4 Amsterdam house price ripple effects in the Netherlands

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Abstract

Purpose: This paper examines the existence of the ripple effect from Amsterdam to the housing markets of other regions in the Netherlands. It identifies which regional housing markets are influenced by house price movements in Amsterdam.

Design/methodology/approach: The paper considers the ripple effect as a lead-lag effect and a long-run convergence between the Amsterdam and regional house prices. Using the real house prices for second-hand owner-occupied dwellings from 1995q1 to 2016q2, the paper adopts the Toda-Yamamoto Granger Causality approach to study the lead-lag effects. It uses the ARDL-Bounds cointegration techniques to examine the long-run convergence between the regional and the Amsterdam house prices. The paper controls for house price fundamentals to eliminate possible confounding effects of common shocks.

Findings: The cumulative evidence suggests that Amsterdam house prices have influence on (or ripple to) all the Dutch regions, except one. In particular, the Granger Causality test concludes that a lead-lag effect of house prices exists from Amsterdam to all the regions, apart from Zeeland. The cointegration test shows evidence of a long-convergence between Amsterdam house prices and six regions: Friesland, Groningen, Limburg, Overijssel, Utrecht and Zuid-Holland.

Research limitations/implications: The paper adopts an econometric approach to examine the Amsterdam ripple effect. More sophisticated economic models that consider the asymmetric properties of house prices and the patterns of interregional socio-economic activities into the modelling approach are recommended for further investigation.

Originality/value: This paper focuses on the Netherlands for which the ripple effect has not yet been researched to our knowledge. Given the substantial wealth effects associated with house price changes that may shape economic activity through consumption, evidence for ripples may be helpful to policy makers for uncovering trends that have implications for the entire economy. Moreover, our analysis controls for common house price fundamentals which most previous papers ignored.

Keywords: Amsterdam, House prices, Lead-lag effect, Ripple effect, Spatial causality

§ 4.1 Introduction

Real house prices in the Netherlands are reasonably correlated across regions. This may be mostly explained by the exposure to common factors, which are the main macroeconomic house price fundamentals. However, regional differences in real house price development exist, related to housing markets being local markets, subject to local influences. A first glance gives the impression that Amsterdam house prices are the first to move when compared to (some) other regions. This impression has stimulated our interest in the notion that Amsterdam house price development ripples to other Dutch regional housing markets. The ripple effect is conceptually a market phenomenon in which house price shocks in one region spread out their influence to house prices in other parts of the country (Meen, 1999; Nanda and Yeh, 2014; Balcilar et al., 2013). It manifests itself by way of house prices appreciating (down-turning) in one location, and subsequently appreciating (down-turning) in other regions (Giussani and Hadjimatheou, 1991).

There are several factors that may facilitate a house price ripple effect from Amsterdam to other regions in the Netherlands. First, the deterioration of housing affordability in Amsterdam, partly due to the wave of gentrification and urban regeneration, could shift the housing demand to the surrounding areas (Boterman et al., 2010). Second, recent internal migration patterns of certain groups of older adults in the Netherlands have been from urban to rural areas (De Jong et al., 2016). These migration patterns may explain why the housing demand and house prices in regions further away from Amsterdam may be stimulated (Meen, 1999). Third, house price spillovers from one region to another may be related to the general psychology and expectation of home-owners (Boelhouwer et al., 2004; Shiller, 1990). In an environment of low interest rates and higher demand for other regions, price changes in Amsterdam may induce house-owners in the surrounding regions to similarly increase their asking prices beyond what one would rationally expect of the fundamentals (Case and Shiller, 1988; Abraham and Hendershott, 1994).

The existence of ripple effects is an important question for policy makers. Because a house is the largest asset for most households, house price changes have significant wealth effects, which to an extent also determine the degree of economic activity through consumption. The existence of a ripple effect thus suggests some predictability of house price trends in other regions, which may indicate regional wealth distribution and consumptions patterns that may affect the entire economy.

This paper examines the extent of a ripple effect existing from Amsterdam to other regional housing markets in the Netherlands over the period 1995 to 2016. From a more empirical perspective, the literature conforms to the definition that the ripple effect occurs if shocks to house prices in one region impact other regions, causing a lead-lag relationship or long-run convergence between the house prices (Giussani and Hadjimatheou, 1991; Meen, 1999; Payne, 2012). In other words, it is necessary that the pairs of house prices exhibit a lead-lag effect and/or a co-integration relationship if a ripple effect exists. We test for the lead-lag effects via the application of the Toda-Yamamoto Granger Causality procedure. The cointegration relationships between the Amsterdam and regional house prices are estimated using the ARDL-Bounds approach. This method is consistent with the empirical applications by

Giussani and Hadjimatheou (1991), MacDonald and Taylor (1993) and Holmes (2007), who studied the ripple effect for the UK.

This paper furthermore controls for house price fundamentals to eliminate possible confounding effects of common shocks which the previous papers ignored. In conclusion, the cumulative evidence suggests that Amsterdam house price developments may influence (or ripple to) all the regions in the Netherlands, except one. Particularly, the Granger Causality analysis suggests that house price lead-lag effects exist from Amsterdam to all regions, except Zeeland. Whereas the cointegration test finds evidence of a long-run impact existing from Amsterdam to Friesland, Groningen, Limburg, Overijssel, Utrecht and Zuid-Holland. Quarterly real average house price time series data for second-hand owner-occupied dwellings are used for the analyses.

The rest of the paper is structured as follows. Section 4.2 gives a brief overview of the empirical literature on ripple effects in housing markets. Section 4.3 presents an overview of house price developments in the Netherlands, indicating the differences that exist amongst the regions and between Amsterdam and the rest of the country. Section 4.4 discusses the empirical models and the estimation results. Section 4.5 concludes the paper.

§ 4.2 The empirical literature

The ripple effect is a widely studied subject in the housing literature. An elaborate and a more recent review is provided in for example Nanda and Yeh (2014) and Gong et al. (2016b). We only present a brief summary in this paper. Historically, housing researchers observed the ripple effect first in the United Kingdom. This was in the early 1990s when upswings in house prices from parts of the South-East, mostly London, were noticed subsequently in other regions of the UK (see e.g. Giussani and Hadjimatheou, 1991; MacDonald and Taylor, 1993; Meen, 1999). Studies on the subject since then have been carried out in many other countries. Berg (2002) studied the ripple effect on the second-hand market for family houses in Sweden and found evidence for a ripple effect existing from Stockholm to other regions in Sweden.

In the US, Canarella et al. (2012) for example studied the spatial interrelationships of house prices and concluded that ripple effect potentially exist from housing markets in the east and west coast metropolitan areas to the rest of the US. Buyst and Helgers (2013), who analysed the case of Belgium, found that house price shocks are likely to "ripple" from Antwerp to the rest of the country. Gong et al. (2016b) recently studied the case of China and they found a unidirectional causal flow of house price shocks from the eastern-central region to the western parts in the Pan-Pearl River Delta of China.

In the Netherlands, the existence of a potential ripple effect is less certain, even though there is an upswing of house prices seemingly appearing first in Amsterdam and subsequently occurring in other parts of the country. Teye and Ahelegbey (2017) recently studied the house price diffusion process between the Dutch regional housing markets but did not specifically consider the Amsterdam effect. Pollakowski and Ray (1997), argued that the ripple effect may occur between regions that are economically related, although they need not necessarily border each other. Meen (1999), suggested that the ripple effects between regional house prices may be facilitated by economic activities, such as interregional migration, equity transfer and spatial arbitrage.

Meen (1999) was also one of the first scholars to provide a general empirical method for studying the ripple effect in the housing context. His method is equivalent to testing the stationarity of the regional to national house price ratios. Using the traditional augmented Dickey-Fuller (ADF) test, however, Meen (1999) was not personally successful in confirming the ripple effect. In response, other scholars later used more advanced stationarity test procedures based on his empirical framework to study the ripple effect. For instance, the threshold and momentum threshold autoregressive test procedures were adopted by Cook (2003), while Holmes and Grimes (2008) combined unit root test and principal component analysis to examine the ripple effect for the UK. Canarella et al. (2012), also studied the house price ripple effect in the US by combining the generalised least squares version of the ADF with non-linear unit root tests and other procedures that control for structure breaks. The Bayesian and panel seemingly unrelated regressions augmented Dickey-Fuller (SURADF) methods for testing unit roots have also been used by a section of the housing literature (e.g. Balcilar et al., 2013; Lee and Chien, 2011; Holmes, 2007).

Some researchers recently have advocated using dynamic spatial modelling approaches in which shocks from certain dominant regions are allowed to propagate to other locations and to echo back (Holly et al., 2010, 2011; Buyst and Helgers, 2013; Nanda and Yeh, 2014; Gong et al., 2016b). Nevertheless, methods such as Cross-correlations, Granger Causality (GC), Cointegration and Impulse Response Analysis (IRA), are still commonly used for studying the ripple effect (see Giussani and Hadjimatheou, 1991; MacDonald and Taylor, 1993; Holmes, 2007; Vansteenkiste and Hiebert, 2011; Gupta and Miller, 2012a,b; Brady, 2014). The analysis with these methods are relatively simple to perform and this paper adopts similar approaches.

§ 4.3 Regional house price differences from data

Data on average regional house prices for second-hand owner-occupied dwellings in the Netherlands are obtained from Statistics Netherlands (CBS) for the analysis in this paper.[1] The data indicate significant differences between regional average prices of owner-occupied dwellings in the Netherlands. In the last quarter of 2014, for instance, real average house price ranges from an estimated €239,932 in Noord-Holland to about €155,810 in Groningen. These regional house price differences may partly be explained by variations in the demographic and economic structures of the regions.

Table 4.1 presents the summary statistics and Figure 4.1 displays the details of regional real average house price developments in the Netherlands over the period 1995q1-2016q2.[2] The figure shows that real average house prices are higher in Utrecht, Noord-Holland (including Amsterdam), Noord-Brabant and Gelderland, while relatively lower in Groningen, Friesland and in Zeeland. There is also an apparent

1 The Dutch provinces are equated to regions in this paper.

2 Average house prices are not quality adjusted. Real average house prices are in 2010 Euros and are obtain by deflating the nominal values with consumer price index (CPI) obtained from the OECD.

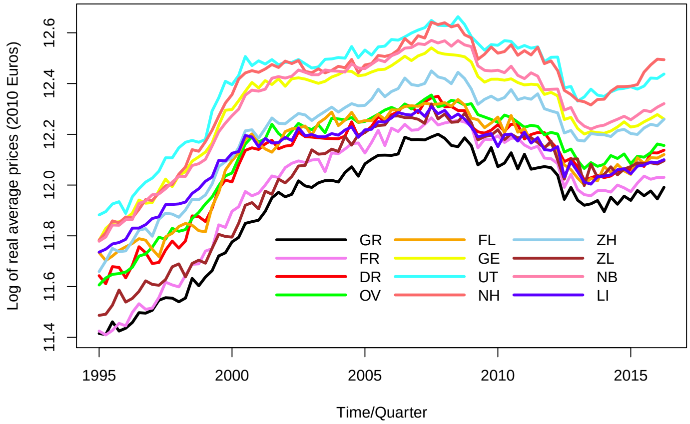

FIGURE 4.1 Regional real average house prices in the Netherlands (1996q1-2016q2).

Note: GR = Groningen, FR = Friesland, DR = Drenthe, OV = Overijssel, FL = Flevoland, GE = Gelderland, UT = Utrecht, NH = Noord-Holland (including Amsterdam), ZH = Zuid-Holland, ZE = Zeeland, NB = Noord-Brabant, LI = Limburg.
Source: Statistics Netherlands, OECD

co-movement between the regional house prices that may be explained by the effects of common fundamentals.

Figure 4.2 exhibits a clearer picture of the differences in development of real average house prices between Amsterdam and the rest of the Netherlands. As in Table 4.1, Figure 4.2 equally indicates that houses in Amsterdam are on average more expensive than elsewhere in the Netherlands, which may be because Amsterdam is the capital where demand is extremely high. The differences in the average house prices between Amsterdam and the rest of the Netherlands are not constant, however. These tend to widen during an upswing and narrow in a downturn. This may be because Amsterdam

TABLE 4.1 Summary statistics for real average house prices and the control variables.

Region	Minimum	Median	Mean	Maximum	Standard deviation
AM	11.76	12.48	12.41	12.70	0.24
GR	11.41	11.98	11.92	12.20	0.23
FR	11.41	12.04	11.98	12.26	0.24
DR	11.61	12.15	12.09	12.35	0.20
OV	11.61	12.19	12.12	12.35	0.20
FL	11.70	12.16	12.11	12.34	0.19
GE	11.78	12.39	12.30	12.54	0.20
UT	11.88	12.48	12.40	12.66	0.20
ZH	11.66	12.25	12.19	12.45	0.20
ZL	11.49	12.09	12.01	12.32	0.24
NB	11.78	12.38	12.31	12.57	0.21
LI	11.74	12.16	12.11	12.31	0.15
r	-1.22	2.00	1.91	5.15	1.48
gdp	13.16	13.46	13.43	13.57	0.11

All values are in log except interest rates. GR = Groningen, FR = Friesland, DR = Drenthe, OV = Overijssel, FL = Flevoland, GE =Gelderland, UT = Utrecht, NH = Noord-Holland, ZH = Zuid-Holland, ZE = Zeeland, NB = Noord-Brabant, LI = Limburg, r = Real interest rate.

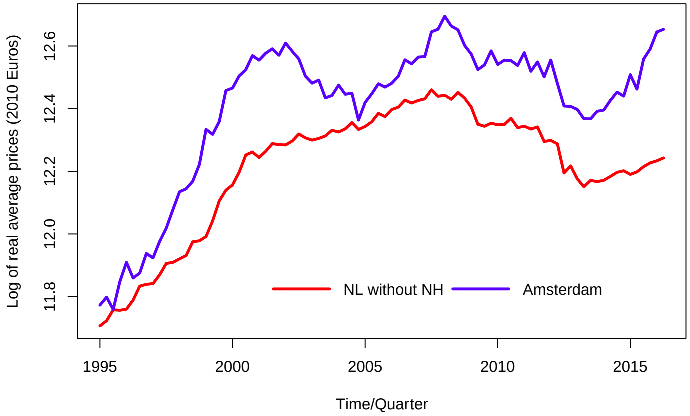

FIGURE 4.2 Quarterly regional average prices of owner-occupied dwellings (1996q1-2016q2).

Note: NL = The Netherlands, NH = Noord-Holland. The series for NL without NH are obtained as deflated weighted average of average house prices in all provinces of the Netherlands, leaving out NH. We calculate the weights as the percentage of total houses sold in the Netherlands at the provinces' level.
Source: Statistics Netherlands, OECD

house prices grow faster than other regions during an upswing (see Van Dijk et al., 2011).

The figure also clearly reveals that house prices in Amsterdam are potentially the first to move during an upswing or downturn in the Netherlands. Following the 2007-08 Global Financial Crisis (GFC) especially, we can observe that house prices started to decline in Amsterdam in the last quarter of 2008 and a period of one quarter later (2009q1) before the decrease began in the rest of the Netherlands. As discussed in the previous section, observing house price cycles first in Amsterdam and later in other regions may be that house prices are merely more volatile in Amsterdam than in the other regions or possibly the decline of house prices later in the rest of the Netherlands is a direct response to the house price decreases in Amsterdam. The latter would indicate the ripple effect which this paper studies.

§ 4.4 Empirical methods and estimations

Many papers that study ripple effects as a lead-lag relationship use simple cross-correlation (see Giussani and Hadjimatheou, 1991). The cross-correlation is most appropriate for capturing the relationship between two variables when one has a delayed effect on the other (Shumway and Stoffer, 2010). However, one drawback of simple cross-correlation is that it does not allow us to control for the cumulative lag effects of Amsterdam house prices. Moreover, it does not enable us to control for the house price fundamentals that may possibly confound the lead-lag effect. Since these drawbacks may give misleading results, this paper applies Granger Causality and cointegration analyses.

The Granger Causality provides a simple way to correct for the effects of common fundamentals and to account for the cumulative lag effects of Amsterdam house prices. The cointegration analysis provides a framework for determining the long-run convergence between the house prices.

§ 4.4.1 Granger causality analysis

The underlying principle of Granger causality (GC) is that the Amsterdam house prices should add significant information to the prediction of the regional house prices if there is a lead-lag effect (Granger, 1980, 1969). This paper employs the Toda and Yamamoto (1995) GC (TY-GC) test to study the lead-lag effect between the Amsterdam and regional house prices. The same method has been used by Gong et al. (2016b) and Chen et al. (2011) who studied lead-lag relationships between regional house price indices.

There are advantages of using the Toda and Yamamoto (1995) approach for testing GC. In the original formulation, Granger (1969) provided a standard empirical technique for GC analysis that is applicable only for stationary time series. The TY-GC method, on the other hand, is suitable for the GC analysis with one or more time series being non-stationary. It also enables multivariate analysis, making it flexible to control for house price fundamentals that may possibly confound discernment of the lead-lag relationship between the house prices.

Toda-Yamamoto procedure

The TY-GC procedure involves testing linear restrictions in a lag-augmented VAR (Vector Autoregressive) model. More precisely, let x_t and y_{it} be the house price series for Amsterdam and the region i respectively, and suppose they follow the VAR(p) process with control variables(s) z_t defined by

$$\begin{bmatrix} y_{it} \\ x_t \end{bmatrix} = \begin{bmatrix} \alpha_0 + \gamma_1 z_{t-1} + \cdots + \gamma_q z_{t-q} \\ \beta_0 + \delta_1 z_{t-1} + \cdots + \delta_q z_{t-q} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \beta_{11} \\ \alpha_{21} & \beta_{21} \end{bmatrix} \begin{bmatrix} y_{it-1} \\ x_{t-1} \end{bmatrix} + \cdots + \begin{bmatrix} \alpha_{1p} & \beta_{1p} \\ \alpha_{2p} & \beta_{2p} \end{bmatrix} \begin{bmatrix} y_{it-p} \\ x_{t-p} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \tag{4.1}$$

where $p, q \geq 1$. If x_t and y_{it} were all stationary, the standard test that x_t Granger causes y_{it} is equivalent to testing the null hypothesis,

$$H_0 : \beta_{11} = \cdots = \beta_{1p} = 0 \tag{4.2}$$

On the other hand, this test is statistically invalid and needs to be modified if at least one of the series is non-stationary. Toda and Yamamoto (1995) provided a simple modification when there are non-stationary time series. Their method augments the VAR(p) model with k additional lags and then tests H_0 from the resulting VAR$(p+k)$ model, neglecting the extra k lags which have zero coefficients in principle. The lag augmentation is used to preserve the asymptotic distribution of the Wald test-statistics on addition of the non-stationary series (ibid). The value for k is determined as the maximal order of integration between the time series.

TABLE 4.2 Augmented Dickey–Fuller (ADF) test for (log) average real house prices and control variables.

	Levels		First-difference	
Series	Test-statistics	P-value	Test-statistics	P-value
AM	0.88 (0)	0.90	-4.55 (1)	0.00***
GR	0.15 (5)	0.72	-2.13 (4)	0.03**
FR	0.15 (4)	0.73	-2.77 (3)	0.01***
DR	0.64 (0)	0.85	-2.86 (3)	0.00***
OV	0.71 (0)	0.87	-8.55 (0)	0.00***
FL	0.23 (2)	0.75	-5.29 (1)	0.00***
GE	0.12 (0)	0.72	-7.78 (0)	0.00***
UT	0.37 (0)	0.79	-9.81 (0)	0.00***
ZH	0.31 (4)	0.77	-2.88 (3)	0.00***
ZL	0.28 (5)	0.76	-1.87 (5)	0.06*
NB	-0.12 (4)	0.64	-2.69 (3)	0.01***
LI	-0.09 (3)	0.65	-3.87 (2)	0.00***
r	-1.57 (0)	0.11	-6.86 (0)	0.00***
gdp	2.09 (1)	0.99	-4.58 (0)	0.00***

Real interest rate is denoted by r. ADF test regression is estimated separately for each time series without deterministic trend and intercept. The optimal lag, indicated in parenthesis, is estimated using BIC. $*$, $**$ and $***$ denote statistical significance at the 10, 5 and 1% respectively.

Results

The implementation of the TY-GC test requires pre-testing the integration order of the house price series. We use the log real average house prices, which are confirmed as $I(1)$ series by the standard Augmented Dickey-Fuller test in Table 4.2. This also means that k must be set equal to one in each of the region specific VAR model.

Thus, the TY-GC test is performed with a VAR($p+1$) model to estimate the lead-lag effect between the regional and house Amsterdam prices. We include the two most important Dutch house price fundamentals for z_t: real GDP (gdp_t) and real interest rates (r_t) (see De Vries, 2010; Toussaint and Elsinga, 2007; Boelhouwer, 2002, for thorough discussions of the determinants of Dutch house prices). We use the national real GDP as this data is unavailable to us at the regional level. In the Netherlands, the credit market is uniform across all the regions and most mortgage contracts are fixed for five years or longer periods (De Haan et al., 2005). Thus, the long-term real interest rates are used for the estimations.[3] The lag order p is estimated from a VAR model for the four variables y_{it}, x_t, gdp_t and r_t separately for each region i using AIC. The statistically insignificant lags for gdp_t and r_t from the estimated VAR model are dropped to obtain the lag q. For each region i, we find $q = 1$.

To proceed with the Granger Causality analysis, it is empirically important that the residuals from the model (4.1) are serially uncorrelated. If the residuals exhibit serial correlation, p is increased by one until there is at least first-order serial independence at the 5% statistical significance level. The Breusch–Godfrey LM serial correlation test statistics are marked $\chi^2_{SC}(1)$ in Table 4.2(a). The null hypothesis for the Granger Causality test is stated specifically as

3 The paper uses long-term real interest rates and real GDP from the OECD. The long-term real interest rates are obtained as nominal values minus inflation.

TABLE 4.3 Toda-Yamamoto Granger causality test-statistics and regression exhibit.

((a)) Toda-Yamamoto Granger causality test

Region	Test-statistic	Lag (p)	P-value	$\chi^2_{SC}(1)$
GR	3.20	3	0.03**	0.59 (0.44)
FR	5.03	3	0.00***	2.98 (0.08)*
DR	2.19	6	0.06*	0.86 (0.35)
OV	6.67	3	0.00***	0.02 (0.87)
FL	3.27	5	0.01***	0.04 (0.85)
GE	4.87	2	0.01***	3.37 (0.07)*
UT	6.85	2	0.00***	1.81 (0.18)
ZH	5.40	3	0.00***	0.57 (0.45)
ZL	1.22	3	0.31	2.56 (0.46)
NB	8.25	2	0.00***	1.11 (0.29)
LI	3.61	3	0.02**	0.00 (0.99)

((b)) Regression results when Flevoland is the dependent region ($y_t^i, i =$UT)

Independent variable	Estimate	Std. Error	t-value	P-value
Const.	0.40	0.73	0.54	0.58
y^i_{t-1}	0.69	0.12	5.81	0.00***
y^i_{t-2}	0.16	0.11	1.41	0.16
x_{t-1}	0.18	0.08	2.18	0.03**
x_{t-2}	0.10	0.10	0.98	0.33
x_{t-3}	-0.16	0.09	-1.87	0.07 *
gdp_{t-1}	0.00	0.08	0.01	0.99
r_{t-1}	0.01	0.00	1.79	0.08 *

4.2(a): Test is performed separately for each region using VAR(p+1) model with constant term and control variables (real GDP and real interest rates). The lag p is estimated using AIC. The reported test-statistics are the Wald statistics. $\chi^2_{SC}(1)$ is the first-order LM test-statistic (p-value in parenthesis) which indicates the independence of the residuals from the augmented regression equation for each region. 4.2(b): The Amsterdam log real average house prices is represented by the series x_t. Residual standard error = 0.03, multiple r-squared = 0.97 and the adjusted r-squared = 0.96. The Toda-Yamamoto procedure tests for the joint significance of the first p lags of x_t in the regression. Statistical significance is denoted by $*$, $**$ and $***$ at the 10, 5 and 1% levels respectively.

H_0 : *Amsterdam house prices do not Granger cause house prices in the specified region*

A rejection of this null hypothesis implies there is Granger causality, suggesting a lead-lag effect in which Amsterdam house price movements are associated with subsequent house price developments in the respective regions. The results of the test are summarised in Table 4.3.

The table indicates the hypothesis that no Granger causality exists could be rejected at the 5% statistical significance level for all the regions, except in the case of Drenthe and Zeeland. Nevertheless, Granger causality could be weakly confirmed for Drenthe at the 6% statistical level.

§ 4.4.2 Cointegration and long-run relationships

The preceding subsection analysed the lead-lag effects between the Amsterdam and regional house prices using the TY-GC approach. This subsection studies the cointegration relationships between them. A cointegration relationship determines the long-run convergence, which suggests a ripple effect between the Amsterdam and regional house prices (Meen, 1999; Payne, 2012).

We use the Autoregressive Distributed Lags (ARDL)-Bounds cointegration procedure of Pesaran et al. (2001) to test the existence of cointegration relationships in this paper. This approach allows us to control for the house price fundamentals and it is generally flexible enough to enable inclusion of both stationary and non-stationary time series in the test procedure. The ARDL-Bounds approach to cointegration is the most appropriate amongst existing methods for the shorter study period in this paper (see e.g. Narayan, 2005, for a discussion on the choice of cointegration techniques). It was similarly adopted by Payne (2012) who studied the long-run convergence and ripple effects among regional housing prices in the US.

ARDL cointegration procedure The Pesaran et al. (2001) ARDL-Bounds cointegration test between x_t and y_{it}, controlling for the house price fundamentals is performed in several steps. Most importantly, it needs to be ensured that all the time series are not integrated beyond the first order. We can then formulate an unrestricted error correction (UEC) model which forms the basis for the test. The model in this paper is of the form

$$\Delta y_{it} = \alpha + \sum_{j=1}^{p} \gamma_j \Delta y_{it-j} + \sum_{j=1}^{q} \alpha_j \Delta x_{t-j} + \sum_{j=1}^{l} \beta_j \Delta gdp_{t-j} + \sum_{j=1}^{s} \eta_j \Delta r_{t-j} + \pi_1 \, y_{it-1} + \pi_1 \, x_{t-1} + \pi_3 \, gdp_{t-1} + \pi_3 \, r_{t-1} + \epsilon_t \tag{4.3}$$

The lags $p, q, l,$ and s may be optimally chosen using an information criterion. Moreover, they must be adjusted if necessary to ensure that the error sequence ϵ_t is serially independent and that the autoregressive structure of the model (4.3) is dynamically stable.

For region i, the hypothesis that no cointegration exists is performed separately using the Wald statistic and the F-critical bounds provided by Pesaran et al. (2001). The null hypothesis is equivalent to the coefficients of the lags; x_{t-1}, y_{it-1}, gdp_{t-1} and r_{t-1}, in equation (4.3) being statistically insignificant. This may be expressed explicitly as

$$H_0 : \pi_1 = \pi_2 = \pi_3 = \pi_4 = 0 \tag{4.4}$$

Results The ARDL-Bounds cointegration method requires that the house price series and the control variables are not integrated beyond the first-order. The log of the variables which were established as $I(1)$ series in the previous subsection (Table 4.2) are also used here. The lags p, q, l and s are estimated following several steps similar to Giles (2013). To begin, a VAR(p_{min}) model is estimated for the four variables: $\Delta y_{it}, \Delta x_t$, Δgdp_t and Δr_t, separately for each region i, with the lagged terms y_{it-1}, x_{t-1}, gdp_{t-1} and r_{t-1} specified as exogenous variables. The AIC is then used to select the p_{min}. In most cases, we find that the lags for Δgdp_t and Δr_t are not statistically significant beyond the first order. Thus, l and s are set equal to one in the UEC. Next, we estimate the UEC model over the grid $[1, p_{min}] \times [1, p_{min}]$ and select the optimal p and

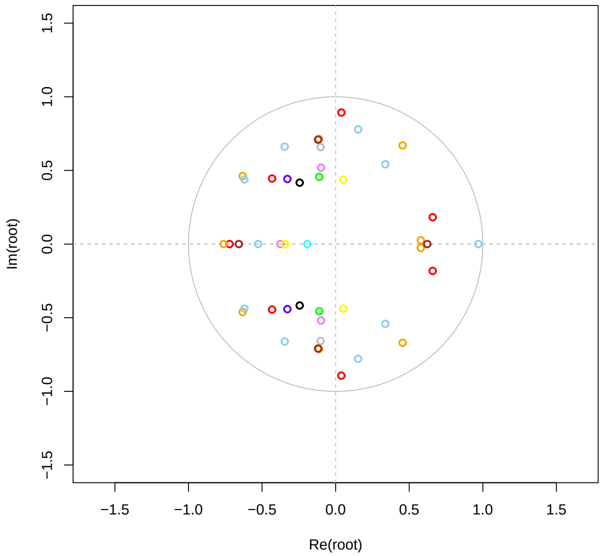

FIGURE 4.3 Inverse roots for AR characteristics equations.

Note: The inverse roots for the regions are coloured as: Black = Groningen, Violet = Friesland, Red = Drenthe, Green = Overijssel, Orange = Flevoland, Yellow = Gelderland, Cyan = Utrecht, Gray = Zuid-Holland, Sky-blue = Zeeland, Brown = Noord-Brabant, Blue = Limburg.

q using the AIC. When necessary, the resulting values are further increased by one until the residuals are serially independent.

Furthermore, the characteristic equation of the autoregressive part of the UEC model is assessed for dynamic stability. The details of the diagnostic statistics are presented in Table 4.4 and Figure 4.3. The models are generally well-specified and stable, with the inverse roots of the characteristics equation all inside the unit circle (see Figure 4.3). Table 4.4 summarises the results of the bound cointegration test. At the 5% level of statistical significance, the results suggest that cointegration exists between Amsterdam and only five regions in the Netherlands: Groningen, Friesland, Overijssel, Limburg and Zuid-Holland. Moreover, cointegration in the case of Utrecht could be confirm weakly at the 10% statistical level, while no evidence exist to conclude on cointegration for the rest of the regions.

The specific long-run cointegration equation for these regions are presented in Table 4.5. The coefficients on Amsterdam house prices are statistically significant and carry the expected positive sign in the long-run equation. In particular, a percentage increase in Amsterdam house prices is estimated to correspond respectively to 0.41%, 0.62%, 0.68%, 0.63%, 0.53% and 0.73% increase in houses prices of the six regions in the long-run.

TABLE 4.4 ARDL cointegration test-statistics and exhibit of the unrestricted error correction model.

((a)) Statistics for ARDL bounds cointegration test performed separately for each region

Region	Model	$\chi^2_{SC}(1)$	$\chi^2_{SC}(3)$	F-stat	Status at 5% level
GR	ARDL(2,2,1,1)	1.03 (0.31)	1.05 (0.79)	4.92**	Cointegration
FR	ARDL(3,3,1,1)	2.48 (0.12)	5.93 (0.12)	4.57**	Cointegration
DR	ARDL(7,6,1,1)	0.58 (0.45)	1.54 (0.67)	2.47	No cointegration
OV	ARDL(2,2,1,1)	0.84 (0.36)	5.30 (0.15)	4.95**	Cointegration
FL	ARDL(9,9,1,1)	1.16 (0.28)	1.68 (0.64)	1.94	No cointegration
GE	ARDL(3,3,1,1)	2.63 (0.11)	3.92 (0.27)	3.16	No cointegration
UT	ARDL(1,1,1,1)	2.40 (0.12)	3.97 (0.26)	3.84*	Inconclusive
ZH	ARDL(2,1,1,1)	0.05 (0.83)	0.40 (0.94)	6.71***	Cointegration
ZL	ARDL(10,9,1,1)	2.54 (0.11)	3.19 (0.36)	2.12	No cointegration
NB	ARDL(4,4,1,1)	0.54 (0.46)	2.78 (0.43)	1.23	No cointegration
LI	ARDL(2,2,1,1)	0.36 (0.55)	3.49 (0.32)	4.04**	Cointegration

Bound critical values

1%		5%		10%	
$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$
4.29	5.61	3.23	4.35	2.72	3.77

((b)) Unrestricted error correction model estimate for GR (y^i_t, i =ZH)

Independent variable	Estimate	Std. Error	t-value	P-value
Const.	0.638	0.66	0.97	0.34
Δy^i_{t-1}	-0.205	0.10	-2.04	0.04**
Δy^i_{t-2}	-0.444	0.10	-4.49	0.00***
Δx_{t-1}	-0.178	0.07	-2.47	0.02**
Δgdp_{t-1}	2.250	0.47	4.77	0.00***
Δr_{t-1}	0.007	0.00	1.40	0.17
y^i_{t-1}	-0.156	0.05	-3.35	0.00***
x_{t-1}	0.135	0.03	4.10	0.00***
gdp_{t-1}	-0.031	0.07	-0.43	0.66
r_{t-1}	0.005	0.00	1.69	0.10*

In 4.4(a), the unrestricted error correction (UEC) model is estimated with a constant for all regions. The lag order is selected with AIC and further adjustment when necessarily to correct for serial correlation and dynamic stability of autoregressive structure of the UEC model. $\chi^2_{SC}(m)$ is the m-order LM residual serial correlation test of the estimated ARDL model. The critical values are taken from Table CI(iii) and and CII(iii) of Pesaran et al. (2001), with $k = 3$. For the regression estimates in 4.4(b), the residual standard error = 0.02, multiple r-squared = 0.46 and the adjusted r-squared = 0.39. Statistical significance is denoted by $*$, $**$ and $***$ at the 10, 5 and 1% levels respectively.

§ 4.5 Discussions and concluding remarks

The extent of house price spillover from Amsterdam to other regions in the Netherlands, the so-called ripple effect, has been examined for the period 1995q1-2016q2 in this paper. In order to determine the existence of spillovers, we corrected for the macroeconomic house price fundamentals; real GDP and real interest

TABLE 4.5 Estimates of long-run relationships for cointegrating regions.

Region	Constant	Amsterdam	gdp	r	Adj. R^2	RSE
GR	-13.51 (1.88)***	0.41 (0.07)***	1.50 (0.19)***	0.05 (0.01)***	0.88	0.08
FR	-11.87 (1.87)***	0.62 (0.07)***	1.20 (0.19)***	0.05 (0.01)***	0.90	0.08
OV	-4.30 (1.57)***	0.68 (0.06)***	0.59 (0.16)***	0.03 (0.01)***	0.89	0.07
UT	-3.99 (1.34)***	0.73 (0.05)***	0.54 (0.13)***	0.04 (0.01)***	0.92	0.06
ZH	-7.59 (1.46)***	0.53 (0.06)***	0.98 (0.15)***	0.04 (0.01)***	0.90	0.06
LI	2.60 (1.21)**	0.63 (0.05)***	0.12 (0.12)	0.03 (0.01)***	0.88	0.05

Standard errors are reported in parenthesis. RSE is the residual standard error for the regression. $*$, $**$ and $***$ denote statistical significance at the 10, 5 and 1% respectively.

TABLE 4.6 Summary of the Granger causality and cointegration test results.

Regions	Granger causality	Cointegration	Granger causality but no cointegration	No granger causality nor cointegration
DR	X†		X	
FL	X		X	
FR	X	X		
GE	X		X	
GR	X	X		
LI	X	X		
NB	X		X	
OV	X	X		
UT	X	X†		
ZH	X	X		
ZL				X

The applicable regions are marked X. † denotes Granger causality or cointegration is only confirmed weakly at statistical level between 5% and 10%.

rates. The ripple effect is studied as a lead-lag relationship and long-run convergence between the house prices, for which we respectively applied Granger Causality and cointegration analyses.

Using real house price data series for second-hand owner-occupied dwellings, the results summarised in Table 4.6, can be divided into four categories. The first category contains one region for which there is no evidence of cointegration nor Granger Causality from Amsterdam (Zeeland). The second category constitutes four regions for which there is only Granger Causality from Amsterdam but no cointegration (Drenthe, Flevoland, Gelderland and Noord-Brabant). The third category shows the regions for which there is evidence of both cointegration and Granger causality from Amsterdam (Friesland, Groningen, Limburg, Overissel, Utrecht and Zuid-Holland). The fourth category exhibits evidence of Granger Causality from Amsterdam (includes all regions except Zeeland).

In conclusion therefore, the cumulative evidence suggests that Amsterdam house prices have some level of influence on (or ripple to) all the regions in the Netherlands, except Zeeland. The cointegration test which finds a long-run convergence between Amsterdam and Zuid-Holland or Utrecht is expected due to the close proximity. However, the cointegration in the case of the four regions (Friesland, Groningen, Limburg and Overijssel), is particularly interesting. This is because these regions are much distant from Amsterdam and also among the highly affordable regions with the lowest average house prices especially after 2005 (see Figure 4.1).

Further research could shed more light on the economic mechanisms underlying these long-run convergence and ripple effects. Meen (1999) suggests that inter-regional migration may facilitate ripple effects between regional housing markets. One direction for further investigation might be to consider the extent to which housing affordability motivates house movers and internal-migrants from Amsterdam. The high affordability may be a pull-factor for certain class of households and individuals migrating from Amsterdam, which subsequently could affect house prices significantly. As neither Granger causality nor cointegration is established between Amsterdam and Zeeland, which is also among the cheapest, this could mean that Zeeland is not a preferred destination for movers from Amsterdam. Yet we leave the confirmation of these suggestions to future research regarding the underlying explanations for the ripple effects.

It might also be useful to consider other approaches for studying the long-run convergence and ripple effect between Amsterdam and the regional house prices in a future research. Cook (2003, 2006), for instance, opined that the asymmetric properties of house prices may obscure how they interrelate spatially. This asymmetric property may also be considered for further investigation, in which a distinction is made between the nature of the house price ripple effect from Amsterdam to the other regions during upswings and downturns. Furthermore, an economic model that controls for the interregional socio-economic activities may be adopted to explicitly trace their role in the house price spillover effect.