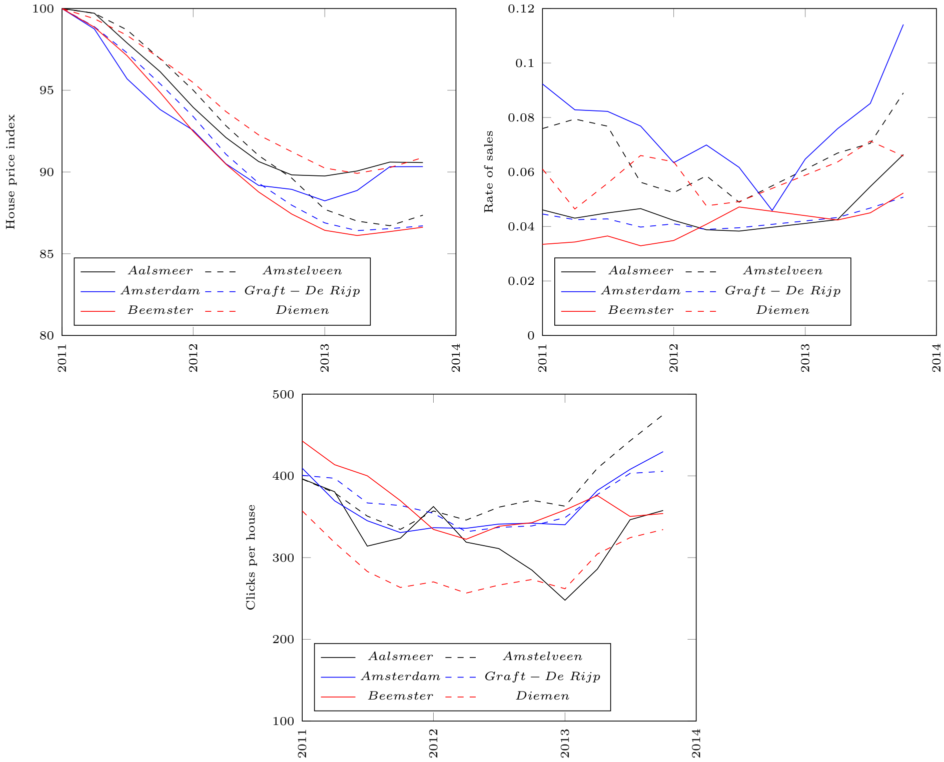
The R^2, RMSE and N denote the R-squared Root Mean Squared Error and the number of observations of the HTM in the respective COROP-region.

Table 7: Estimatates of the coefficients of house characteristics on the log of transaction price in COROP region 23 (Amsterdam region).

	Dep var: Log transaction price	
Variable	Beta	T-stat
Log housesize smaller than $350m^3$	0.655	144.2
Log housesize 350 - $500m^3$	0.030	57.8
Log housesize larger than $500m^3$	0.056	80.8
Log lotsize smaller than $500m^3$	0.103	48.9
Log lotsize 500 - $1500m^3$	0.001	1.5
Log lotsize larger than $1500m^3$	0.001	0.5
Number of rooms	0.027	41.2
Built before 1905	0.338	93.8
Built 1906 - 1930	0.173	57.1
Built 1931 - 1944	0.149	39.5
Built 1945 - 1959	0.046	13.3
Built 1960 - 1970	-0.031	11.7
Built 1971 - 1980	-0.045	16.5
Built 1981 - 1990	(omitted)	(omitted)
Built 1991 - 2000	0.071	28.5
Built after 2001	0.087	23.1
HT Simple	-0.029	5.9
HT Single-family	(omitted)	(omitted)
HT Canal House	0.453	55.2
HT Mansion	0.153	53.3
HT Living Farm	0.135	10.0
HT Bungalow	0.266	42.5
HT Villa	0.310	61.6
HT Manor	0.338	23.0
HT Estate	0.399	3.1
HT Ground floor app.	0.134	28.6
HT Top floor app.	0.086	25.5
HT Multiple level app.	0.054	7.7
HT app. w/porch	0.077	15.7
HT app. w/gallery	-0.017	2.9
HT Nursing home	-1.091	31.4
HT Top and ground floor app.	0.173	11.2
Very poor maintenance	-0.230	16.3
Very poor to poor maintenance	-0.208	7.6
Poor maintenance	-0.145	25.4
Poor to average maintenance	-0.166	13.2
Average maintenance	-0.094	32.4
Average to good maintenance	-0.081	16.6
Good maintenance	(omitted)	(omitted)
Good to excellent maintenance	0.088	17.4
Excellent maintenance	0.084	40.0
No parking	(omitted)	(omitted)
Parking	0.068	34.5
Market conditions	Common trend (Local Linear Trend)	
Location	Municipal trends (Random Walk)	
R^2	0.842	
RMSE	0.175	
Observations	61,618	

HT = Housetype, app. = apartment

Figure 5: Price indexes (top left panel), rate of sales (top right panel) and times watched per house (bottom panel) of six municipalities within COROP region 23 (Amsterdam region).



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