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Alfred L. Teye

Delft University of Technology, Research for the Built Environment (OTB),
Delft, The Netherlands

Jan de Haan

OTB, and Division of Corporate Services, IT and Methodology, Statistics Netherlands
(CBS), The Hague

Marja G. Elsinga

Delft University of Technology, Research for the Built Environment (OTB),
Delft, The Netherlands

House Price Risk and Sub-District House Price Dynamics: The Case of Amsterdam

Alfred L. Teye[a,*], Jan de Haan[b], Marja G. Elsinga[a]

[a] *Delft University of Technology, Research for the Built Environment (OTB), Delft, The Netherlands*
[b] *OTB, and Division of Corporate Services, IT and Methodology, Statistics Netherlands (CBS), The Hague*

Abstract

The recent Global Financial Crisis has lent even greater urgency to the need for households to understand the risks and dynamics of the residential property market better. This paper uses a rich dataset on individual residential property transactions between 1995 and 2014 in Amsterdam to study the risks and the inter-dependency of house prices in the sub-district housing markets. The paper also examines the impact of house price growth in Amsterdam on the wider national trend. Simple summary statistics are adopted to characterise the dynamics and to compute the risks, while the inter-dependencies and the city-wide impact are analysed using Granger causality and cointegration techniques. The analysis establishes that house prices are generally higher, growing at faster and more volatile rates as we move from the peripheral to the districts into the central area. Furthermore, the appreciation rate of property prices in Amsterdam has a significant impact on the national trend, while there is limited systematic inter-dependency among the sub-markets themselves.

Keywords: Cointegration, Financial crisis, Granger causality, Housing market, Risk, The Netherlands

1. Introduction

The need for a better understanding of the dynamics and risks of the residential property market for households, particularly following the 2007-08 financial crisis cannot be over-emphasized. At the same time, however, a thorough empirical study of the market is either carried out using complex theoretical models that are beyond the grasp of ordinary households or impeded by a lack of data. For the data problem, it is common in the literature to resort to country-wide or regional studies using aggregated data. This practice, however, reduces the understanding of the market conditions at the smaller district and neighborhood levels.

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*Corresponding author at: Delft University of Technology, Research for the Built Environment (OTB), Faculty of Architecture and the Built Environment, P. O. Box 5043, 2600 GA, Delft, South-Holland, The Netherlands. E-mail: a.l.teye@tudelft.nl

In this paper, the aim is to study the housing market in the smaller sub-districts in order to understand the dynamics and risks, as well as the inter-dependency of price developments between these sub-markets. This information may also be of interest to other institutions that invest in particular sub-districts and policy makers who wish to control the overall functioning of the housing market. We obtained a rich dataset on individual house transactions between 1995 and 2014, which enabled us to analyse the case of the City of Amsterdam in the Netherlands. First of all, we created customised house price indexes for the city's local sub-districts using the time dummy hedonic method. Secondly, we used relatively simple summary statistics to compare the characteristics and risks in the different districts. Specifically, the metrics used included: statistical deviation, semi-deviation, 'decline severity' and a version of the semi-deviation, which we refer to as the 'inter-district deviation'.

The standard deviation is the measure of the dispersion or variation in house prices from the average, while the 'decline severity' is intended to capture the impact of the recent economic crisis on property price developments in the individual sub-districts. This was defined here simply as the percentage decrease from the peak to the trough in average prices between 2007 and 2013 - the period following the global economic crisis when Dutch house prices declined sharply. The semi-deviation is a version of the standard deviation that considers the average deviation of values below the mean only. This is one of the common downside risk measures for investment analysis in the mainstream finance literature, but it is used surprisingly seldom in the housing context (see Foo and Eng, 2000; Grootveld and Hallerbach, 1999; Wolski, 2013).

We defined the inter-district deviation as the variation of the annual average house price in one local area from the averages across all the districts. During the course of their lives, it is not unusual for Dutch households to purchase a property in a less desirable location with the intention of moving to a more desirable location when their disposable income increases (Banks et al., 2015; Droes et al., 2010; Englund et al., 2002; Sinai and Souleles, 2003; Van der Heijden et al., 2011). This tendency, however, could be affected by the extent of variations

in house prices in different locations. The inter-district deviation captures these locational house price differences and may indicate the largest amount of money needed to augment the value of the owned property to enable a move within the municipality. All things being equal, the areas with larger inter-district deviations will have lower outflow mobility opportunities because the current dwelling in those locations provides a limited hedge for another property elsewhere in the municipality for those households that decide to move.[1]

The rest of this paper is structured as follows. The mathematical construction of the metrics is specified in Section 4, following a brief review of the literature in Section 2 and a description of the data in Section 3. Section 5 discusses the empirical estimates of the metrics while Section 6 analyses the inter-dependencies between the sub-district housing markets. In Section 7, we study the impact of changes in house prices in Amsterdam on the national trend. Section 8 summarises the results and concludes the entire paper

2. Overview of the Literature

This paper focuses mainly on the property price risks and the interaction between the house price developments. Property price risk is referred to here as the potential loss on investment in residential properties due to a fall in property prices. It is important to study this risk because changes in house prices tend to affect other significant parts of the economy (Dolde and Tirtiroglu, 2002; Duca et al., 2010; Miller and Peng, 2006a). The recent Global Financial Crisis (GFC) has particularly lent some credence to the notion that stress in the Financial Sector may ensue from a collapse in real estate prices (Aalbers, 2009a,b; Baker, 2008; Hilbers et al., 2001; Rebelo et al., 2012).

Many authors use the volatility defined by the standard deviation to measure the property price risk in the literature (e.g. Dolde and Tirtiroglu, 2002; Miller and Pandher, 2008; Miller and Peng, 2006a; Ross and Zisler, 1991). However, it is well-known that the volatility accounts

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[1] A hedge may be considered as an asset or portfolio that is intended to cover for the risks or the price variations of another asset or portfolio.

only for the variations in the house price distribution from the average and does not necessarily capture the downside risk, which would be preferable. Jin and Ziobrowski (2011) proposed using the value-at-risk (VaR) instead of the standard deviation. This measure is a downside risk metric that indicates the worst-case loss at a portfolio held over a short period of time given a certain confidence level (Crouhy et al., 2006).

Although widely used in mainstream financial literature, many researchers criticise the VaR for violating certain mathematical axioms, which, it is argued, disqualifies it from being a coherent risk measure (see Acerbi and Tasche, 2002; Szegö, 2002; Yamai and Yoshiba, 2002).[2] The metric is also known to be more sensitive to the underlying distribution of the price return. Where the returns are not normally distributed, for instance, it is observed that the VaR may inaccurately estimate losses, which may then tempt investors to choosing portfolios with risky profiles (see Hull, 2006).

This article aims to compare house price risks in smaller sub-district markets using summary statistics. Simple summary statistics are perhaps more important than complex theoretical models for the individual households that need to make decisions on investing in the housing market of a particular sub-district. Four metrics (standard deviation, semi-deviation, decline severity and inter-district deviation) were used, which are based on localised price indexes constructed for each of the sub-districts. We created the indexes using the time dummy hedonic method (TDHM). The TDHM is a widely used approach that is based on the notion that house prices can be described by their physical and locational attributes (de Haan, 2003; de Haan and Diewert, 2013; Malpezzi et al., 2003; Rosen, 1974). Our dataset contains details on these physical and locational features, in order to apply the TDHM in this paper.

The procedure for the TDHM mainly involves a regression of time dummy variables and the

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[2] By definition, the VaR is not sub-additive and thus not considered as a (coherent) risk measure. Heath et al. (1999) enumerates 4 axioms for which a metric must satisfy in order to be a coherent risk measure. Sub-additivity is one of these requirements, and means the measure of risk of a portfolio must be less or equal to the sum of the risk measure of the individual assets that make up the portfolio.

characteristics in question on the log of property prices observed. This regression equation can easily be estimated by the method of ordinary least squares (OLS) and it was then possible to convert the coefficients estimated into a constant quality price index (time dummy hedonic price index). The background and introduction to these techniques is described extensively in, for example de Haan and Diewert (2013) or Hill (2013) and we provide a summary of this in Section 4.

3. Background, Description and Cleaning of Data

Within the Netherlands, the residential property market of the capital city Amsterdam is a very interesting case to study. Average house prices in Amsterdam are usually higher than in other cities in the country and the price development pattern there is also somewhat different (see Figure 1). For example, following the recent Global Financial Crisis, house prices in Amsterdam declined more sharply but also recovered more quickly than in other major Dutch cities such as The Hague, Rotterdam and Utrecht. Moreover, whereas average property prices in Amsterdam fell by almost 11% between 2003 and 2006, there was an upward trend in the rest of the Netherlands during the same period. Recalling that this period coincided with the aftermath of some notable global financial mishaps (the Turkey crisis, the Enron and Worldcom accounting scandals, etc), it may also be argued that the Amsterdam property market is more sensitive to prevailing international economic conditions than the other parts of the country.

In terms of demography, Amsterdam has a large population by Dutch standards and a significant proportion of international residents. The city's total population[3] in 2015 was about 850,000, with an estimated 431,370 households (average of 2 persons per household) in 2013. There is also significant variation in the composition of households in terms of culture, religion and ethnicity. The total housing stock in 2013 was about 400,000, and given its relatively large population, Amsterdam generally has a significant housing supply shortage, which manifests itself in very long waiting lists for social rental dwellings.

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[3] Amsterdam's population growth rate between 1990 and 2013 was about 6.5% according to the CBS.
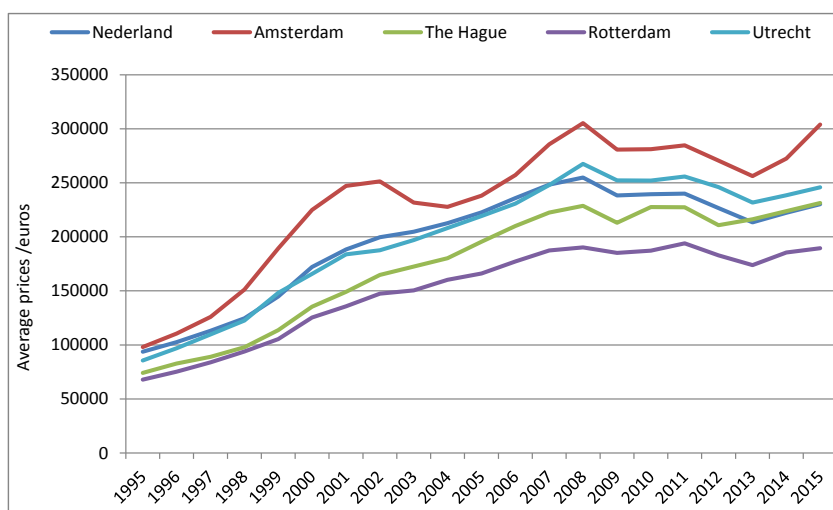
Figure 1: Annual average house price developments in four major Dutch cities.
source: The Statistics Netherlands (CBS)

The analysis in the rest of paper uses data with records on individual sale transactions in Amsterdam between 1983 and 2014. We obtained this dataset from the realtor organisation NVM.[4] In total, we received information on about 150,000 transactions. The NVM's coverage of sales information in the Netherlands has been improving over the years. The average coverage per year is generally known to be about 75%. However, we discovered that prior to 1995, a large portion of the sales reported by the NVM did not include the characteristics of the dwellings. Since these characteristics were needed to construct our time dummy hedonic indexes, we discarded the observations before 1995.

For the rest of the dataset, we sought to construct house price indexes for existing dwellings and we therefore removed new-build homes, which totalled 4,169. Observations with missing transaction prices (set to -1 by the NVM) and those with unusual values (e.g., 0s, 9s) were excluded. We also omitted observations with recorded transaction prices in excess of €4

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[4] NVM is the Dutch National Association of Property Brokers. The association makes data available on request, following a number of strict procedures, and the sales data used in this paper were not directly accessible by the authors.
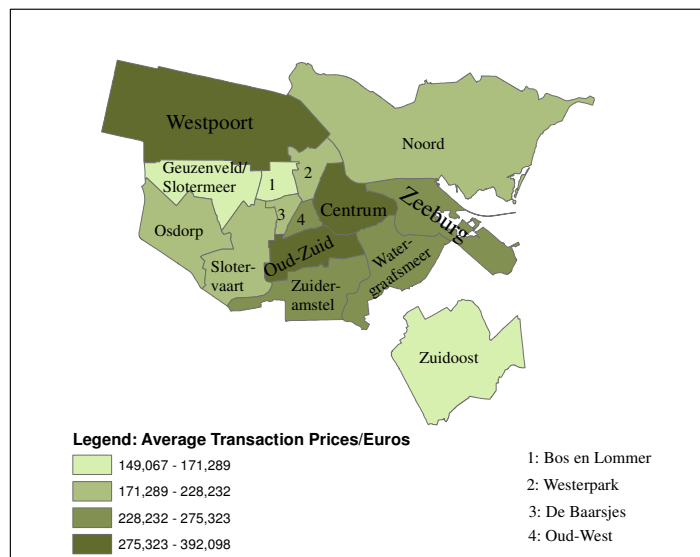
Figure 2: Local districts and neighborhoods in the city of Amsterdam. Average transaction prices are based on NVM data from 1995 to 2014. **source**: CBS and NVM

million (74), and those below €10,000 (404). Records with extremely small house sizes[5] (below 20m^2) in addition to the observations with unavailable structure sizes (3642 in total) were also excluded. Furthermore, we deleted 5 observations for which the property type was unavailable or unknown. The rest of the data - a total sample size of 116,446 - was finally divided into the fifteen smaller local districts of Amsterdam, which are shown in Figure 2. These sub-districts are chosen for our study because they represent the official spatial segmentation of Amsterdam according to by Statistics Netherlands (CBS) for statistical purposes. Moreover, the NVM included a key variable that enables the separation of the dataset.

The Table 1 and Figure 2 and 3, present the summary statistics and distribution for the remaining data. A brief look at the table and the figures shows that, during the study period, properties in Amsterdam sold for an average of about €261,513. Average house prices in less expensive areas like Zuid-Oost, Geuzenveld en Slotermeer, Bos en Lommer and Noord were below €200,000. The more expensive districts include the central business district (Centrum) and its immediate surroundings (Westpoort and Oud-Zuid), where average price were above

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[5] Properties with extremely small sizes (below 20m^2) are almost not-existent in the Netherlands.
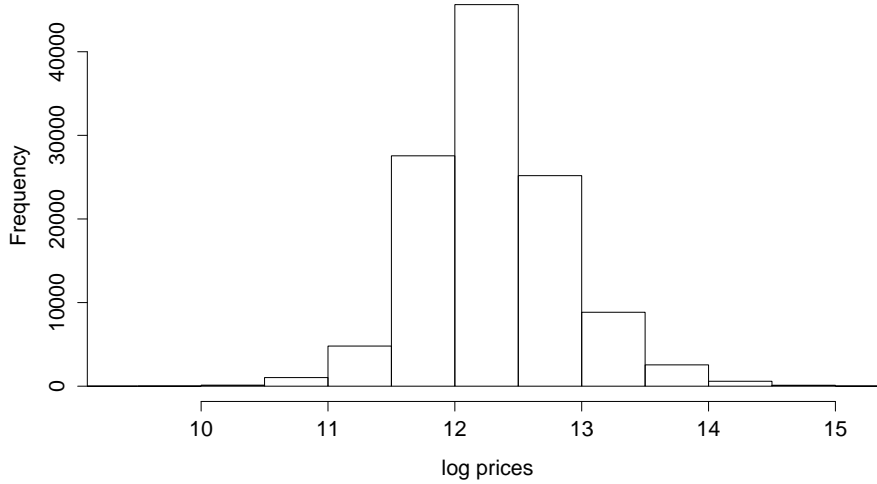
Figure 3: Distribution of log transaction prices for the entire Amsterdam: 1995 to 2014.
source: NVM

€300,000. In addition to the locational attributes, there is significant disparity in the average disposable income of local residents, which may contribute to house price variations between the sub-districts (see Amsterdam, 2013; Karsten et al., 2006; Musterd and Deurloo, 1997).

4. The Time Dummy Hedonic Method and Definition of Price Risk Indicators

Rosen (1974) defines hedonic prices as the "implicit prices of attributes that are revealed to economic agents from observed prices of differentiated products and the specific amounts of characteristics associated with them". The TDHM includes the period of transaction as one of the characteristics, following the definition of Rosen (1974). In the notations of de Haan and Diewert (2013), the estimating regression equation of the TDHM could be described by the model:

$$\ln p_n^t = \beta_0 + \sum_{\tau=1}^{T} \delta^\tau D_n^\tau + \sum_{k=1}^{K} \beta_k z_{nk}^t + \varepsilon_n^t \tag{1}$$

where p_n^t is the price of the n property in the period t from the sample of N_t properties with K number of characteristics $z^K = (z_{nk}^t)_{k=1}^{K}$. ε_n^t is the error term assumed to be white noise process whereas D_n^τ is the time dummy that takes the value one if p_n^t belongs to the sample N_t and zero otherwise. By omitting one of the dummy variables (usually the base period), equation (1) may be estimated on the pooled data by the method of OLS and the

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District	No. of Obs.	Avg Price (€)	Std. Dev.	Avg Size (M^2)	Avg. BP
Centrum	16 805	344 293.0	238 061.9	97.0	3.1
Westpoort	0 041	392 098.4	174 284.3	87.8	8.5
Westerpark	5 958	228 231.9	126 395.0	69.9	3.2
Oud-West	7 633	275 323.4	184 124.0	80.4	2.2
Zeeburg	7 628	266 334.1	142 666.7	88.7	6.2
Bos en Lommer	5 009	171 289.3	81 045.08	69.0	3.1
De Baarsjes	6 547	202 730.7	102 998.6	71.8	2.5
Noord	8 521	193 182.5	111 130.2	89.9	5.1
Geuzenveld en Slotermeer	3 720	164 187.6	79 909.1	83.7	5.4
Osdorp	5 518	194 725.1	110 606.0	97.6	6.4
Slotervaart en Overtoomse Veld	4 565	225 467.8	123 070.2	101.0	6.8
Zuid-Oost	6 842	149 067.1	72 615.4	86.3	6.7
Watergraafsmeer	8 409	258 422.4	142 885.8	87.2	3.5
Oud-Zuid	18 830	348 942.8	278 432.5	96.8	2.3
Zuideramstel	10 420	272 807.0	185 531.9	93.8	3.9
Whole of Amsterdam	116 446	261 512.6	193 972.7	88.9	3.9

Table 1: Summary statistics for transactions from 1995 to 2014. The building period is indicated by BP and the original data is categorized for properties built in the period: < 1500, 1500-1905, 1906-1930, 1931-1944, 1945-1959, 1960-1970, 1971-1980, 1981-1990, 1991-2000, ≥ 2001 respectively by 0, 1, 2, 3, 4, 5, 6, 7, 8 and 9. The higher the average BP, the more recent are the buildings in the district.
Source: Authors' computations based on NVM data.

index tracking the growth rate from time 0 to τ is simply obtained with the exponentiation $\pi^\tau = \exp(\hat{\delta}^\tau)$. Here, $\hat{\delta}^\tau$ is the estimated value of δ^τ.

For each of the sub-districts (x say), we followed the above procedure to estimate the house price index from 1995:Q1 to 2014:Q4 using 1995:Q1, as the base year. After that, the variance (σ_x^2) and the inter-district variance (γ_x^2) for the respective districts are then specified as in the equation 2 below.[6]

$$\sigma_x^2 = (T-1)^{-1} \sum_{t=1}^{T} (d_t^x - \mu_x)^2$$

$$\gamma_{x,t}^2 = L^{-1} \sum_{y=1}^{L} \left(\max(\theta_t^y - A_t^x, 0) \right)^2 \tag{2}$$

Here, $\mu_x = T^{-1} \sum_{t=1}^{T} d_t^x$ is the mean house price return in the sub-district x and L is the total number of designated sub-districts. The return is defined for a version of the original indexes that was first smoothed using a simple fourth-order moving averages. In a slow (or thin) market with few transactions (which was the case with some of the districts studied), the hedonic house price index becomes very volatile, exhibiting extreme short-term fluctuations that are mostly due to sampling errors (see Figure 4 and Schwann, 1998). By taking moving averages, these short-term sample variances are smoothed out from the indexes and the resulting growth rate may then be considered as the long term quarterly house price return (Diewert, 2010). This return is defined as the log differences of the smoothed indexes but it is in the earlier notation mathematically equivalent to

$$d_t^x = \ln \left[(\pi_x^t + \pi_x^{t-1} + \pi_x^{t-2} + \pi_x^{t-3})/(\pi_x^{t-1} + \pi_x^{t-2} + \pi_x^{t-3} + \pi_x^{t-4}) \right]$$

The quantity $\gamma_{x,t}^2$ in equation (2) is the modified semi-variance statistically expressed as the squared deviations of the average house prices θ_t^y in the sub-districts y that falls above the average house price A_t^x in the district x from where an household intends to move at time t. This inter-district variance $\gamma_{x,t}^2$ is viewed as a measure of the premium involved in moving up to the higher-priced locations within the municipality. The original semi-variance is used,

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[6] The deviations can be calculated by taking the square roots of the variances.

on the other hand, for the risk of the growth rate. Using the appropriate notations, the definition of the semi-variance is similar to $\gamma_{x,t}^2$ with the function max(.) replaced by min(.). The semi-variance is a downside risk metric that has a more appealing connotation for risk than the variance because it considers only values below the mean or some other predefined threshold.

5. Empirical Estimations of the House Price Index and Risk Indicators

5.1. Sub-district House Price Index

The localised house price indexes were constructed for fourteen of the Amsterdam sub-districts using the TDHM. Westpoort was omitted because there were too few observations and these did not cover the entire study period.[7] The implementation of the TDHM first required a choice to be made about which dwelling characteristics to include in the regression equation (1). We began with several characteristics and then excluded those features that were statistically insignificant across the fourteen districts using the p-values. The final regression used the log transaction prices as dependent variable and only seven co-variates, most of which were also categorised into several groups described in Table 2.

Including the time dummies (the base period 1995:Q1 omitted for identifiability), the adjusted R-squared showing the proportion of variation in log transaction prices explained across the 14 districts ranged from 82.5% to about 92%. The same factors plus the location (district) dummies indicating the districts of transaction explained nearly 88.72% of the variation in sale prices across the whole Amsterdam. The regression result for the entire city is presented in Table 3 (the time dummy variables are omitted however to preserve space).

It is noticeable that the estimated coefficients of most of the explanatory variables are statistically significant (even at the 1% level) and that they also carry the expected signs. More specifically, the coefficients of the log structure size, the number of rooms and the number of

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[7] The lower observations in Westpoort was because the district is relatively new and the majority of the houses were recently built.

Variable	Description	Unit
log(M2)	logarithm of the structure size	m^2
NKAMERS	number of rooms	integer
NVERDIEP	number of floors	integer
VERW	system of heating	$0, \cdots, 3$
ONBI	maintainance level inside the property	$1, \cdots, 9$
BWPER	Building period	$0, \cdots, 9$
HOUSETYPE	Type of house	$2, \cdots, 7$
LOC	The district in which property is located	$0, \cdots, 14$

Table 2: Definition of Explanatory variables. The respective heating types are: no heating system, gas/stove heating, central boiler heating and air condition/solar heating. The categories of the building period is as described in Table 1. The maintenance level are rated as: bad, poor to moderate, moderate, moderate to reasonable, reasonable, reasonable to good, good, good to excellent and excellent. The properties were classified as: row house, town house, corner house, semi-detached house, detached house and apartment, and the location of the properties was categorised into 15 using the codes specified in Table 1. **Source:** Extract from NVM data

floors are all positive and statistically significant. The location of the house and the property type also play an important role in determining the property prices, as expected. Compared to the central district (Centrum), the regression results show that prices are lower in all other districts except in Westpoort. The maintenance level inside the property also has a positive impact on the price of the property. We note, however, that the maintenance level compiled by the NVM is rather more subjective to the property valuer during the transaction.

As expected, the coefficients of the construction periods are also correctly signed in general. A careful look at Table 1 and Figure 2 reveals that the districts in and around the central area of the city have comparatively older dwellings, except Westpoort. These areas, in spite of the age of the buildings, also have expensive houses in accordance to the bid-rent geographical economic theory (Alonso, 1960; Alonso et al., 1964). In fact, older dwellings tend to be more expensive also because many Dutch people prefer them, especially when they are located along monumental streets and close to museums or other public areas.

Variable	estimate	sd deviation	p-value	Variable	estimate	sd deviation	p-value
Intercept	7.590672	0.022811	$< p***$	LOC36308	-0.519670	0.003823	$< p***$
log(M2)	0.865394	0.002111	$< p***$	LOC36309	-0.515659	0.003299	$< p***$
NKAMERS	0.011584	0.000582	$< p***$	LOC36310	-0.471955	0.003449	$< p***$
NVERDIEP	0.003173	0.001032	0.002106 **	LOC36311	-0.646286	0.003235	$< p***$
VERW1	-0.042580	0.003065	$< p***$	LOC36312	-0.213398	0.002596	$< p***$
VERW2	0.048703	0.002333	$< p***$	LOC36313	-0.045943	0.002153	$< p***$
VERW3	0.154269	0.041770	0.000221 ***	LOC36314	-0.151450	0.002651	$< p***$
ONBI2	0.023265	0.026203	0.374599	BWPER1	0.032283	0.016585	0.051593 ·
ONBI3	0.035788	0.012390	0.003871 **	BWPER2	0.002877	0.016569	0.862141
ONBI4	0.042677	0.014851	0.004058 **	BWPER3	-0.006407	0.016659	0.700554
ONBI5	0.075381	0.011789	1.62e-10 ***	BWPER4	-0.076595	0.016768	4.93e-06 ***
ONBI6	0.099165	0.012134	3.05e-16 ***	BWPER5	-0.189582	0.016655	$< p***$
ONBI7	0.165570	0.011661	$< p***$	BWPER6	-0.118114	0.016822	2.21e-12 ***
ONBI8	0.234712	0.012091	$< p***$	BWPER7	-0.079620	0.016645	1.73e-06 ***
ONBI9	0.257581	0.011714	$< p***$	BWPER8	0.012892	0.016632	0.438239
LOC36301	0.049984	0.029251	0.087492 ·	BWPER9	-0.018505	0.016767	0.269724
LOC36302	-0.183326	0.002901	$< p***$	HOUSETYPE3	0.118812	0.011428	$< p***$
LOC36303	-0.107175	0.002640	$< p***$	HOUSETYPE4	0.038909	0.004004	$< p***$
LOC36304	-0.269886	0.002762	$< p***$	HOUSETYPE5	0.231907	0.006615	$< p***$
LOC36305	-0.392107	0.003351	$< p***$	HOUSETYPE6	0.327736	0.005939	$< p***$
LOC36306	-0.275391	0.003003	$< p***$	HOUSETYPE7	-0.053797	0.002440	$< p***$
LOC36307	-0.510009	0.002837	$< p***$				

Table 3: Hedonic regression estimates for Amsterdam (time dummies omitted). $p = 2e - 16$. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1 ' ' 1. Residual standard error: 0.1864 on 116324 degrees of freedom; Multiple R-squared: 0.8868, Adjusted R-squared: 0.8867; F-statistic: 7530 on 121 and 116324 DF, p-value: $< 2.2e - 16$. **Source:** Author's computation

Figure 4: The city-wide Amsterdam and the local residential property prices indexes compared. **Source:** Author's estimate from NVM data

Figure 4 compares the sale price indexes from the 14 districts with the city-wide Amsterdam index. The plot reveals that a few of the sub-markets (Centrum, Oud-Zuid and Zuidamstel) mimic the city-wide average price outlook over time, whereas the sub-districts that are more peripheral have lower price levels as noted earlier (see Figure 2 & 4). Furthermore, we can also see that over time, those sub-markets that are closer to city centre tend to have relatively higher price levels. This may not be so surprising because gentrification in and around the centre of Amsterdam is also a common phenomenon (see Gent, 2013; Hochstenbach et al., 2015).

5.2. House Price Returns and Volatility (Risks)

This subsection reports the average house price returns and risks (volatility) in the sub-markets. We should recall here that the average returns are obtained from the log differences of the fourth-order moving average version of the original hedonic price indexes. The plots of the moving average indexes are exhibited for selected sub-markets in Figure 5a. The basic

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risk measures are the standard and semi-deviation of the returns series and are indicated in Figure 5b.

The growth rate, according to Figure 5b is highest (more than 1.4% per quarter) in Westerpark, Oud-West, Oud-Zuid, Centrum and areas closer to the central business district. These locations also exhibit higher house price volatility (risk). On the other hand, we find that the peripheral districts show relatively lower price growth rates and lower volatilities. For instance, the Nieuw-West district (Osdorp, Noord, Slotervaart en O. Veld, Geuz. en Slotermeer) and Zuid-Oost which are further away from the city centre, tend to have smaller returns (of about 1.1%) and are less volatile (see Figure 5b).

5.3. Impact of the Global Financial Crisis

After the World War II, house prices in Amsterdam began a persistent upward trend starting in the early 1950s and lasting until the late 1990s, mainly as a result of the rising population, growth in disposable income and government stimulation of the owner-occupied sector (De Vries, 2010; Dröes and Van de Minne, 2015; Elsinga, 2003; Minne et al., 2015). Between 2001 and 2004, however, average property prices in Amsterdam decreased almost by 11%. This was a period of some global economic turbulence such as the 2000 oil crisis, the Turkey crisis, Enron and the Worldcom accounting scandals, among others. Interestingly, house prices in the rest of the Netherlands continued to increase during this period, although prices in Amsterdam only started to recover from 2005. From 2005, average property prices in Amsterdam grew at an even stronger annual rate of about 4.5% until 2008 (see Figure 1).

In the last quarter of 2008, the Dutch housing market was hit again by the Global Financial Crisis (GFC). Following the crisis, between 2008 and 2013, average house prices in Amsterdam fell by almost 16.3%. However, the effect of the GFC on house prices varied between the different sub-districts in terms of speed and severity. The impact was felt quicker in Westerpark, Geuzenveld en Slotermeer, Zeeburg and Zuid-Oost, where house prices in 2010 had declined by 8.5% to 14% from their levels in 2008 (Figure 6a). In the long term, the impact of the crisis was more severe in Nieuw-West district (Geuzenveld/Slotermeer, Osdorp and Slotervaart

(a) Exhibit of the moving average index for selected sub-markets
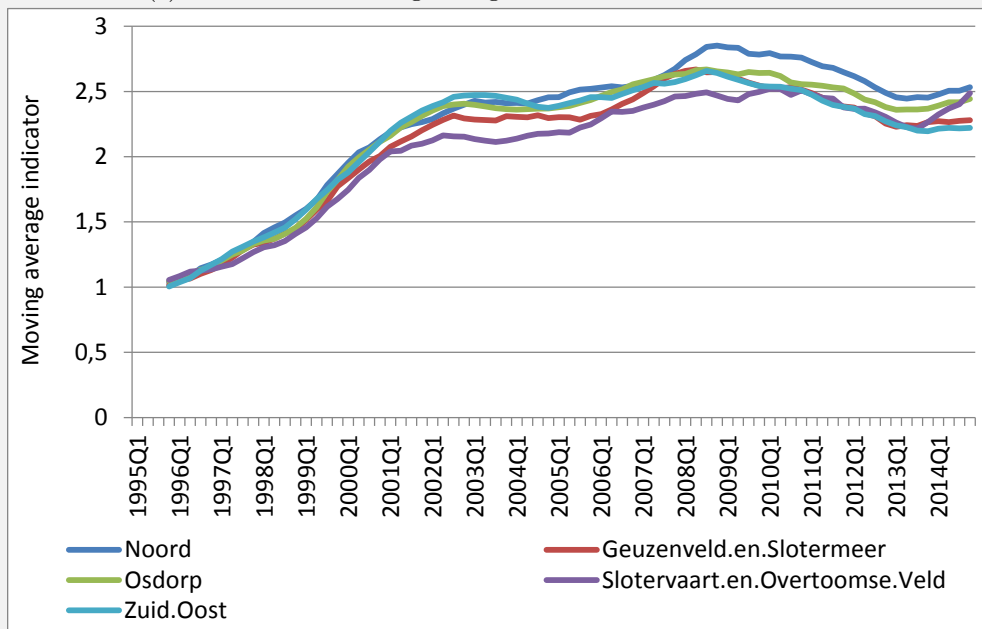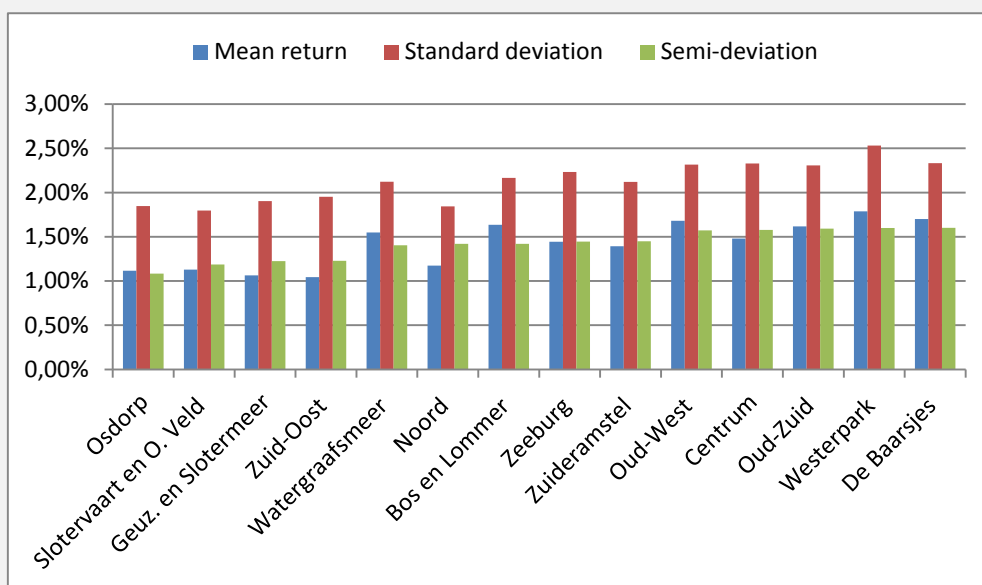
(b) return and risk indicators

Figure 5: Exhibition of the smooth version of the price index for selected sub-districts, returns and indication of risk. **Source**: Author's computations based on NVM data

area), where a large proportion of residents (about 25%) had been unemployed over the past 2-3 years in 2010 (Figure 6b). The percentage house price decrease from the peak of 2007 to the trough of 2013 in these districts was about 20% to 23.5%. Noord, Westerpark, Zeeburg and De Baarsjes were also among the worst hit areas over the long term, while the impact was minimal in Watergraafsmeer and Oud-West.

It is interesting to note that apart from Zeeburg, the central business districts (Centrum, Oud-Zuid, Watergraafsmeer and Zuidamstel) were affected less by the GFC over the long term (15% to 17% decrease), even though house prices are higher in these areas. This observation departs from the earlier findings of Van der Heijden et al. (2011). These authors argue that the Dutch housing market is generally dynamic - meaning that households are able to move from cheaper segments of the market to the higher priced segments (and vice versa) during the course of the life cycle. They concluded that the upper-priced sub-markets are affected the most during an economic crisis because when disposable income decreases, the upward movement is curtailed. This then leads to a reduction in the number of transactions and a subsequent decline in house prices at the upper segment of the market.

In their analysis, however, Van der Heijden et al. (2011) do not consider the possibility that the impact of the crisis on income may vary geographically. In general, decreases in disposable incomes during any economic downturn are linked to unemployment, which will differ between the districts (see Figure 6b). Spatially, therefore, it is reasonable to assume that house prices will be more affected in those sub-markets where the labor force suffers the most during the crisis. A closer look at the Figure 6 suggests that the impact of the crisis on house prices does indeed correlate with the effect of the GFC on employment in the relevant districts. The more expensive segments of the market are not necessarily more severely impacted since the labor force in these areas may be affected less by the crisis (see Figure 6).

5.4. Inter-District House Price Deviation

As described by Van der Heijden et al. (2011), the Dutch housing market is dynamic. Households often tend to move from the cheaper to the more expensive segment of the market

(a) Percentage decrease in average house prices
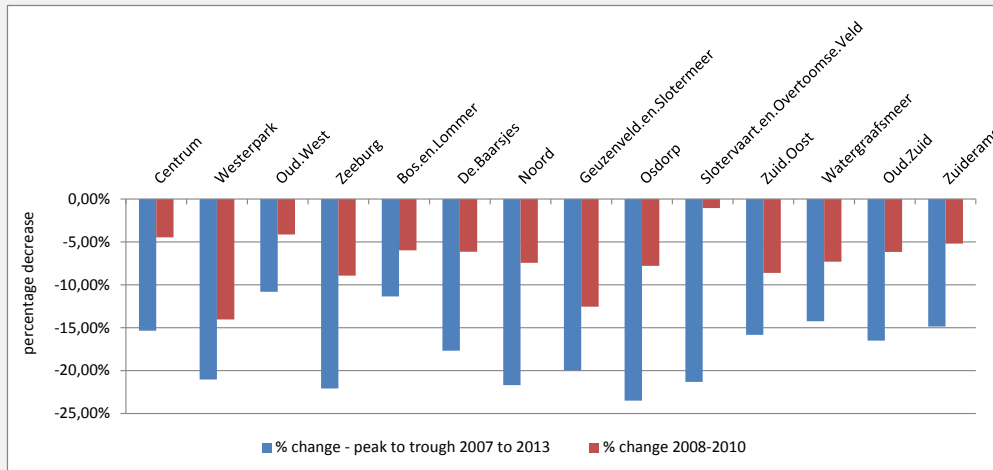
(b) % of job seekers without employment in the past 2-3 years in 2010
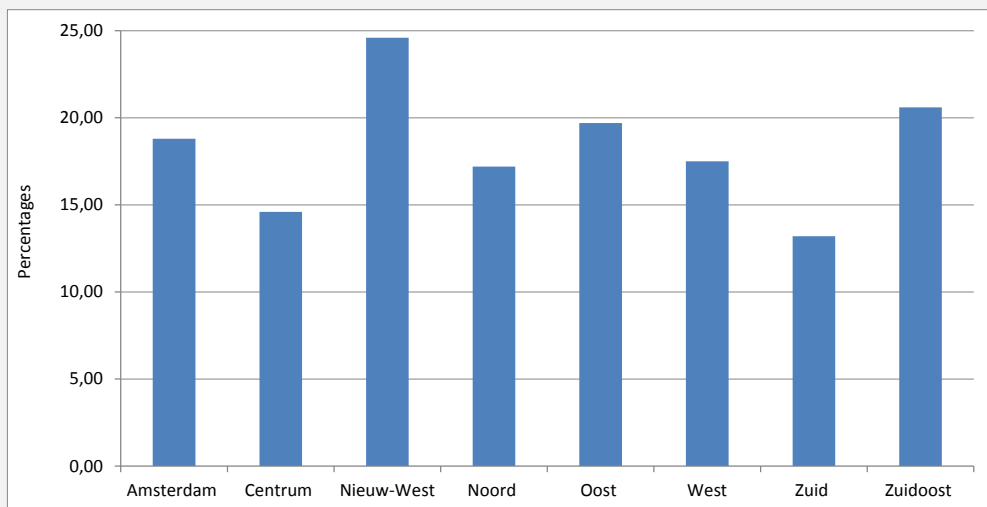
Figure 6: House price and employment statistic following the crisis. **Notice:** Zeeburg and Watergraafsmeer are currently classified as Oost; Geuzenveld/Slotermeer Osdorp and Slotervaart area form Nieuw-West; Bos en Lommer, Westerpark, De Baarsjes, Oud-West constitute West. **Source:** NVM, (Amsterdam, 2004, 2013, 2014)

as disposable income permits or if enough equity is built up in the current dwelling. The inter-district deviation is a single statistic that tracks the maximum rise in value that households need in their current dwelling in order to move up to higher-priced market segment in another location. As expected, the areas with cheaper houses have higher inter-district

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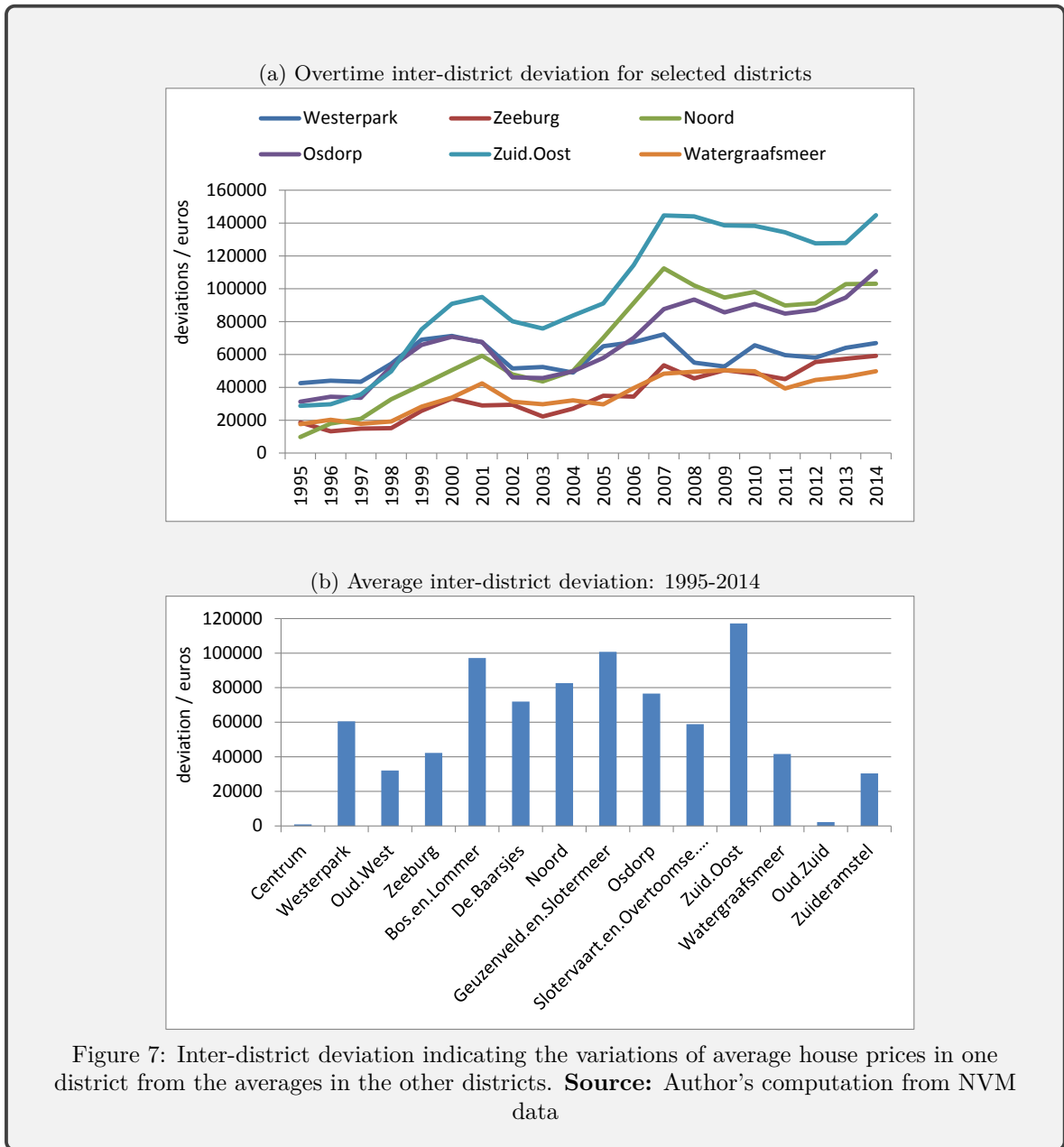deviations (Figure 7b). Moreover, the inter-district deviations increased over time during the study period, particularly in the districts with the cheaper house prices (Figure 7a). This may indicate the widening gap between house prices in the cheaper and more expensive districts over the years.

In general, the inter-district deviation is highest in Zuid-Oost, Geuzenveld en Slotermeer, Bos en Lommer and Noord (Figure 7b). More than €80,000 is needed to augment an average house price in these areas to facilitate a move to the other higher-priced locations. In the Centrum and Oud-Zuid, where property prices are higher, the inter-district deviation is negligible. A household may move from these higher-priced districts to other areas without much financial rigidity. In the other areas however, the inter-district property price variations are substantially high. In addition to the already large transaction costs involved in sales of properties in the Netherlands[8], this considerable inter-district variations may constitute part of the reasons why Dutch homeowners in general tend to move less frequently than those who rent, as has been confirmed in the literature (Chan, 2001; Droes et al., 2010; Helderman et al., 2004; Hochstenbach et al., 2015).

6. Sub-markets Inter-dependencies

We have so far compared the basic house price dynamics (growth rate, risk and inter-district deviation) for the sub-districts. This section continues with analysis of the inter-dependencies between the sub-markets. Although the sub-markets may differ fundamentally in many ways, house price trends in one geographical area may generally correlate with the growth in other places. This correlation may be due to some common house price fundamentals (e.g. interest rates, government regulations) or as a result of parallel economic and industrial expansion (Vansteenkiste and Hiebert, 2011). On the other hand, through in-migration and speculative activities, among other factors, it is likely that development of house prices in one area may have a lag or spillover effect on the price growth in other locations (Meen, 1999). Holly et al.

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[8] Transaction cost for dwellings in the Netherlands is about 10% of the value of the home (including 6% property transfer tax).

Figure 7: Inter-district deviation indicating the variations of average house prices in one district from the averages in the other districts. **Source:** Author's computation from NVM data

(2011), for instance, found that shocks to property prices in London spread to the other regions in the UK and this impact may occur for more than two years.

Many other journal articles have reported on this issue of house price spillovers from one statistical region to another, between cities and even across countries (Guozhi and Xun, 2011; Holly et al., 2010, 2011; Vansteenkiste and Hiebert, 2011; ZHANG et al., 2015). However,

there is little literature from the Netherlands on this subject. We can contribute to filling this gap here by analyzing the across-district lagged house price effects for Amsterdam within the Granger Causality framework. The concept of Granger Causality (GC), popularized in the literature by Granger (1969), is one of the widely used empirical methods for testing the lag dependency between two time series. More formally, the author referred to one time series x_t as a cause of another y_t if the information about x_t till now can improve the prediction of future values of y_t beyond the use of only the information already known about y_t.

We use this idea to analyse the interaction of house price growth between pairs of all 14 sub-markets and also investigate the inter-dependencies amongst property price developments in the upper and lower-priced market segments. Investigating these inter-relationships is important in understanding the mechanism by which shocks may possibly spread and hence to monitor systemic risk within the city-wide housing market.

6.1. Pairwise Granger Causality

This sub-section uses the growth rates to investigate the lag-dependencies between pairs of the sub-markets. However, because the operation of moving averages introduces auto-correlation into the resulting time series, the smoothed version of the growth rates obtained earlier cannot be used for the regressions on which the GC analysis thrives. Regression requires that the data is independently generated. Therefore, we first obtained an adjusted version of the house price growth rate that did not introduce this serial correlation. The adjusted rate was defined for each sub-markets, following Andersen et al. (2000) by dividing the log growth rate from the original hedonic index by the volatility (constructed as the square of the log-growth rate). These standardised growth rates are generally more stable than the non-standardised log growth rates from the original indexes (see an exhibit in Figure 8).[9]

For the adjusted growth rates x_t^i and x_t^j from the respective sub-markets i and j, the empirical

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[9] The Augmented Dickey-Fuller (ADF) test shows stationarity of the standardised growth rate for all sub-districts at the 5% level.
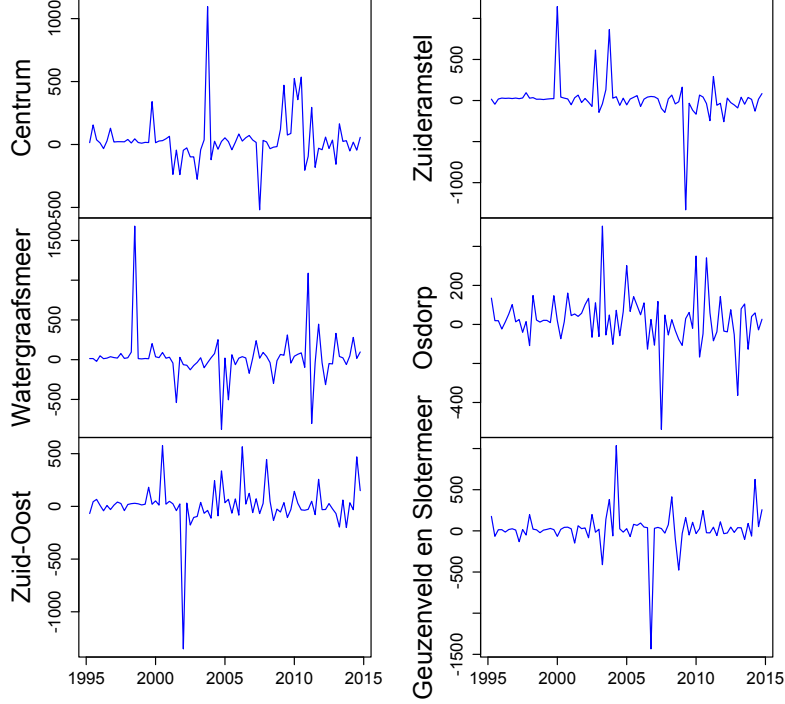
Figure 8: Exhibition of the standardised growth rates for selected districts

procedure for the pairwise GC test is to first estimate the simultaneous regression equations:

$$x_t^i = \alpha_0 + \sum_{k=1}^{p} \alpha_{1k} x_{t-k}^i + \sum_{k=1}^{p} \beta_{1k} x_{t-k}^j + \epsilon_{1t}$$

$$x_t^j = \beta_0 + \sum_{k=1}^{p} \alpha_{2k} x_{t-k}^i + \sum_{k=1}^{p} \beta_{2k} x_{t-k}^j + \epsilon_{2t} \tag{3}$$

where ϵ_{1t} and ϵ_{2t} are uncorrelated disturbance terms. The lag order p is usually determined with an information criterion (AIC or BIC). We say formally that x_t^j Granger cause x_t^i if the estimated parameters $\beta_{11}, \cdots, \beta_{1p}$ are statistically different from zero (i.e, the hypothesis $H_0 : \beta_{11} = \cdots = \beta_{1p} = 0$ is rejected at a reasonable statistical significant level). Similarly, x_t^i Granger cause x_t^j if we can reject the hypothesis $H_1 : \alpha_{21} = \cdots = \beta_{2p} = 0$.

For our purposes, both BIC and AIC selected the value of p as 1 in all 182 sub-market pairs. The pairwise GC test-statistics and the p-values are presented in the Table B.8. Figure 9 gives a pictorial view of the lag-dependencies between the sub-markets based on the result in
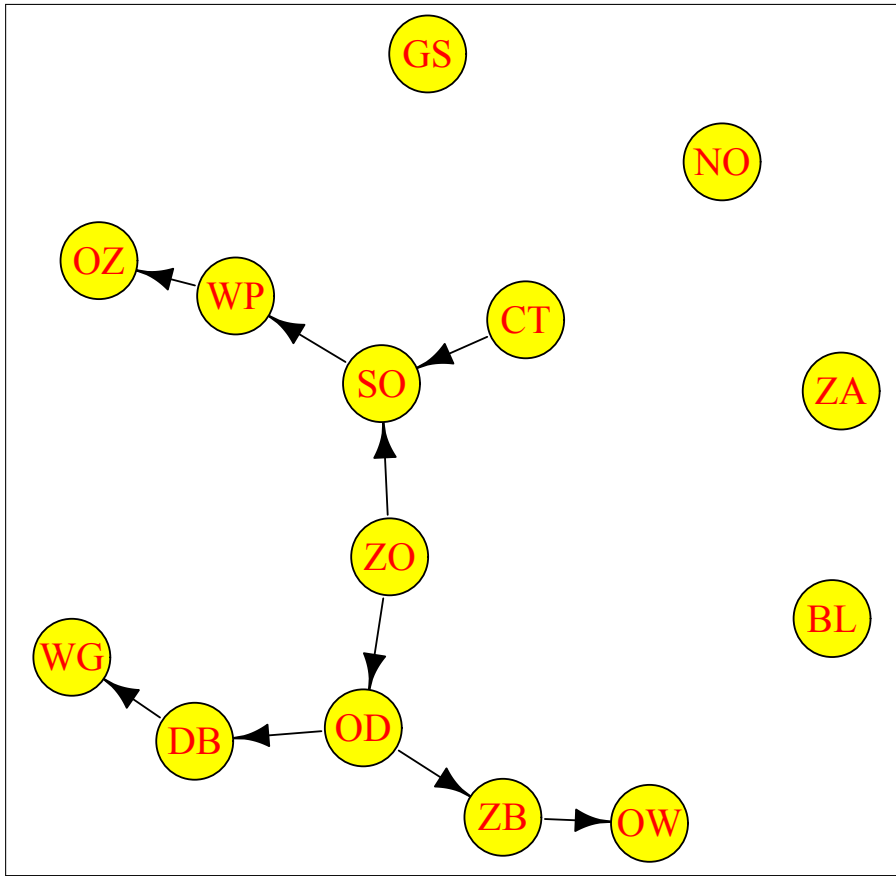
Figure 9: Lag dependency between sub-markets based on pairwise Granger Causality at the 5% level. **Note:** The directed arrow is from the independent to the dependent sub-market. **CT**=Centrum, **WP**=Westerpark, **OW**=Oud-West, **ZB**=Zeeburg, **BL**=Bos en Lommer, **DB**=De Baarsjes, **NO**=Noord, **GS**=Geuzenveld en Slotermeer, **OD**=Osdorp, **SO**=Slotervaart en Overtoomse Veld, **ZO**=Zuid-Oost, **WG**=Watergraafsmeer, **OZ**=Oud-Zuid and **ZA**=Zuideramstel.

the table. The figure shows that the sub-markets do not form a connected network.[10] There are particularly four districts (Noord, Zuideramstel in the south as well as Bos en Lommer and Geuzenveld en Slotermeer in the western part of Amsterdam) that have no interaction at all with any of the other districts. However, there is a subset of the districts that interact systemically with Zuid-Oost, Osdorp and Slotervaart en Overtoomse Veld playing dominant roles.

More specifically, there is a systematic house price lag effect from Zuid-Oost to both Osdorp and Slotervaart en Overtoomse Veld. Osdorp also has a lag-dependency on two other districts,

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[10] A directed network is connected if there is a path between any two nodes in the network.

whereas Slotervaart en Overtoomse Veld is Granger caused by two of the sub-markets. In summary, the most central districts where systemic shocks could spread are Zuid-Oost and Osdorp. Slotervaart en Overtoomse Veld, on the other hand, will probably be subject most shocks, although the topology of the network (Figure 9) suggests that propagation of house price shocks from one district is limited to, at most, three other sub-markets.

6.2. Lower and Upper Market Segment Interaction

In this sub-section, we test the lag dependency between the lower and upper-priced segments of the market. This illuminates our understanding as to whether house prices in the different market segments grow independently or there is systematic development from the upper to the lower-priced segment (or vice versa). The sub-markets are first categorized into four according to the average transaction prices as already shown in Figure 2. Denote these upper to lower market segments by **Q1**, **Q2**, **Q3**, **Q4**, then the respective groups are:

Q1: {Oud-Zuid, Centrum}; **Q2**: {Oud-West, Zeeburg, Watergraafsmeer, Zuidamstel}
Q3: {Noord, Westerpark, De Baarsjes, Slotervaart en Overtoomse Veld, Osdorp}
Q4: {Zuid-Oost, Geuzenveld en Slotermeer, Bos en Lommer}

The lag dependency between these segments were analyzed with both pairwise multivariate Granger causality (PMGC) scheme discussed in Lütkepohl (2005) and multivariate partial Granger causality (MPGC) of Guo et al. (2008). The PMGC is a multivariate version of (3), while the MPGC controls for confounding effects of the other segments when the Granger causality between two pairs are considered. The estimates for the tests are presented in the Table B.9.

The two methods (PMGC and MPGC) both yield the same conclusion from the empirical results at the 5% significance level. In general, there is no lag effect from the upper to the lower market segment (and vice versa) except from the fourth (**Q4**) to the third (**Q3**) segment of the market. In other words, the only Granger causality is from the very lowest level (**Q4**) to the next immediate upper segment of the market (**Q3**). This also implies that the growth

of house prices at the level **Q3** could be affected by shocks to house prices at the **Q4** segment. On the other hand, shocks are unlikely to be spread amongst the rest of the market segments.

7. Impact of Amsterdam House Price Appreciation on the General Dutch Trend

In a previous section, we discussed the unique development of Amsterdam house prices in the Netherlands. Given the central role that the city plays in the economy, the question arises of whether changes in house prices in Amsterdam have any impact on the nation-wide price outlook. For example, Teye and Ahelegbey (2016) argue that in a network of the twelve Dutch provincial housing markets, Noord-Holland significantly influences the growth of property prices in the other Dutch provinces. The authors explained this might come about because Noord-Holland is home to the national capital, which has a dynamic property market and also serves as the economic hub for the whole country. Similarly, Guozhi and Xun (2011) and ZHANG et al. (2015) find that house price movement in certain economically important districts of China affect property prices in neighbouring cities.[11]

In this section, we examine the impact of the growth of house prices in Amsterdam on the price developments in the Netherlands as a whole. We use a cointegration equation that specifies the equilibrium relationship between the house price growth rates in Amsterdam and the whole of the Netherlands. Cointegration models are perhaps the most widely used in the literature for detecting long-run associations among time series variables. The cointegration equation could be flexibly estimated using a wide range of methods and the framework also allows for the analysis of the short-term equilibrium correction mechanism. Importantly, however, the cointegration approach avoids the estimation of spurious regressions by providing a way to model time series that are not stationary or which change in a non-constant manner over time (Granger, 1983, 1981; Granger and Newbold, 1974). The Pesaran et al. (2001) ARDL bounds approach to cointegration is applied here in our analysis.

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[11] Holly et al. (2011) discussed this issue of house price spillover and diffusion in the case of UK, while the instance of the USA was analysed by for example Meng et al. (2014), Miller and Peng (2006b) and Holly et al. (2010).

7.1. Cointegration and Equilibrium Relationship

Before the year 2000, the methods for testing cointegration existed only for time series that exhibited unit root or if they had the same order of integration. Pesaran et al. (2001), however, later provided a straight forward way to test the cointegration and estimate the equilibrium relationship between a mixture of stationary and non-stationary variables. This is much appealing since in empirical work it is common to have different test procedures giving contradictory results on the stationarity order of time series.

In application, one only needs to ensure that none of the data series is integrated beyond the first order to use the ARDL bounds cointegration approach. Here, the procedure is applied to the house price index for the whole of Amsterdam and the entire Netherlands, shown in Figure 10. First of all, we employed the Zivot and Andrews (2002) unit root test and found that the indexes in log-levels both for Amsterdam and the Netherlands are $I(2)$ at the 5% level (see Table 2). When cross-checked with the Becker et al. (2006) stationarity test, these time series were detected as $I(1)$.[12] The cointegration test is therefore conducted for the log growth rates (first-differences of the logged index) since then we have a mixture of $I(1)$ and $I(0)$ series that makes the application of the ARDL approach viable.

Following the cointegration test procedure described in the Appendix A and B, the null hypothesis that no cointegration exists is rejected at the 1% significance level. Hence, we concluded that there exists an equilibrium relationship between the log growth rate of house prices in Amsterdam (denoted by *Arate*) and the entire Netherlands (denoted by *Nrate*). The long-run equilibrium equation is described by the $ARDL(2,1)$ model given by

$$Nrate_t = 0.275Nrate_{t-1} + 0.492Nrate_{t-2} + 0.136Arate_{t-1} + \hat{v}_t \qquad (4)$$

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[12] Since the time we are dealing with covers period for the recent financial crisis where there are potential breaks (see Figure 10), we based the decision of stationarity on tests that factor in possible structure breaks although the conclusions are not different when the usual ADF and KPSS are adopted. The Zivot and Andrews (2002) test considers one break point whereas the Becker et al. (2006) procedure controls for infinitely many break points.
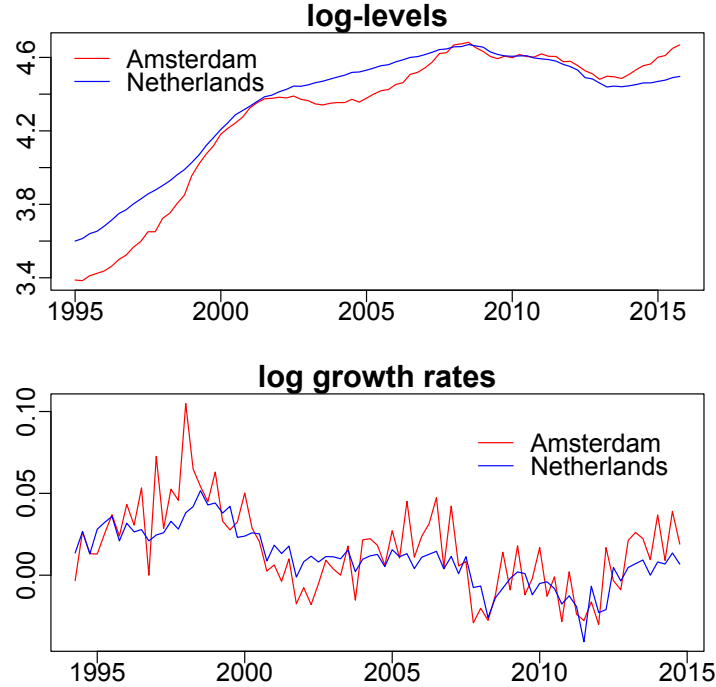
Figure 10: SPAR House price indexes and the log growth rates for the whole of Amsterdam and the entire Netherlands. **source**: Statistics Netherlands

where $\hat{v}_t$ is the equilibrium correction term. The regression coefficients are highly significant statistically and the adjusted R-squared is about 83.8%. The diagnostic regression statistics are presented in the Table B.6. From equation (4), we can discern that in equilibrium, the growth rate in the Dutch house prices nation-wide for the current quarter is dependent on the national growth rate in the previous two quarters and the Amsterdam's growth rate in the quarter immediately previous. The long-run impact of a change in the log growth rate of property prices in Amsterdam on the national price growth rate is about 0.586. This means if the log growth rate of house prices changes by 1 unit in Amsterdam, there will be a corresponding change in the log growth rate in house prices nation-wide of about 0.586 unit in the long-run. This impact is very significant and seems to suggest that the growth of house prices in Amsterdam play a major role in the long term development of the national trend.

7.2. Equilibrium Correction Mechanism

The fundamental socio-economic and political climates on which house prices thrive change over time and from place to place. Consequently, it is quite possible that the national house price growth rate may also deviate from its equilibrium relationship with the pattern in Amsterdam. Nevertheless, if the two are truly co-integrated, such deviation must be eventually corrected for the equilibrium relationship to be sustained. This equilibrium correction mechanism could be analysed using the so-called equilibrium or error correction model (ECM) described in the Appendix A. In our case, we estimated an ECM model of the form

$$\Delta Nrate_t = -\,0.081\,\Delta Nrate_{t-1} + 0.213\,\Delta Arate$$
$$+\,0.255\,\Delta Arate_{t-1} + 0.153\,\Delta Arate_{t-2} - 0.553\,\hat{v}_{t-1} + e_t \tag{5}$$

where the innovation $\Delta y_t = y_t - y_{t-1}$, e_t is a random disturbance term, and the other variables are as defined before. The equation is estimated with ordinary least square (OLS) method and the summary statistics are presented in the Table B.7. We note that the coefficients on the Amsterdam growth rate terms are all positive and statistically significant. These show the positive impact of the growth of house prices in Amsterdam on the national trend in the short term. Furthermore, the coefficient on the correction term $\hat{v}_{t-1}$ has the expected minus sign, which confirms the cointegration and equilibrium adjustment mechanisms. The speed of equilibrium adjustment is very fast, estimated at 0.553, which also implies that the half-life of the equilibrium deviation is about 1.25 quarters. In other words, 50% of the deviation of the national house growth rate from the equilibrium level in any period is corrected before the end of the next two quarters.

Finally, we display the in-sample fits from the long and short-run models (4) and (5) in Figure 11. The figure confirms that these models capture the house price dynamics between Amsterdam and entire Netherlands quite well. Equation (4) in particular reveals that the national house price growth rate (and consequently the price levels) can easily be predicted once we observed the trend in the past quarter and what is happening currently in Amsterdam.
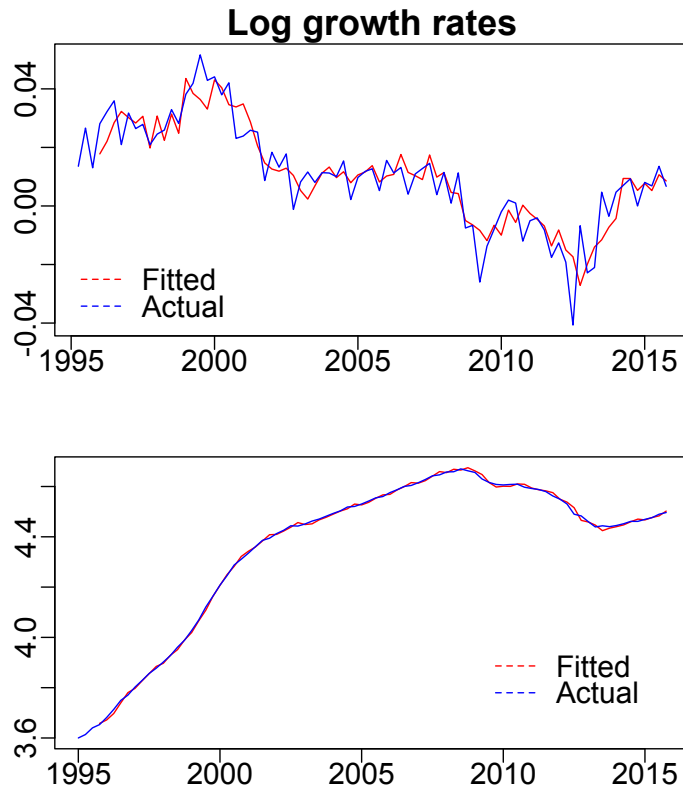
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Figure 11: In-sample fit for log growth rate and log-level price index for the Netherlands. The log-level fitted series are obtained as $\hat{NLI}_t = NLI_{t-1} + \hat{Nrate}_t$, where NLI_t is the log-level price index for the whole of the Netherlands and $\hat{Nrate}_t$ is the fitted log growth rate from the equation (4). The fitted log growth rates are obtained similarly from the model (5).

Conclusion

Following the recent financial crisis, both institutional investors and households need to understand the dynamics and risks of the housing market better. Using a very rich and unique dataset on individual house transactions in Amsterdam, with many characteristics and covering almost twenty years, this paper has compared the risks and dynamics of house prices in the local sub-districts of the city. The inter-dependencies of property price development between the sub-district as well as the impact of the Amsterdam city-wide price development on the general national trend have also been analysed. The methodology of the paper adopted simple summary statistics in order to compare the risks, while the inter-dependencies and the city-wide impacts were studied within the Granger causality and cointegration frameworks. These methods are more flexible for the purpose of obtaining indicators that easily explain

the market dynamics and risks to individual households who decides to invest in the housing market.

The key conclusions of the paper are the following: (1) house prices generally grow at a more stronger rate and are also more volatile as we move from the peripheral to the city centre; (2) the gap between house prices in the cheaper and more expensive districts widened over time from 1995 to 2014; (3) the sub-districts display a dis-connected network topology, although a subset exists where shocks could spread systematically; and (4) there is a long-run equilibrium relationship between the growth of house prices in Amsterdam and the national trend, with the growth rate in Amsterdam showing a significant impact on the growth of property prices in the Netherlands as a whole.

These results provide useful information for regulatory purposes and also for individual households. Policy makers may particularly focus regulation on the inter-dependent subset of the sub-markets to prevent systemic risk. Households, meanwhile, could take into account the widening gap between house prices in the cheaper and expensive segments of the city-wide housing market to plan their pathway in the owner-occupied sector. Moreover, the geography of house price risk established in this paper should help households to choose a location that matches their risk preferences.

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A. ARDL Bounds Cointegration Test

The Pesaran et al. (2001) ARDL bound cointegration test can be applied for the time series y_t and x_t that are not integrated beyond the second order. There are three steps involved in the procedure. In the first step, the conditional autoregressive distributed lag (ARDL) model in the equation A.1 is formulated.

$$\Delta y_t = \alpha + \beta t + \sum_{k=1}^{p} \beta_k \Delta y_{t-k} + \sum_{k=0}^{q} \alpha_k \Delta x_{t-k} + \delta_0 y_{t-1} + \delta_1 x_{t-1} + \mu_t \tag{A.1}$$

The constant and the trend term may be excluded in the equation A.1 depending on the stationarity conditions. The lags p and q are usually chosen optimally using an information criterion (e.g. AIC or BIC) to ensure the serial independence of the error sequence μ_t and the dynamic stability of the model.

Next, the F-statistic is obtained for the null hypothesis that y_t and x_t are not cointegration given by $H_0 : \delta_0 = \delta_1 = 0$. The asymptotic distribution for this test-statistic, however, is non-standard. According to Pesaran et al. (2001), this distribution depends on the statationarity property of y_t and x_t. The authors considered the separate cases when these time series are all stationary and when they all contain unit root. They compiled critical values for each of the cases, which they called critical bounds. In general, these bounds will also differ according to the number of time series involved in the cointegration test. If the F-statistic is greater than the upper critical bound, we conclude that y_t and x_t are co-integrated. The null is not rejected if the F-statistic is less than the lower bound and the test becomes inconclusive when the figure falls between the critical bounds.

Once we conclude in favour of cointegration, the respective long-run and equilibrium correction equations A.2 and A.3 can then be formulated in the final stage to analyse the dynamic associations between y_t and x_t.

$$y_t = \alpha + \beta t + \sum_{k=1}^{p} \beta_k y_{t-k} + \sum_{k=0}^{q} \alpha_k x_{t-k} + \hat{\nu}_t \tag{A.2}$$

$$\Delta y_t = \alpha + \beta t + \sum_{k=1}^{p} \beta_k \Delta y_{t-k} + \sum_{k=0}^{q} \alpha_k \Delta x_{t-k} + \gamma \hat{\nu}_{t-1} + e_t \tag{A.3}$$

where e_t is a disturbance term and the lags p and q must be chosen optimally as before. $\hat{\nu}_t$ is the error correction term and γ is the speed of equilibrium correction in the short term. A cointegration relationship is confirmed for $\gamma < 0$ which also means that any deviation in the short term will be eventually corrected.

B. Stationarity, Granger Causality and Cointegration Test Results

To estimate the equation A.1, we first used BIC and AIC to first check the optimal values of p for an underlying VAR(p) model involving the log house price growth rates for Amsterdam ($Arate_t$) and the Netherlands ($Nrate_t$). AIC suggested $p = 3$ while BIC chose $p = 1$. We therefore varied p from 1 to 3, excluding the constant and trend terms. The statistically insignificant lags are also neglected to ensure residual serial independence and the stability of the autoregressive structure of the model. The version of A.1 used for the co-integration test and its diagnostic statistics are shown in Table B.5. Table B.4 indicates the associated Pesaran et al. (2001) critical bounds.

Test	10%	5%	1%
F-bounds	(2.44,3.28)	(3.15,4.11)	(4.81,6.02)
t-bounds	(-1.62,-2.28)	(-1.95,-2.60)	(-2.58,-3.22)
Computed F-statistic		13.749	
Computed t-statistic		-5.087	

Table B.4: F and t-critical bounds taken from Pesaran et al. (2001) Tables $CI(i)$ and $CII(i)$ with $k = 1$.

Dependent variable: $\Delta Nrate_t$		
$\Delta Nrate_t$-1	-0.2765**	(0.0936)
$\Delta Arate_t$	0.2176***	(0.0427)
$Nrate_{t-1}$	-0.3862***	(0.0759)
$Arate_{t-1}$	0.2758***	(0.0552)
Observations		81
R^2		0.495
Adjusted R^2		0.469
Residual Std. Error		0.0072 (df = 77)
F Statistic		18.85 *** (df = 4; 77)

Table B.5: The conditional autoregressive distributed lag for the co-integration test. **Note:** Standard errors are in brackets, *p<0.1; **p<0.05; ***p<0.01. For serial correlation test, the two-sided dwtest statistics is 2.0528 (p-value = 0.7777) and fourth-order LM statistics is 1.7262 (p-value = 0.1534). The model is dynamically stable with the absolute value of root of the characteristics equation equal to 3.61677.

Dependent variable: $Nrate_t$		
$Nrate_{t-1}$	0.275**	(0.123)
$Nrate_{t-2}$	0.492***	(0.096)
$Arate_{t-1}$	0.136**	(0.055)
Observations		81
R^2		0.844
Adjusted R^2		0.838
Residual Std. Error		0.0082 (df = 78)
F Statistic		141*** (df = 3; 78)

Table B.6: Estimated ARDL(2,1) long-run equilibrium model. **Note:** Standard errors are in brackets, *p<0.1; **p<0.05; ***p<0.01.

Dependent variable: $\Delta Nrate_t$		
$\Delta Nrate_{t-1}$	-0.081	(0.153)
$\Delta Arate$	0.213***	(0.045)
$\Delta Arate_{t-1}$	0.255***	(0.056)
$\Delta Arate_{t-2}$	0.153***	(0.044)
$\hat{\nu}_{t-1}$	-0.553***	(0.176)
Observations		80
R^2		0.494
Adjusted R^2		0.460
Residual Std. Error		0.007 (df = 75)
F Statistic		14.64*** (df = 5; 75)
$\chi^2_{SC}(4)$		3.474 (p-value = 0.482)
X'tics Root (Abs. Value)		12.3671

Table B.7: The error-correction model (ECM) based on the ARDL(1,2) long-run equilibrium model. **Note:** Standard errors are in brackets, *p<0.1; **p<0.05; ***p<0.01.
$\chi^2_{SC}(4)$ is the 4th LM residual serial correlation test

| | Dependent variable | | | | | | | | |
Independent variable	2	3	4	6	9	10	11	12	13
1 Centrum						5.3389**			
2 Westerpark				3.5898*					11.3944***
3 Oud-West									
4 Zeeburg		9.0798***							
5 Bos en Lommer									
6 De Baarsjes								6.6566**	
7 Noord									
8 Geuzenveld									
9 Osdorp			4.3929**	5.9153**					
10 Slotervaart	6.4056**								
11 Zuid-Oost		3.3769*			7.0261***	52.5574***			
12 Watergraafsmeer									
13 Oud-Zuid									
14 Zuideramstel									

Table B.8: F-statistics from the pair-wise Granger Causality test. **Note:** The numbers at the top correspond to the districts on the LHS. Those districts that have no Granger causative districts are eliminated from the list of dependent variables to preserve space. Moreover, only F-statistics that are significant up to 10% level is reported here. *; **; and *** imply statistical significance at the 10%, 5% and 1% levels respectively.

Multivariate partial Granger Causality

Dependent	Cause/Independent	Control	F-statistic	Bias	Standard Error	95% CI
Q2	Q1	Q3, Q4	1.4027	-0.6272	0.6128	(-0.084,2.601)
Q3	Q1	Q2, Q4	0.8350	0.1064	0.9921	(-1.379,1.448)
Q4	Q1	Q2, Q3	0.2898	0.3550	0.4312	(-1.109,0.393)
Q3	Q2	Q1, Q4	0.3858	0.5252	1.0576	(-2.452,0.556)
Q4	Q2	Q1, Q3	0.2530	0.3379	0.3735	(-1.087,0.374)
Q4	Q3	Q1, Q2	0.0993	0.4923	0.4340	(-1.649, 0.086)
Q3	Q4	Q1, Q2	2.1341	-1.4656	0.8721	(2.134,4.142)
Q2	Q4	Q1, Q3	1.4717	-0.6284	1.0263	(-0.504,2.777)
Q1	Q4	Q2, Q3	0.1436	0.2951	0.4330	(-1.468,0.206)
Q2	Q3	Q1, Q4	0.4330	0.1183	0.9137	(-1.814, 0.729)
Q1	Q3	Q2, Q4	0.3025	0.1234	0.4373	(-0.999,0.528)
Q1	Q2	Q3, Q4	0.1992	0.2644	0.4945	(-1.960, 0.321)

Pairwise Multivariate Granger causality

	Q1	Q2	Q3	Q4
Q1	-	NO	1,7084 (0.075)	NO
Q2	NO	-	NO	NO
Q3	1,6661 (0.0857)	NO	-	3.9497 (0.0000)
Q4	NO	NO	NO	-

Table B.9: Lag effect analysis between market segments. **Note:** The confidence interval (CI) for the multivariate partial Granger causality was boostrapped using 2000 replications. There is Granger causality according to the partial scheme only if the lower band of the CI is greater than zero. Only the F-statistics for which the p-values (in bracket) are below 10% are reported for the pairwise multivariate Granger causality.

| Growth rate series | ZA-Test | | | | BEL-Test | |
| | Levels | | First-difference | | Levels | First-difference |
	Model A	Model C	Model A	Model C	Intercept only	Intercept only
Amsterdam	-3.4214	-3.3034	-9.2917***	-9.3143***	0.05494(1)	0.11870(2)
Netherlands	-4.0285	-3.7164	-9.0731***	-9.0329***	0.12356(1)	0.07725(1)
ZA Critical values	1%	5%	10%			
Model A	-5.34	-4.80	-4.58			
Model C	-5.57	-5.08	-4.82			
BEL Critical Values	k	1	2	3	4	5
1%		0.27366	0.65845	0.70496	0.72563	0.73219
5%		0.17241	0.39761	0.43237	0.44693	0.44932
10%		0.12889	0.30060	0.32415	0.33251	0.33562

Table 2: ZA-Zivot and Andrews (2002) and BEL-Becker et al. (2006) unit root and stationarity tests for the log house price indexes. The ZA critical values are taken from Zivot and Andrews (2002) while the BEL critical values are obtained with T=120 and 50,000 Monte Carlo simulations following (Becker et al., 2006, pg. 388). The k values in the BEL procedure are in the bracket and the truncation parameter is set equal to 11 in all cases using the long option in Pfaff (2008). The lags in the ZA test regression is 1 in all cases according to the BIC. *** and ** indicate significance at the 1% and 5% levels.

Faculty of Architecture
OTB - Research for the Built Environment
Delft University of Technology
Julianalaan 134, 2628 B Delft, The Netherlands
Postbus 5030, 2600 GA Delft, The Netherlands

Phone +31 (0)15 278 30 05
Fax +31 (0)15 278 44 22
E-mail mailbox@otb.tudelft.nl
www.otb.tudelft.nl