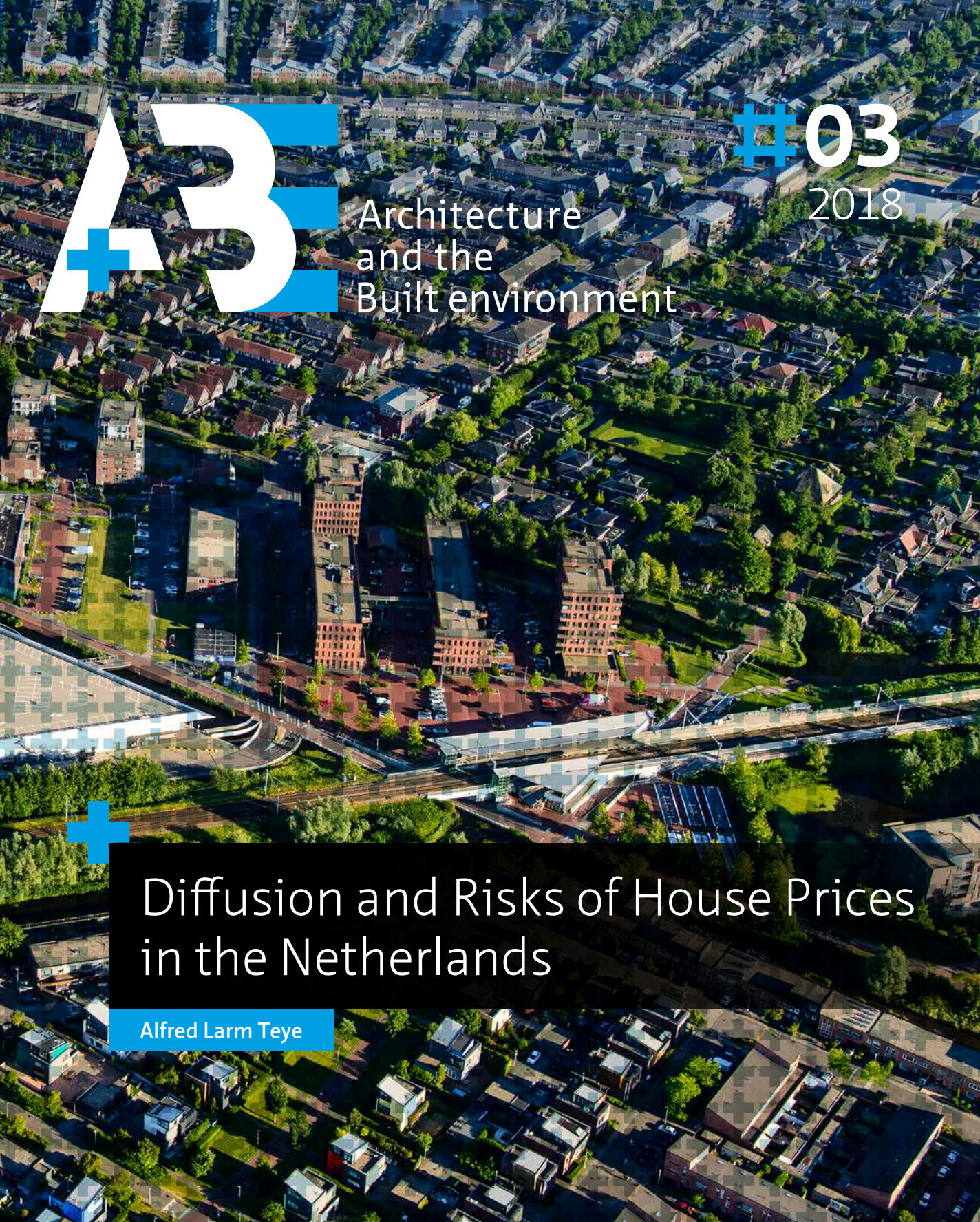

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Diffusion and Risks of House Prices in the Netherlands

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Contents

Preface

The four years of PhD has been a great leaning opportunity for me. During the period, I developed skills in time management, problem solving, project management, and most importantly to mature as an independent researcher. I give the glory to the Holy Trinity for giving me the strength to overcome the challenges during the process and for granting me wisdom to realise my dream of completing this dissertation. Eventually, the completion of the dissertation has been possible through the support of many people.

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I also want to thank editors and reviewers of my articles whose comments have been helpful in improving my research insights and my ability to present sound scientific arguments. I particularly want to appreciate the editor and reviewers of Regional Science and Urban Economics and Journal of European Real Estate Research for their critical comments on my manuscripts. My gratitude also goes to Gavin Wood and Daniel Melser for commenting on my work. To all my co-authors, I say a big thanks for allowing me to learn from your wealth of experience. I also appreciate my committee members for their objective assessment of my dissertation.

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My love goes to my sweetness Glory for being solidly behind me through the thin and tall and to our lovely baby boy Ezra Philibert who was born at the time of finalising this dissertation. Ezra, your birth has given me joy and extra motivation to complete this dissertation. I dedicate it to you and I pray that you reach extraordinary heights and that you become a channel of blessings to your generation.

Summary

The rate of home-ownership has increased significantly in many countries over the past decades. One motivating factor for this increase has been the creation of wealth through the accumulation of housing equity, which also forms the basic tenet of the asset-based welfare system.

In generating the home equity, house price developments play an important role. Generally, house prices show an increasing trend over long time period, however, there are short term negative appreciations that may have inherent risks for the housing equity. Following the 2007-08 Global Financial Crisis (GFC), for example, the collapse of house prices has caused many recent home buyers to run into negative equity.

Some housing researchers and experts have suggested that a better understanding of the spatial diffusion mechanisms of house prices will aid resuscitating the housing market after the GFC. Others also advocated adopting insurance schemes to protect the home equity that yields the welfare benefits. Unfortunately, however, little research insight exists on the Dutch house price diffusion process, although there are empirical results for countries such as the UK, US and China, where the contexts differ from the Netherlands. Furthermore, the current existing home-value insurance scheme in the literature is found to be less efficient and eliminates only up to 50% of the house price risks.

This dissertation covers important aspects of house price diffusion and risks in the Netherlands. The aim is to better understand the diffusion mechanism and the risks of house prices, while it also contributes to the measurement of these housing risks. More specifically, there are three objectives: first, to discover the diffusion mechanism of house prices in the Netherlands and the pattern particularly from the capital Amsterdam; second, to examine the spatial distribution of the house price risk; and third, to investigate the efficiency of the index-based home-value insurance for reducing the house price risk in the Dutch context

The diffusion mechanism relates to the so-called ripple or spillover effect, for which movements of house prices in one location temporarily or permanently spread over their influence to other regions. The risks analyses capture the probability of selling the residential property below the purchase price. The index-based home-value insurance scheme is concerned with the reduction of the house price risk, while its efficiency and loss coverage are analysed.

The contributions of the dissertation are specifically elaborated in five chapters. The chapters are self-contained, four of them having been published separately in international journals and the other being currently under review.

Chapter 2 is a literature study that presents the general trend and an overview of the risks in home-ownership. It particularly discusses the government mortgage guarantee

and tax deduction, among other factors, which contribute to home-ownership in the Netherlands. Mortgage default risk and house price risk, which are the two important risks from the perspective of the home-owners are also discussed in the context of the Dutch market.

Chapter 3 investigates the house price diffusion mechanism between the twelve provinces in the Netherlands. The methodology adopts a new Bayesian graphical approach which enables a data driven identification of the important regions where the diffusion may predominantly emerge. Using quarterly house price indexes, the findings suggest that house price diffusion exists in the Netherlands with a pattern varying over the period of time. Focusing specifically on the period prior to the 2007-2008 Global Financial Crisis (GFC), the house price diffusion predominantly originated from Noord-Holland.

House prices in Amsterdam – the capital and an important economic hub of the Netherlands, are more likely to diffuse to other parts of the country. Thus in Chapter 4, attention is paid to the house price diffusion pattern from the capital Amsterdam to the other Dutch regional housing markets. The Granger causality and cointegration techniques are used, while controlling for the important house price fundamentals. The results suggest a possible house price diffusion existing from Amsterdam to all regions in the Netherlands except for Zeeland. The strongest long-run impact of Amsterdam house price diffusion potentially occur in Utrecht.

As one of the largest and most dynamic in the Netherlands, the Amsterdam housing market is itself an interesting case study. One part of Chapter 5, therefore, deals with the diffusion pattern by studying the spatial interrelationships between house prices in Amsterdam. The other part of the chapter studies the house price risks. Using the Granger causality test, a general causal flow of house prices is observed from the central business districts to the peripherals. Simple statistics similarly reveal that house prices grow faster and are more risky in the central business districts than those on the peripherals of the city.

Chapter 6 is concerned with the efficiency and loss coverage of the index-based home-value insurance scheme. It proposes a modification of the index-based home-value insurances policy, which seeks to reduce the large idiosyncratic residual house price risks. The modification uses aggregate measures of the reference index. Using the hedonic and repeated sales indexes, the empirical analysis suggests the proposed modified scheme is highly efficient and may eliminate up to 70% of the residual risks.

In general, the dissertation adopts innovative empirical methodological approach that combines standard statistical analyses and more recent and complex econometric modelling techniques in the study of the diffusion and risks of house prices in the Netherlands. The application of the graphical approach to the study of diffusions particularly in Chapter 3, is the first of its kind in the context of the housing market.

Furthermore, this dissertation is among the first to entirely provide a comprehensive analysis and the much needed body of knowledge regarding the house price diffusion and risks for the highly regulated Dutch housing market. The results have important policy implications and applications for households, commercial investors and

financial institutions in the Netherlands. The results may also generally apply and replicable in other countries and economies with similar housing market conditions.

Samenvatting (Dutch Summary)

In de afgelopen decennia is het eigen woningbezit is in veel landen sterk toegenomen. Een van de aanleidingen voor deze toename was de ambitie van huishoudens om vermogen op te bouwen via de woning: "een appeltje voor de dorst". Dit is ook het basisprincipe van op particulier vermogen gebaseerde sociale zekerheid (asset based welfare) dat in zwang is in landen als het Verenigd Koninkrijk, de Verenigde Staten en Australië, maar ook meer en meer opdoemt in Europese debatten.

Bij het opbouwen van eigen vermogen in de woning speelt de huizenprijsontwikkeling een belangrijke rol. Huizenprijzen vertonen over het algemeen een stijgende trend, maar op korte termijn kunnen ze dalen, wat risico's oplevert voor het woningvermogen. Na de financiële crisis van 2007-2008 zorgde de sterke daling van de huizenprijzen bijvoorbeeld voor een negatief eigen vermogen bij veel en met name recente huizenkopers.

Sommige onderzoekers en woningmarktexperts dachten dat een beter begrip van de ruimtelijke dynamiek van huizenprijzen kon bijdragen aan herstel van de woningmarkt na de financiële crisis. Anderen stelden verzekeringen voor die huiseigenaren beschermen tegen het risico van prijsveranderingen. Helaas ontbreekt het aan grondige kennis van de huizenprijsdiffusie en huisprijsrisico's in Nederland die nodig zijn voor een goede beoordeling van deze opties. Er zijn weliswaar empirische resultaten voor landen zoals het Verenigd Koninkrijk, de Verenigde Staten en China, de vraag is echter of die relevant zijn in de Nederlandse context. Verder blijkt de voorgestelde woningwaarde verzekering niet erg efficiënt te zijn en niet meer dan 50% van de huizenprijsrisico's te elimineren. Er is dus behoefte aan grondige kennis van huisprijsdiffusie en huisprijsrisico's in Nederland.

Dit proefschrift beoogt enerzijds het diffusiemechanisme en de risico's van huizenprijzen beter te begrijpen en anderzijds bij te dragen aan het meten ervan. Meer concreet zijn er drie doelstellingen: in de eerste plaats een beschrijving geven van het diffusiemechanisme van huizenprijzen in Nederland, met speciale aandacht voor de hoofdstad Amsterdam; ten tweede het onderzoeken van de ruimtelijke verdeling van het huizenprijsrisico; en ten derde nagaan of de efficiëntie van de (op een huizenprijsindex gebaseerde) woningwaarde-verzekering in de Nederlandse context kan worden verbeterd.

Het diffusiemechanisme heeft betrekking op het zogenaamde ripple of spillover effect, waarbij veranderingen in de huizenprijzen in de ene regio tijdelijk of permanent de huizenprijzen in andere regio's beïnvloeden. De risicoanalyses berekenen de kans dat de woning onder de aankoopprijs wordt verkocht. De (op een huizenprijsindex gebaseerde) woningwaarde-verzekeringsregeling is bedoeld om het huizenprijsrisico te verminderen; de efficiëntie en verliesdekking van de verzekering zijn van belang.

Dit proefschrift bestaat uit vijf op zichzelf staande hoofdstukken. Vier hoofdstukken zijn als artikelen gepubliceerd in internationale tijdschriften, het vijfde is bij een tijdschrift ter beoordeling ingediend.

Hoofdstuk 2 is een literatuurstudie naar het eigen woningbezit en de risico's die daarmee gepaard gaan. Er wordt onder andere ingegaan op het beleid gericht op het verhogen van het aandeel eigenwoningbezit in Nederland, waaronder de hypotheekgarantie van de overheid (NHG) en de hypotheekrenteaftrek. De twee belangrijkste risico's vanuit het perspectief van huiseigenaren - het betalingsrisico op de hypotheek en het woningprijsrisico - worden besproken in de context van de Nederlandse markt.

Hoofdstuk 3 onderzoekt het diffusiemechanisme van huizenprijzen tussen de twaalf Nederlandse provincies. De toegepaste methodologie is een nieuwe Bayesiaanse grafische benadering met een data driven identificatie van de belangrijke regio's waar de diffusie voornamelijk ontstaat. De bevindingen op basis van kwartaalcijfers suggereren dat huizenprijsdiffusie in Nederland inderdaad voorkomt, volgens een patroon dat varieert in de tijd. Tijdens de periode voorafgaand aan de financiële crisis in 2007-2008 overheerst de diffusie van huizenprijzen vanuit Noord-Holland.

Het is aannemelijk dat veranderingen in de huizenprijzen in Amsterdam - de hoofdstad en een belangrijk economisch knooppunt van Nederland – zich verspreiden naar andere delen van het land. Hieraan wordt in hoofdstuk 4 aandacht besteed. In de analyse worden Granger causaliteits- en co-integratietechnieken toegepast die corrigeren voor de belangrijkste economische fundamentals voor de huizenprijs. De resultaten bevestigen een mogelijke diffusie van de huizenprijzen van Amsterdam naar alle andere regio's in Nederland, behalve Zeeland. De sterkste lange termijn impact van de Amsterdamse huizenprijsdiffusie lijkt zich voor te doen in Utrecht.

Als een van de grootste en meest dynamische huizenmarkten in Nederland is Amsterdam een interessant studieobject. Hoofdstuk 5 bestudeert daarom het diffusiepatroon van huizenprijzen tussen wijken in Amsterdam. Met behulp van de Granger causaliteitstest wordt een effect waargenomen vanuit het Central Business District (CBD, hier de Amsterdamse binnenstad) naar de andere wijken. Het hoofdstuk behandelt ook de huizenprijsrisico's. Eenvoudige maatstaven laten zien dat de huizenprijzen in het CBD sterker stijgen dan die in de buitenwijken en ook dat de risico's groter zijn.

Hoofdstuk 6 gaat over de efficiëntie en verliesdekking van woningwaarde verzekeringen die op een huizenprijsindex zijn gebaseerd. De analyse resulteert in een aanbeveling om polissen zodanig aan te passen dat grote individuele woningprijsrisico's worden verminderd. De aanbeveling is gebaseerd op geaggregeerde maatstaven van de referentie-index. Een empirische analyse met behulp van zowel hedonische als "repeat sales" prijsindexen toont aan dat het voorgestelde schema zeer efficiënt is en de resterende risico's met 70% kan verlagen.

Dit proefschrift past een innovatieve methode toe om de diffusie en risico's van huizenprijzen in Nederland te bestuderen; standaard statistische analyses worden gecombineerd met recent ontwikkelde complexe econometrische modelleringstechnieken. De toepassing van de grafische benadering voor het

bestuderen van diffusies in hoofdstuk 3 is de eerste in zijn soort in de context van de woningmarkt.

Dit proefschrift geeft voor het eerst een uitgebreide analyse van de diffusie van huizenprijzen en de risico's in de gereguleerde Nederlandse woningmarkt. De resultaten hebben belangrijke implicaties voor huishoudens, commerciële investeerders, financiële instellingen en beleidsmakers in Nederland. De resultaten zijn naar verwachting ook relevant voor andere landen en economieën met een vergelijkbare woningenmarktcontext.

1 Introduction

The rate of home-ownership across Europe and in many countries has increased significantly in recent decades. This is partly because most governments have promoted home-ownership as part of an asset-based welfare system with the notion that home-ownership will generate wealth for households through the accumulation of housing equity.

Changes in house prices play an important role in the generation of the housing equity and the wealth inherent in home-ownership. In general, house prices change in cycles of upward and downward trends. Each of these cycles may be driven by different sets of fundamental determinants and by the prevailing conditions in the wider economy.

Over the long term, home-owners usually accumulate significant housing equity, yielding welfare benefits. However, even periods of brief house price decline can erode the value of housing equity accrued over several years. Following the 2007-08 Global Financial Crisis (GFC), for example, the severe decline in house prices caused many recent home-owners to run into negative equity. Figures from Statistics Netherlands show that following the GFC, in the Netherlands alone the total wealth in residential properties declined from €738,449 million in 2009 to €721,018 million by the end of 2012.

In effect, home-ownership involves significant financial risk, which can adversely affect the balance sheets of households. These risks require a better understanding and proper measurements. However, it is also important to first understand house price dynamics, which significantly affect the process of equity generation. A thorough understanding of house price dynamics is necessary if we are to identify innovative ways of insuring against the risks associated with home-ownership.

§ 1.1 Gap in the literature

Research has shown that home-ownership has several advantages for society and households. According to some housing researchers, home-ownership facilitates the development of a stronger society and neighbourhoods (Andrews and Sánchez, 2011; Elsinga, 2003). These researchers also argue that home-owners are more likely to invest in maintenance, are more committed to the development of their neighbourhoods and tend to be actively involved in the political process (Doling and Elsinga, 2006; Doling et al., 2010). Other scholars also argue that home-ownership fosters better family connections and provides a healthier environment for child development (Toussaint and Elsinga, 2007; Haurin et al., 2002).

According to Elsinga and Hoekstra (2005), however, some benefits derived from home-ownership depend on the national context and on the characteristics of the household. They argue that lower-income earners in the owner-occupied sector usually cluster in poorer and deteriorating neighbourhoods, which becomes societally disadvantageous. Elsinga and Hoekstra (2005) also argue that in certain countries, home-ownership is simply an individual preference and does not necessarily have benefits over other forms of tenure. In countries with a substantial and well-maintained social housing sector, for example, they point out that tenants are equally likely to be actively involved in their neighbourhoods. Similarly, these renters may enjoy a healthy and cohesive social environment, so this is not exclusive to home-owners.

For most households, however, home-ownership is a desirable tenure choice because it allows them the flexibility to adapt their property and yields financial benefits. The financial benefits of home-ownership, especially in the Netherlands, are inherent in the accumulation of home equity over a long period of time, partly through the preferential tax treatments available to home-owners (Boelhouwer, 2002; Toussaint and Elsinga, 2007). Another financial benefit derived from home-ownership is the relative security that it provides against high and random rent increases (Zehnder, 1998; Elsinga, 2008).

Furthermore, home-ownership tends to be beneficial during retirement (Haffner, 2008). Retired home-owners are likely to have paid off their mortgages and would be able to withdraw cash from their home-equity to supplement their regular pension. These attractions of home-ownership have drawn attention to the property-based welfare system, which encourages individuals to take the responsibility for their welfare needs by investing in property assets (Torgersen, 1987; Toussaint and Elsinga, 2009). Property-based welfare depends largely on housing equity, which is directly influenced by changes in house prices. Unfortunately, however, the characteristic volatility of house prices means that equity accumulation involves a degree of uncertainty. The chance of negative equity and sale price risk usually intensifies when house prices are more volatile, limiting the welfare benefits of home-ownership. Particularly since the substantial house price decline and uncertain prospects of home-ownership following the 2007-08 Global Financial Crisis (GFC), researchers and policy makers have been more critical about the sustainability of the asset-based welfare system (see, De Decker and Dewilde, 2010; Doling and Ronald, 2010; Malpass, 2008; Torgersen, 1987).

In effect, some researchers now argue that depressed house prices could be stimulated through policy regulations once the dynamics are well understood (Blanchard et al., 2010; Taylor, 2009; Andrews, 2010; Ambrose et al., 2013; Dol et al., 2010). According to one strand of literature, the spatial interactions between house prices are the most important factor to understand. The argument is that house prices are spatially interrelated and these interrelationships are pivotal in detecting the regional housing markets where intervention should be focused (Holmes and Grimes, 2008; Holly et al., 2010; Meng et al., 2014; Gong et al., 2016b). This reasoning has led to a line of research that is usually referred to in the housing literature as the house price ripple effect or diffusion (Meen, 1999; Lee and Chien, 2011; Holly et al., 2011).

On the other hand, a different strand of housing literature advocates using home-equity insurance to reduce the sale price risk directly (Case Jr et al., 1993; Swindler, 2012). Home-equity insurance allows home-owners to pool the sale price risk through advanced portfolio risk management and offers them a way to overcome

the constraints of negative equity (Shiller, 2003; Chan, 2001; Iacoviello and Ortalo-Magne, 2003). Unfortunately, however, the currently proposed home-value scheme would only cover up to 50% of the sale price risks (Sommervoll and Wood, 2011). A great deal of the research into both the house price diffusion and sale price risk has been done in the UK, US and China, while the context of the Netherlands is significantly different.

This dissertation provides insight into the house price diffusion mechanisms and the sale price risk in the Netherlands. It also analyses the potential profitability of home-value insurance scheme in the Dutch market and proposes a modified scheme which could eliminate up to 70% of sale price risks. The Dutch housing market is unique in terms of its regulation and the dynamics of the mortgage market (Tu et al., 2016). This dissertation provides exclusive research into the house price diffusion mechanism and sale price risk within the Dutch context.

§ 1.2 Aim and research questions

This dissertation examines important aspects of house price diffusion and risks in the Netherlands. The aim is to better understand the diffusion mechanism and the risk of house price fluctuations, and to contribute to measuring these housing risks. Specifically, there are three objectives: first, to understand the diffusion mechanism of house prices in the Netherlands and particularly from its capital city, Amsterdam; second, to examine the spatial distribution of house price risk; and third, to investigate the efficiency of index-based home-value insurance as a tool for mitigating house price risk in the Dutch context. The related research questions are addressed in four separate chapters. Figure 1.1 shows the overall structure of the dissertation and the chapters associated with these objectives.

To begin with, Chapter 2 provides a general perspective of the risks of home-ownership and an overview of the Dutch housing market. This provides important background information which puts into perspective the rest of the research, which rather attempts to draw conclusions with the home-owner in view and within the context of the Dutch housing market.

In Chapters 3, 4 and 5, the diffusion mechanism of house prices in the Netherlands is explored extensively. The research questions for Chapter 3 can be specifically formulated as:

> *To what extent does house price diffusion exist in the Netherlands? Which regions predominate in the house prices diffusion mechanism? How does the diffusion mechanism vary over time?*

As the capital city and a major economic hub in the Netherlands, changes in the housing market in Amsterdam may have implications for other regions. Chapter 4 focuses specifically on house price diffusion in Amsterdam. It addresses the research question that relates to the extent to which house price movements in Amsterdam drive house prices in other regions of the Netherlands. The diffusion mechanism within Amsterdam itself is examined in Chapter 5, which relates in part to the house price interrelationships between the various districts of Amsterdam.

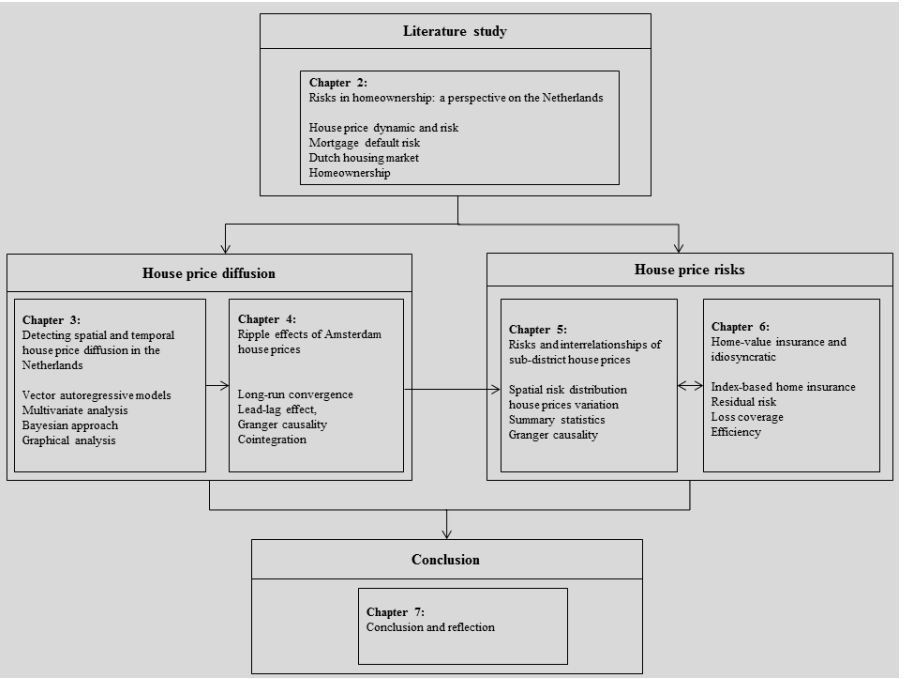

FIGURE 1.1 Chapter outline in relation to the research objectives

Chapter 5 also explores the spatial distribution of house price risk. The main research questions here relate to the degree of the variation in house price risk from the central business district (CBD) to the periphery of a city and the spatial variation of house prices over time. The research questions can be formulated as follows:

> *What is the pattern of house price risk and return from the CBD to peripheral areas? To what extent do house prices differ over time between regions in the CBD and peripheral areas?*

Chapter 6 considers home-value insurance. It focuses on the question of the efficiency of the index-based home-value insurance policy for mitigating sale price risk. Index-based home-value insurance, characteristically, does not cover the entire sale price risk and residual risks may vary across sub-markets. Chapter 6 investigates the extent of these residual risks further in relation to various house classes in the Netherlands.

§ 1.3 Methodology

This dissertation contributes to the literature by providing comprehensive analyses of the diffusion dynamics and risks of house prices in the specific context of the

Netherlands. Its innovation, however, lies in its empirical methodological approach, which combines standard statistical analysis and more recent and complex econometric time series models. The details of the empirical approaches for house price diffusion and risks are provided in the respective chapters and they are summarised here briefly, as follows.

§ 1.3.1 House price diffusion

After the discovery of house price diffusion by British scholars in the 1990s, simple empirical methodology, such as the ratio test, correlations, Granger causality and co-integration tests, have widely been adopted to confirm the existence of diffusion dynamics in house prices (see Holmans, 1990; Giussani and Hadjimatheou, 1991; Meen, 1996, 1999). One common drawback with these empirical methods is that they involve the assumption that house diffusion is known a priori to exist, and moves from major economic centres in large cities to peripheral regions. Most research papers also apply these methods without controlling for the common fundamentals that may possibly confound the spatial interactions between house prices.

In this dissertation, a data-driven approach is adopted which does not require the direction of house price diffusion to be known a priori. The method is based on the Bayesian graphical vector autoregressive (GB-VAR) approach recently proposed by Ahelegbey et al. (2016a). The GB-VAR is a multivariate time series approach that combines vector autoregressive models with Bayesian graphical methods. The method is flexible and allows any necessary prior information regarding the direction of the diffusion to be incorporated into the analysis. The graphical component of the method ultimately enables the direction of the diffusion mechanism to be obtained through network statistics. The graphical method is applied in relation to the housing market for the first time in this dissertation (see Chapter 3).

The diffusion pattern of house prices may be altered by a regime shift (Aue and Horváth, 2013; Chien, 2010). Thus the diffusion mechanisms between regions in the Netherlands are considered for different sub-periods. Methodologically, a rolling window is adopted to estimate the BG-VAR model and identify the diffusion mechanism in the sub-periods. Moreover, a structural break test is performed to formally identify regime shifts and to delineate the sub-periods for the estimation of the BG-VAR model.

The subsequent analysis (Chapter 4), in which the Granger causality and co-integration methods are applied to test the diffusion pattern of house prices from the capital Amsterdam to other regions in the Netherlands, includes controls for the common house price fundamentals, which the existing literature had mainly ignored. The Granger causality analysis adopts the more versatile Toda-Yamamoto technique (Toda and Yamamoto, 1995). The Toda-Yamamoto approach has the advantage that both stationary and non-stationary time series variables can be included in the empirical test. The co-integration analysis similarly adopts the autoregressive distributed lag (ARDL) bounds approach proposed by Pesaran et al. (2001), which allows for both stationary and non-stationary time series variables. The ARDL bounds technique is generally more appropriate for testing co-integration between shorter time series (Narayan, 2005).

§ 1.3.2 House price risk

Although more advanced models may be applied, the empirical method adopted in the analysis of the spatial distribution of house price risk is standard and quite straightforward. Separate hedonic house price indexes are first created for different spatial units. Then, using these house price indexes, summary statistics, particularly the standard deviation and variants of the semi-deviation are obtained to compare the house risks across the different spatial units. In addition, the summary statistics are computed with a rolling window to discern the risk variations over time across the spatial units (Chapter 5).

Further analysis of the house price risk uses the method recently proposed by Sommervoll and Wood (2011). This approach assumes that each property has insurance cover, which pays benefits at the time of resale of the property, based on the general housing market decline depicted by a reference house price index. Since the reference house price index only captures market movements, losses incurred on a property may not be fully covered by the index-based insurance scheme. Sommervoll and Wood (2011) argue that the residual losses not covered may best be described as the idiosyncratic risks for individual properties. This approach is used to compare the idiosyncratic risks for different property types in this dissertation. Modifications of the index-based home-value insurance schemes are then proposed, which minimise the residual idiosyncratic risks (Chapter 6).

§ 1.3.3 Data

The complete details of the data used are provided in each chapter. To summarise, the empirical analyses in this dissertation mainly use time series data. In analysing the diffusion mechanism between regions in the Netherlands and the pattern from Amsterdam (Chapter 3 and 4), the house price index compiled by Statistics Netherlands is used. Statistics Netherlands is the official Dutch statistics bureau, which compiles house price indexes using the sale price appraisal ratio (SPAR). The SPAR indexes combine transaction data with annually appraised values into price ratios, which are chained to correct for the appraisal bias (de Haan et al., 2009). Given the available data, the SPAR index is the most reliable index of house prices in the Netherlands, although it does not adjust for quality changes in individual properties (e.g. due to depreciation). It does adjust for changes in the quality mix, however (De Vries et al., 2009).

The empirical analyses of the house price risk and home-value insurance scheme (Chapter 5 and 6) use individual transaction data relating to Amsterdam collected over an extended period (1995-2014). The dataset was obtained from the Dutch National Association of Property Brokers. It contains several property characteristics, and as such is appropriate for constructing hedonic price indexes. The dataset also includes details of the location of properties, enabling aggregation into various spatial units. The extended period covered by the dataset enables information to be extracted for repeated transactions, which is particularly useful for the analysis of the efficiency and loss coverage of the index-based home-value insurance scheme.

§ 1.4 Introduction to chapters

The chapters of this dissertation are journal articles, each of which addresses aspects of the research questions specified in the previous section. The chapters are therefore self-contained, four of them having been published separately in international journals and the other being currently under review.

Chapter 2 presents a literature study of the risks involved in home-ownership and introduces the two perspectives from which the literature studies the risks involved in home-ownership. The chapter discusses the key factors that have contributed to the increase in home-ownership over recent decades. The background to home-ownership is also presented for the Netherlands, which the analyses in the rest of the dissertation focus on. The chapter goes on to present a taxonomy of the various financial risks inherent in home-ownership identified in the literature, with a particular focus on the main risk factors for Dutch home-owners. The chapter concludes with a discussion of the two main types of financial risks faced by home-owners: the risk of mortgage default and the risk of house price changes, both of which are in turn related to several other factors.

Chapter 3 examines the diffusion mechanism of house prices between the twelve provinces in the Netherlands using the Bayesian graphical vector autoregression (BG-VAR) recently proposed by Ahelegbey et al. (2016a). House price diffusion, also known as the ripple effect or spill-over effect, is a housing market phenomenon whereby house price shocks move from one region to other regions, with a transitory or permanent effect (Meen, 1999; Holly et al., 2011; Balcilar et al., 2013). This chapter provides an introduction to the spatial diffusion mechanism between house prices and a brief overview of the methodologies used for its study. The chapter then proposes the use of graphical methods which enable a data-driven approach to identifying the main regions in which diffusion may play a role. The graphical approach is demonstrated using house price indexes for the twelve provinces of the Netherlands. The empirical results suggest evidence of spatial diffusion patterns in house prices from different regional sub-markets within distinct time periods in the Netherlands. The diffusion of house prices prior to the GFC was predominantly observed from the province of Noord-Holland.

Chapter 4 focuses specifically on house price diffusion from the Dutch capital Amsterdam to other regions in the Netherlands, which is referred to using the synonymous term 'ripple effect'. Adopting the simple approach of confirming ripple effect as a lead-lag effect or a long-run convergence (Holmes and Grimes, 2008; Giussani and Hadjimatheou, 1991), the Granger causality and cointegration tests are applied for the empirical analysis. To eliminate the effects of common shocks, the empirical estimation includes controls for house price fundamentals. The cumulative evidence suggests that Amsterdam house prices influence all Dutch regions, except Zeeland. In particular, the Granger test concludes that there is a lead-lag effect of house prices from Amsterdam to all regions, apart from Zeeland. The cointegration test, on the other hand, shows evidence of long-convergence between Amsterdam and six other Dutch regions: Friesland, Groningen, Limburg, Overijssel, Utrecht and Zuid-Holland.

Chapter 5 is concerned with the spatial distribution of risks and interrelationship of house prices within Amsterdam. It specifically explores whether house prices are exposed to more risk in the CBDs than in peripheral areas, house price variations over time in CBDs and peripheral areas, and the pattern of house price interrelationships between the various districts that make up Amsterdam. The empirical approach adopts simple indicators, which suggest that house prices grow faster but are less stable in the central business district and immediate surrounding areas than in peripheral areas. Decreasing inter-variations between house price growth in different districts over time were also observed. Furthermore, the findings indicate that a lead-lag and house price causal flow generally exists from more central districts to the more peripheral districts.

Chapter 6 focuses on home-value insurance. Specifically, it examines the pay-out efficiency and loss coverage of the index-based home-value insurance scheme for the Dutch market (see Case Jr et al., 1993; Shiller and Weiss, 1999). The index-based home-value insurance scheme typically has low loss coverage, meaning that there are significant residual risks for home-owners. Sommervoll and Wood (2011) and Sommervoll and de Haan (2014) have observed that the loss coverage of the index-based home-value insurance rarely exceeds 50%. Chapter 6 proposes a modification to the existing scheme in order to eliminate this large residual idiosyncratic property price risk for home-owners. The empirical analysis uses transaction data from Amsterdam between 1995 to 2014. The findings, based on the repeated sales and hedonic indexes, both indicate that the proposed insurance policy would have higher pay-out efficiency, better loss coverage and a greater pay-out probability than the scheme originally suggested by Case Jr et al. (1993).

All the chapters of the dissertation are thematically related. Chapters 3 and 4 relate to the house price diffusion. Chapters 5 and 6 concern house price risk and home-value insurance. Part of Chapter 5 also deals with house price interrelationships, which relate to diffusion (see Figure 1.1).

2 Risks in home-ownership: a perspective on the Netherlands

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Abstract

Purpose: Risk in home-ownership from mortgage providers' perspectives within the euro zone has received more attention than individual home owner's perspectives in the literature following the financial crisis in 2007/2008. The purpose of this paper is to explore the risk factors in home-ownership from the individual household's perspectives within the owner-occupied housing sector of the Netherlands.

Design/methodology/approach: The paper adopted a broader review of extant literature on the different concepts and views on risk in home-ownership. These concepts are unified into a framework that enhances our understanding of the perceived sophisticated risk within the owner-occupied sector in the Netherlands.

Findings: From the perspective of the home owner, two main types of risks were identified: mortgage default and property price risk. The paper has unearthed a quantum number of factors which underline the above risks. The mortgage default risk factors include the initial amount of mortgage loan taken out, the future housing expenses and the income development of the owner-occupier. Family disintegration is also identified as one of the main causes of mortgage default in the Netherlands. Property price risk is influenced by income, interest rates and conditions in the social and private rental sectors.

Research limitations/implications: Findings of the paper are based on review of the extant literature in the context of the Dutch housing market. Possible rigorous situational analysis using other tools are recommended for further research.

Originality/value: This paper contributes to the much needed body of knowledge in the owner-occupied sector and provides a better understanding of risk in home ownership from the individual perspectives.

Keywords: Housing markets, Risk, Dutch housing market, Home ownership, Mortgage providers, Owner-occupation

§ 2.1 Introduction

Subsequent to the subprime mortgage crisis of the USA, risk in the owner-occupied sector has received extensive consideration in the housing literature (Aalbers, 2010; McGreal et al., 2009; Bardhan et al., 2012; Kramer, 2010; Cano Fuentes et al., 2013; Aalbers, 2015). While these prior efforts shed light on the spectrum of risks in home-ownership, the arguments for home-ownership has often been skewed mostly towards the perspectives of the financial institution supplying credits for the home financing. The debates and arguments on the pitfalls from the owners' position are quite limited in extant literature. It is clear nonetheless that the risks for the credit providers could be minimised if steps are taken to understand and manage the exposures at the level of the individual home buyers. Borrowing on "predatory terms", for instance, could be avoided if households are informed on the nature of the associated risks they are likely to encounter.

It is centrally advocated in this paper therefore that attention be given to the risks in the owner-occupier sector within the level and perspectives of the households. The paper provides an overview of risks in home-ownership from the viewpoint of the homeowner, especially, those financing their purchase with mortgage loans. Two inherent risk factors are identified: repayment and property price risks. While repayment risk pertains to mortgage repayment, property price risk consists of loss of investment capital as a result of decline in house prices within the period of concern. Also, mortgage repayment default depends on three factors: the initial debt level, income and cost development after the loan agreement has been contracted. For property price risk, the factors are quite varied and have to do with the multiplicity features which influence the development of house prices.

The approach of this paper is mainly to offer a careful discussion of the various risk types, their effects and causalities by unifying the different concepts as dispersed in both academic and non-academic literature into a concise framework. Also, the paper clarified the nature of risk in the owner-occupied sector from the individual household's perspectives that constitute the larger majority who are mostly non-professionals. It gives brief background to home-ownership in the Netherlands, discusses general views on default and property price risk as well as the factors heightening the probability of their occurrence. The consequence of default and property price decline are also discussed in the light of the Dutch and concludes with suggestions on reducing the risks in home-ownership and how to create awareness amongst households in the Netherlands.

§ 2.2 Growth of home-ownership in the Netherlands

Growth of home-ownership in the Netherlands has been steady over the decades. Between 1971 and 2012, the home-ownership rate increased from 35.1% to about 60.0% as shown in Figure 2.1. The Dutch government's stimulation of the owner-occupied sector through income tax deductions and later by the National Mortgage Guarantee (NMG) scheme played an important role in the above achievement. Other factors include the investment and social benefit which homeowners accrue in the Netherlands. Over the years, the Dutch's perception of

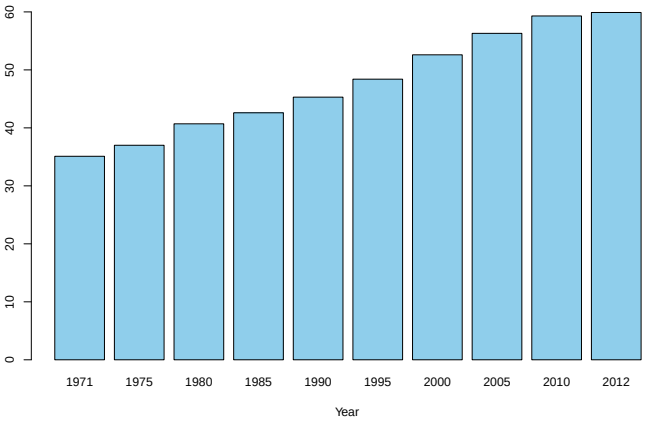

FIGURE 2.1 Evolution of home-ownership (per cent of total housing stock)

Source: ABF Research B.V (2010), Eurostat

home-ownership had shifted from just having roof over one's head to having some independence from landlords and finding a way to foster deeper connection with their relations and family (Toussaint and Elsinga, 2007). Somewhat, there appears to be the idea to "immortalise" marital relationships with joint home-ownership that usually drive most people to buy private homes at the time when they are starting up their marital relationships (Neuteboom and Horsewood, 2006; Toussaint and Elsinga, 2007). To others, home-ownership gives a wider choice and freedom to adapt the residential property to a more fulfilling and a self-suiting style (Elsinga, 1998; Toussaint and Elsinga, 2007). Such liberty to adjust the external features of the dwelling is generally not available in the rental sector.

From an investment perspective, Dutch households find home-ownership as an instrument that can be used to build equity and/or earn additional income to augment the regular pay cheque or pension (Boelhouwer, 2002; Haffner, 2008; Toussaint and Elsinga, 2010; Toussaint, 2013). Such practice evolves around buying an extra home to rent out in the private rental market and later selling it entirely when enough equity has been built. Minority also rent out a room or two in their own apartment. The fiscal treatment where mortgage interest payments are deducted from income tax also offers extra saving opportunity on mortgage outlays (Boelhouwer, 2002; Elsinga, 1998). Many have argued that, "when you rent, your money just flows away, but when you buy, it comes back to you and you can build up capital" (Toussaint and Elsinga, 2007, pp. 182). The reference here relates to the tax-deductibility which is discussed in the next section.

§ 2.2.1 National mortgage guarantee

From the mid-1980s, the ambition of the Dutch government shifted towards home-ownership in the quest to shed part of the responsibility for providing housing for the population. Various policies were engineered to fulfil this new vision of the government. One such regulation is the rebranding and reconstruction of the municipal guarantees into what is now known as the Dutch National Mortgage

Guarantee [Nationale Hypotheek Garantie (NHG) in the Netherlands]. The NHG was founded in 1993 and currently administered by the voluntary public foundation called Home-ownership Guarantee Fund [Waarborgfonds Eigen Woningen (WEW)]. It has the full backing of the municipalities and the central government. The Fund primarily thrives on a premium on the mortgage amount received from the borrowers (CPB, 2013; Van Leeuwen and Bokeloh, 2012). The premium is presently 1.0% but used to be 0.36% in the early years of the Fund, 0.28% for 2005-2006 and 0.85% in other previous years.

The aim of the Fund is to stimulate home-ownership by lowering the mortgage threshold for young and lower income groups. The guarantee also serves as a safety net for those entering into foreclosure for reasons such as divorce, job redundancy, ill health and other unforeseeable events. If a homeowner is able to demonstrate faithfulness, he/she is relieved from the duty to pay back to the guarantee fund.

Despite the above, Dutch mortgage banks are usually hesitant in advancing credits to individuals with weak financial circumstances. However, when a borrower signed up to the NHG, the credit institutions could grant loans with loan-to-value (LTV) ratios exceeding 100 per cent. Although the maximum LTV is expected to be reduced to 100 per cent by 2018 and subsequently to about 85 per cent later (DNB, 2014), the current higher LTV ratio facilitated by the NHG generally enhances the ownership rate particularly among the lower income and younger age groups. These social classes ordinarily would not qualify for mortgage loans. In addition, the banks grant discount on the mortgage interest rate up to about 0.6 per cent for those who signed unto the NHG. This also offers most Dutch people an extra financial relief, which motivates them to consider home-ownership (Fitzsimons, 2013).

Another way the scheme encourages home-ownership is the impetus it gives financial institutions to readily advance credit. Because of the backing of the central government and the municipalities, there is assurance that any credits in default will eventually be recovered. This means that the (credit) risk of the banks is reduced and they would not need to hold large regulatory or solvency capital. The banks, consequently, could issue as many loans as possible so that inaccessibility to mortgage loans is not much of a concern if the borrower opts to sign unto the scheme (CPB, 2013; Fitzsimons, 2013). However, in the opinion of Elsinga et al. (2014), since the reduction of the maximum LTV ratio in 2013, it has became extremely difficult for the younger and lower income groups in the Netherlands to enter into the owner-occupied sector.

§ 2.2.2 Tax deductibility

Since the nineteenth century, Dutch homeowners have been enjoying the advantage of fully deducting mortgage interest rates from income tax (Haffner, 2002). This began with the private landlords but was later extended to individuals in support of home-ownership (Rouwendal, 2007). In its current form, the income tax deductions give homeowners the opportunity to recover part of their mortgage expenses equal to the product of the marginal tax rate and the gross interest on the mortgage loan. The marginal tax rate normally ranges from 42 to 52 per cent, depending on the income level (Van Leeuwen and Bokeloh, 2012; Rouwendal, 2007).

The generosity of the tax regime has a number of influences on the Dutch housing market in many ways. First, the income tax deductions lowers the cost of mortgage and

this provides a huge stimulation for home-ownership in the Netherlands. It is however debated that the tax rebate partly contributes to house price increases (Boelhouwer et al., 2004; Toussaint and Elsinga, 2007). Second, the tax regime has made strong influence on mortgage servicing in the Netherlands. Several mortgage products were engineered purposely to optimise the benefits from the tax deductibility (Boelhouwer, 2002; Rouwendal, 2007). These products were associated with the so-called interest-only and endowment mortgages in the Dutch mortgage market. Third, the tax regulation influences the borrowing behaviour of Dutch homeowners. For instance, the wealthy in the Dutch society who could purchase a dwelling out-rightly would rather acquire a mortgage. This is due to the construction of the tax system which enables the rich to get the largest savings (Van Leeuwen and Bokeloh, 2012).

Following the reforms in 2013, however, the fiscal tax deductibility has been restricted to only amortising (or classical mortgage) loans with at least an annual redemption. Whereas homeowners with origination date before January 2013 still continue to enjoy the benefits of the old tax structure, first-time buyers are constrained by the current regulations. The implication therefore is that the cost of mortgage has increased significantly for first-time buyers, making them quite hesitant to enter into the market. Also, the production of interest-only loans has reduced substantially since they are no longer deductible from income tax and have become less appealing to housing consumers.

§ 2.2.3 Risk attitude prior to the crisis

Until the crisis, Dutch homeowners had focused mostly on the generosity of the fiscal tax deductibility which practically enabled them to recoup a substantial percentage of their mortgage repayments. There was little perception of the risks associated with home-ownership in the Dutch society. This fact was acknowledged by Van Gent in his chapter in (Doling and Elsinga, 2006) edition. He emphatically noted that owner occupation was being championed in the Netherlands with the assumption that it will automatically generate asset gains for individuals and greater responsibility within the Dutch society. The revelations in a survey by Toussaint and Elsinga (2007) were even more striking. They argue that as at 2006 (the year of survey), many homeowners were not much aware of any risks nor did they dread any event which possibly might affect them as homeowners. Generally, respondents of that survey felt they were much secured except concerns they had with regards to ill health and policy changes that might affect their tax break.

Certainly, the story changed after the 2007/2008 global financial crisis. The inherent risk became more apparent after the crisis as house prices declined by more than 25 per cent and the number of homeowners in arrears has increased considerably (see DNB, 2014, Figure 2.2 and 2.5). The impacts of these price declines and growing defaults on financial institutions and on the government purse have been substantially discussed and debated (De Vries, 2010; Brounen and Eichholtz, 2012; Van Leeuwen and Bokeloh, 2012; Elsinga et al., 2014). On the other hand, the implications for the individual homeowner are usually overlooked.

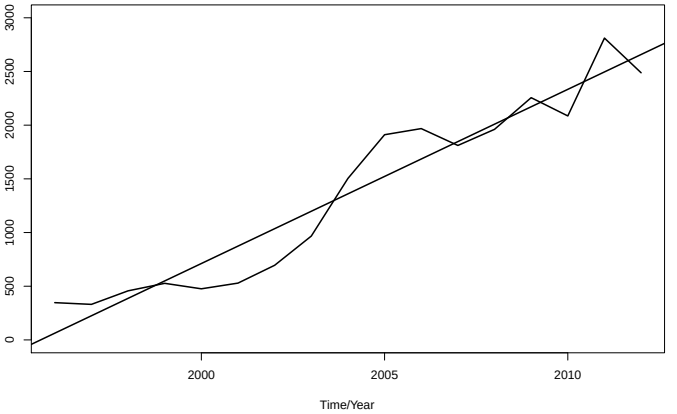

FIGURE 2.2 Auction foreclosure sales in the Netherlands

Source: Kadaster

§ 2.3 General overview of risk in home-ownership

Generally, extant literature identifies risks in home-ownership from two main categories of factors. The first is often referred to as payment or default risk which deals with the ability of homeowners to pay the monthly mortgage expenses. The second has to do with volatility of house prices and is usually termed as property price risk. Depending on the scale of these risks, however, there is also systemic risk which could develop to affect the entire housing market. This systemic risk and its consequences typically extend beyond the individual homeowners (Stephens, 2006). However, the discussions would be confined to that of payment and property price risk.

§ 2.3.1 Payment risk

Due to the huge financial consequences involved, mortgage default is one of the most significant risk factors in home-ownership. Formally, default or repayment risk is used in reference to the risk arising from homeowner inability to live up to the mortgage repayment obligations. To reduce such risk, mortgage lenders normally set the initial LTV and the loan-to-income (LTI) ratios to levels they believed are bearable for the homeowner. Particularly, if the LTV and LTI ratios are very low, the hope is that the default probability will be minimal. However, Neuteboom (2008) argue that these initial lending conditions do not fully reveal occurrence of default in the future. In this author's estimation, the cause of default rests with events occurrences during the tenure of the mortgage which do not necessarily have any bearing with the initial statistics collected.

Causes of default in repayment of mortgage

There are two distinct hypothesis underlying mortgage default, which according to many (Lambrecht et al., 1997; Yang et al., 1998; Neuteboom, 2008), are the equity and ability to pay hypotheses. In the equity hypothesis, homeowners default on the

basis of comparison between the costs and returns inherent in the continuation or termination of a mortgage contract (Neuteboom, 2008; Kim, 2015; Chan et al., 2016; Connor and Flavin, 2015; Nield, 2015). In other words, default is an outcome of a thoughtful reflection in the sense that if mortgage repayment were to be continuing, it would be mainly due to the anticipated profit. In the USA, for example, where at the time of foreclosure, homeowners are not held liable for residual debts, the choice to default on mortgage obligations is much appealing when the incidence of negative equity looms or is envisaged. Basically, owner-occupiers motivated by investment reasons fall under this hypothesis, as they are mostly inclined to default not because they cannot afford but for reasons that defaulting presents a gain in disguise. That notwithstanding, the recent hike in the use of credit reports and concerns by individuals to maintain a clean credit history should gradually restrain this issue of reneging on purpose.

For countries where there is right of recourse and homeowners can be held liable for residual debts, the equity hypothesis ceases to operate. In such environments, the problem of monthly expenses being too high in relations to the household income is more important. According to Boelhouwer et al. (2005), these monthly expenses may depend on the mortgage interests and deposits, maintenance cost, insurance premiums, taxes and inflation rate (high inflation eventually depletes the mortgage loan in real terms). They may also be affected by the type of mortgage loan and the policies on tax deductions

Many authors also considered the issue of personal mismanagement and how household financial revenues are managed instead of the inflow of income (Neuteboom, 2008; Kloth, 2005). In the account of (Andrews and Sánchez, 2011; Neuteboom and Horsewood, 2006), the phenomenon of income misappropriation is generally found to associate with young people and the less educated in most of the Organisation for Economic Co-operation and Development (OECD) countries studied by the authors. It is argued that such class of people may have problems planning and estimating future expenses or possibly end up trading one debt for another in a manner which could be referred to as "mis-prioritisation" in servicing debts. Generally, it is also observed that homeowners who hold other non-housing debts along with mortgage are much constrained when it comes to repayment (Neuteboom and Horsewood, 2006). As a rule of thumb, it could be postulated that the higher the periodic debt-service ratio, the greater the exposure to payment problems. This as well implies naturally that households with lower income and those with subprime or variable interest rate mortgage loans are much more vulnerable to payment difficulties.

Consequences of default in repayment of mortgage

From the individual homeowner perspective, payment difficulties have three progressive dimensions and stages. It begins with the mortgage costs increasingly becoming burdensome. Subsequently, arrears develop and potentially this often leads to repossession (Neuteboom, 2003). The consequences of repossession or better put as dispossession, on the other hand, span beyond the individual homeowner. The owner-occupier usually suffers loss of the investment capital and could also fall into residual debts. Psychological problems could also develop as a result of one losing the property. The effect of psychological problems could even be much adverse. There could equally be reduction in performance at work and family breakdowns particularly

where some have resort to the use of home-ownership as a means of consolidating marital relationships.

Also, as evidenced in the 2007/2008 crisis, repossession could trigger systemic risk with adverse implications for the financial system and economic stability (Stephens, 2006; Colin and Richardson, 2014). In particular, where mortgage defaulters can freely walk away from residual debts at the time of foreclosure such as in the USA, it is probable that lenders will suffer significant loses from mortgages in negative equity. Even in situations where borrowers are liable for residual debts on negative equity, it is not always practically possible to retrieve the last penny (Neuteboom, 2008; Van der Heijden et al., 2011). There are lengthy legal procedures involved which may cause the mortgage debt to deplete in value through high inflation. Personal bankruptcy laws may equally affect efforts to recover loans in default. The national government would normally also suffer if repossessions are intensified. The government in such situations would have to increase social benefits and accommodate evicted households. Substantial sums would further have to be spent on bank bailouts to prevent bankruptcy and redundancy. In 2009, for instance, the Dutch government expended almost 48 billion Euros on bank bailouts alone (Van der Heijden et al., 2011).

Furthermore, if foreclosure persists, the number of dwellings available for sale may eventually increase. This could affect house prices as supply grows from the intensifying repossession rates (DiPasquale, 1999; Baker, 2008). In some places also, bad omen are often associated to repossess properties which makes their resale extremely difficult unless they are highly discounted (DiPasquale, 1999; Boelhouwer and Van Weesep, 1988).

§ 2.3.2 Property price risk

Besides the credit or (re)payment risk associated with owner-occupation, the other risk is property price risk which others also referred to as equity price risk or simply asset risk. In the financial literature, asset risk is normally used in relation to the volatility or variation of the asset price over time (Crouhy et al., 2006; Crouhy, 2010; Jin and Ziobrowski, 2011). In the context of housing research, it is mostly restricted to the risk inherent in the decrease of the property price. Essentially, there are at least four reasons why decrease in house price is (or should be) of much concern to the homeowner. The most comprehensible and well-known is negative equity – the situation where the price of the property falls below the outstanding loan. The other reasons are immobility, loss of investment capital and general insecurities related to the collapse of house prices (Toussaint and Elsinga, 2007; Phang, 2010). The general dynamics of property price developments is discussed below.

Dynamics of house price development

Given the adverse consequences of decreasing house prices, it is important to understand the factors which underpin price development in the market. In general, the extent literature acknowledges the existence of some equilibrium price around which the market constantly adjusts itself (Case and Shiller, 1988; Malpezzi, 1999). Prior research (Abraham and Hendershott, 1996; Case and Shiller, 1988; Malpezzi, 1999; Ambrose et al., 2013) has therefore studied long-term effect of price equilibrium in the housing market. In view of these prior findings, house prices are thought to converge to a long-term equilibrium level which periodically gets corrected

in reaction to changes in the fundamental price determinants. Highly inspired by microeconomic theory, the equilibrium hypothesis considers that prices are driven by factors fundamental to demand and supply (Malpezzi, 1999; De Vries, 2010; DiPasquale, 1999). Here, demand is mostly driven by factors such as income, rent, demographic features, mortgage interest rates, tax structure, amongst others (Abraham and Hendershott, 1996; Ortalo-Magné et al., 2000; Muellbauer and Murphy, 1997). On the supply side, the determinants are construction cost, land regulations and availability of old homes arising from forced sales, conversion of rental dwellings and sales by existing owner-occupiers (Reichert, 1990; Muellbauer and Murphy, 1997; DiPasquale, 1999; Baker, 2008).

Contrary to the equilibrium hypothesis, prices have increasingly demonstrated trends quite unexplainable by the market fundamentals (Case and Shiller, 1988). In explaining the phenomenon, it is argued that fluctuations from the equilibrium price level are temporal and signify influences from external factors or exogenous shocks (Abraham and Hendershott, 1996; Andrews, 2010). Furthermore, it is also believed that depending on the market forces, these shocks may gradually fade away or have a long-lasting effect on future prices to possibly create new price equilibrium. Other scholars also focus on explaining the factors behind this shift in price equilibrium. Case and Shiller (1988), for instance, argue that psychological effects and consumer expectations largely underpin house price booms. As explained by these authors, expectation of owner-occupiers is usually thought to result in creating excessive demand so that due to rigidity of housing supply, sharp increase in prices become eminent.

In general, consumer expectations tend to affect prices in two ways: either there is upward swing in prices because of excess demand or prices decline as a result of consumer withdrawal. As also noted by Boelhouwer et al. (2004), consumers are usually responsive to the prevailing price settings at hand. In anticipation, that price might continue to rise, there are those who might want to buy to avoid extremely high and unaffordable future prices as well as others who might venture buying to sell and make profit from future price appreciations. The reaction of home buyers to future prices decline is contrary, as there is always a withdrawal in such situations. These consumer reactions may create the situation where demand becomes volatile and subsequently induces instability in house prices, particularly because of the lag in housing supply. These dynamics of demand and supply disparities may also explain a greater percentage of the boom and burst in the housing market (Case and Shiller, 1988; Reichert, 1990; Levin and Wright, 1997; Dröes, 2011).

Other researchers (Muellbauer and Murphy, 1997; Poterba et al., 1991; Boelhouwer and Neuteboom, 2003; Aalbers, 2008; Agnello and Schuknecht, 2011; Andrews, 2010; Andrews and Sánchez, 2011; Galati and Teppa, 2013) have also recognised the significant contribution of government policy to the development of house prices. These authors attribute high volatility of house prices partly to the deregulations and reregulations of the mortgage market. The case of tax reforms, down payment and income constraints relating to LTV and LTI ratios are particularly noteworthy. As emphasised by Reichert (1990), though income and employment may affect house prices depending on the regional features, when it comes to mortgage interest rates, the response is uniform across board. Andrews and Sánchez (2011), on the same issue also found that there is a general upward movements of house prices when tax treatments are somehow generous.

Housing/property bubbles

Property price bubble is an important phenomenon in house price development in the housing market. The term bubble is normally used to describe the dynamics of house price movements where there is a very high percentage increase in prices (boom) over a period, followed by a sharp decline (bubble-burst). Formation of a bubble usually begins with a "normal" price appreciation as a result of "an innovation" in the housing market until prices have reached an unsustainable level by the very innovation that seemed to have ignited the upward price adjustments. For example, it is mostly believed that the recent US house price bubble began as a result of innovations in the mortgage market where incredible number of mortgage products became available to homeowners but were not well managed (Baker, 2008; Mizen, 2008; Aalbers, 2009b). In other countries including the Netherlands, it is mostly considered that the boom was initiated by the comparatively high LTV ratio, new mortgage products and generous tax rebates.

Historically, most house price booms had ended in bubble-bursts with equal persistence according to Agnello and Schuknecht (2011). The implication is that though the length of the boom might not be readily known, once it sets in, there is a high probability that prices might sharply decline in the future. Put in another context, house price bubbles are highly fragile. The phenomenon nonetheless has allures. It is normally during those seasons of booms in which homeowners seem to take on the highest risk by taking large loans for expensive homes. Furthermore, issues such as over-valuation, predatory lending and other underhand market practices are mostly prevalent during price booms (Case and Shiller, 1988; Cecchetti, 2006; Aalbers, 2008). Remarkably, until the bursting phase, bubbles are usually not noticed and one of its distinctive features is that bubbling prices are usually driven by factors other than market fundamentals to which some researchers allude to psychological and speculative reasons (Case and Shiller, 1988; Shiller, 1990; Stiglitz, 1990; Flood and Hodrick, 1990; Abraham and Hendershott, 1996). For example, Flood and Hodrick (1990) and (Stiglitz, 1990), define bubble as a phenomenon which occurs when current price increments are mainly due to expectation of high future selling prices which are unsubstantiated by the market fundamentals. Empirically, bubbles are modelled as the percentage change between the equilibrium and market price levels (Flood and Hodrick, 1990; Abraham and Hendershott, 1996) with the boom(burst) phase implied by the instances where market prices persistently exceed (fall below) the equilibrium level.

§ 2.4 Risk profile of Dutch housing market

This section focuses attention on the risks in home-ownership in the context of the Netherlands. Here, a consideration is given to the outlook of risk and the causative factors in relation to payment risk, property price and systemic risks.

§ 2.4.1 Payment risk

The recent mortgage foreclosure rate in the Netherlands as in Figure 2.2, has shown quite an increasing trend. Family breakdown, and divorce particularly, has been identified as the main factor behind the current upsurge in the foreclosure rate

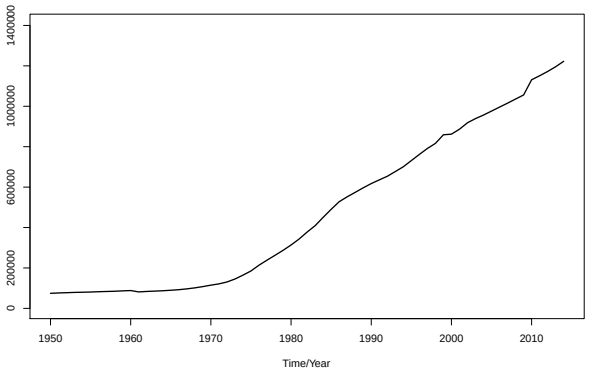

FIGURE 2.3 Yearly number of divorce in the Netherlands

Source: Statistics Netherlands (CBS)

(Van Leeuwen and Bokeloh, 2012; Van Dalen et al., 2013). The number of divorces has been very high as can be seen from Figure 2.3; however, as noted earlier, the general societal trend has been that most Dutch citizens enter into home-ownership at the beginning of their marital relationships at which time also their combined income qualifies them to access large mortgage loans. The challenges then arise, where in the event of a breakup of these marital relationships, a single income would no longer become adequate to service the monthly housing expenses. Interestingly, however, due to the munificent social security and compulsory unemployment insurance for permanent Dutch workers, job redundancy usually does not lead to mortgage delinquency in the Netherlands (Neuteboom and Horsewood, 2006). Moreover, there have been some concerns about the risks of the interest-only loans and whether they contribute to the repossession rate in the Netherlands (Van Leeuwen and Bokeloh, 2012). A careful study of the nature of these products reveals that, though they motivate people to taking up larger sum of mortgage loans, their impacts on payment problems may not be that pronounced except there is an issue of divorce or redundancy (NVB, 2014). They rather give home owners the benefit of paying lower monthly expenses.

Despite the tremendous increase in the foreclosure rate, in terms of numbers and actual percentages, it should be argued that the number of forced sales in the Netherlands is quite low. In 2013, for instance, the total forced sales as a percentage of all transactions is only around 2.0 per cent (Van Dalen et al., 2013). Compared to other European Union (EU) countries, the Dutch foreclosure rate has generally been one of the lowest and falls only behind that of Sweden and Denmark (Fitzsimons, 2013). This is somewhat interesting especially when the Netherlands has continuously been cautioned for the high level of mortgage debts as shown in Figure 2.4. A number of factors account for the low foreclosure rates. First, though the financial crisis had hit hard on the Dutch labour market with unemployment rate growing from an average of 4.9 per cent before crisis to an average of about 8.5 per cent after the crisis, the generous unemployment and social benefits in the Netherlands seem to have provided sufficient cover against mortgage default as discussed above. Permanent workers in the Netherlands have unemployment insurance schemes which pay about 70-90 per cent of their last month salary up to 38 months (Neuteboom and Horsewood, 2006;

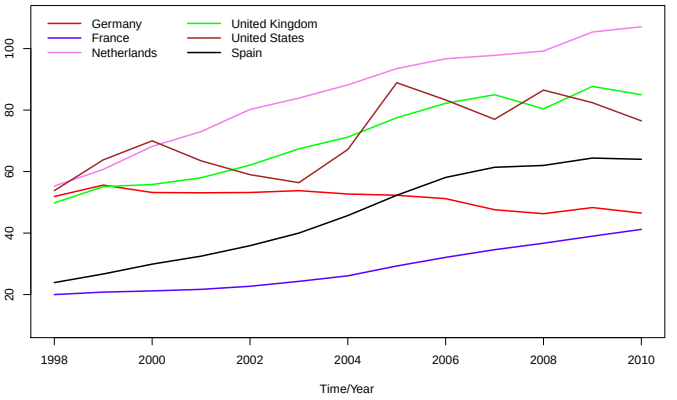

FIGURE 2.4 Dutch mortgage debt as a percentage of GDP (1998-2010)

Source: Database for Institutional comparisons in Europe (CESifo DICE)

Cano Fuentes et al., 2013). The social security system is rather generous and guarantees income of unlimited duration. The redundant homeowner could therefore access such social benefit as long as it can be proven that the cost of staying in one's own home is not more than renting a new dwelling (Fitzsimons, 2013). Beside these, Dutch mortgagors commonly tend to show very good repayment behaviour. This could partly be attributed to the fact that the banks do have full right to recourse. At foreclosure, they are able, by law, to confiscate the dwelling and other assets the defaulter may have as well. Personal bankruptcy laws are also very strict at enforcement so that it is not too easy to abdicate responsibility for the debt in any event.

§ 2.4.2 Property price risk

As depicted in Figure 2.5, although the average property price development in the Netherlands has generally shown an increasing trend, there have also been seasons in which prices have fallen rather sharply. Between 1978 and 1985, for instance, there was a substantial price decrease of almost 29 per cent. Following the recent global financial crisis, there have also been persistent decline in house prices between 2008 and 2013 of about 25% (see Figure 2.5 and 2.6). Pertaining to the recent price decline, effects of the crisis and the Dutch government reregulation of the fiscal tax deductibility have generally been the most significant factors. First, the crisis had not only impacted on unemployment, but also, the credit crunch which had affected most Dutch banks because of their international orientation had led to a tightening up of mortgage provisions in the Netherlands. This has partly restricted access to mortgage and consequently decreased the number of new home purchases (Elsinga et al., 2014). Second, following government's review of the tax incentives for homeowners, the cost of home-ownership for new buyers has significantly increased. Together, the effect of these factors has been an apparent drop in consumer confidence and demand for new homes which have subsequently affected the price development in the market in the Netherlands. Actual loss on sales during these periods of decline to some extent is only suffered to various degrees by those who made purchases close to the peak in 2008. As demonstrated in the Figure 2.5, purchases before 2003, for example, would still accrue

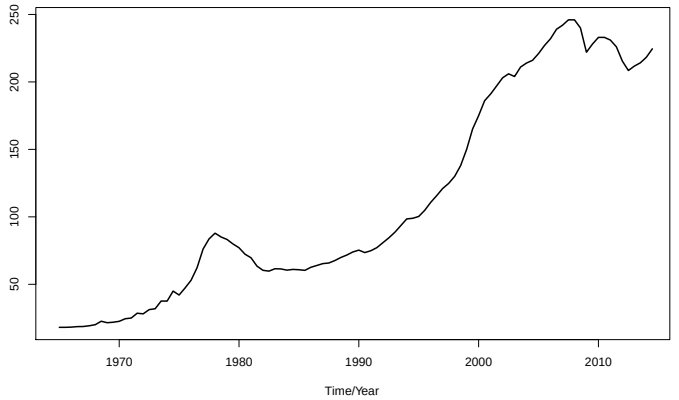

FIGURE 2.5 Average Dutch house prices from 1965 to 2014 (in 1,000s)

Source: Dutch organisation for real estate agents (NVM), Statistics Netherlands (CBS)

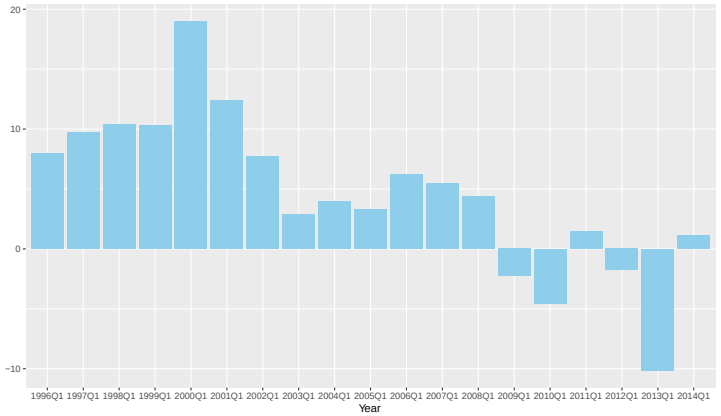

FIGURE 2.6 Change in average house purchase prices (in percentage)

Source: Statistics Netherlands (CBS)

substantial profits if sales were made during the meltdown (see Sommervoll and de Haan, 2014, Figure 2.6).

§ 2.4.3 Systemic risk

As noted earlier, a general concern for the Dutch economy has been the very high mortgage debt-to-gross domestic product (GDP) ratio. However, in contrast to the loan repayment, the response has been quite good with forced sales at only around 2 per cent, which some analysts argue that there is really not much cause to despair. To Van Leeuwen and Bokeloh (2012), for instance, there seems to be rather too much focus on the debt side than the equally high assets held by Dutch households. According to these authors, the Dutch have more assets than debts. By these authors' estimation as at 2011, for every one euro in debt, Dutch households equally have in

reserve 1.76 and 2.41 euros of real estate and financial assets, respectively. Mostly, however, these assets are tied up in pension and insurance reserves. There is also a large amount of equity stored up in residential real estate which should probably be the concern because property prices are never guaranteed. This should be especially important for NHG which insures against residual debts since any significant price decline along with large number of foreclosures could be quite distressful. Of course, there have been concerns recently about the rising foreclosure rates which had eventually led to an increment of the premium from 0.85 to 1.0 per cent.

§ 2.5 Summary and conclusion

From the perspective of the homeowner, two main types of risks are identified: mortgage default and property price risk. The discussions have unearthed a quantum number of factors which underline these risks. Particular to default, these factors relate to the initial amount of mortgage loan taken out, the future housing expenses and the income development of the owner-occupier. In the Dutch case, family disintegration is identified as one of the main causes of mortgage default. As a recent phenomenon, most people enter into home-ownership at the start of their marital relationships. However, problems arise when those households are broken apart and the mortgage cost become too high for a single individual. On property price risk, the factors discussed are those which generally determine property price development and mainly thought to command demand and supply of owner-occupier dwellings. These factors include income levels, interest rates and conditions in the social and private rental sectors. With respect to the Netherlands, the recent price decline traces its roots to the financial crisis. The situation further deteriorated by the introduction of a new code of conduct for lenders and the government's revision of the tax deductibility which led to an increase in the monthly expenses of home ownership.

The study also discussed the consequences of default and declining property prices in which the ultimate problem is foreclosure in combination with negative equity leading to residual debts. For the Dutch households, this implies a loss of investment capital which may subsequently lead to psychological problems. Property price decline may also trigger negative equity, immobility, loss of investment capital and insecurity. More importantly, when default occurs on extremely large scale at the same time with property prices sharply declining, there is the possibility that the financial system might experience systemic instability. For the Netherlands, this risk is insured by the NHG to some extent. In sum, the central theme advanced in the paper is awareness of the individual about the nature of the risks in home-ownership. To enhance the understanding and management of these risks at the household level, a possible consideration might be a thorough education by lenders on the risks of the mortgage products they offer. Future research could therefore consider assessing the individuals' future complications and counselling on strategies to minimise the risks.

3 Detecting spatial and temporal house price diffusion in the Netherlands: A Bayesian network approach

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Abstract

Following the 2007-08 Global Financial Crisis, there have been a growing research interest on the spatial interrelationships between house prices in many countries. This paper examines the spatio-temporal relationship between house prices in the twelve provinces of the Netherlands using a recently proposed econometric modelling technique called Bayesian graphical vector autoregression (BG-VAR). This network approach enables a data driven identification of the most dominant provinces where house price shocks may largely diffuse through the housing market and it is suitable for analysing the complex spatial interactions between house prices. Using temporal house price volatilities for owner-occupied dwellings, the results show evidence of house price diffusion pattern in distinct sub-periods from different provincial housing sub-markets in the Netherlands. We observed particularly prior to the crisis, diffusion of temporal house price volatilities from Noord-Holland.

Keywords: Graphical models, House price diffusion, Spatial dependence, Spillover effect

§ 3.1 Introduction

The collapse of house prices during the 2007-08 Global Financial Crisis (GFC) slowed down economic growth in many countries. After the GFC, researchers and governments alike have been seeking to understand the dynamics of house price development in order to resuscitate the stagnating housing market and the general economy. This has consequently led to a new research agenda that specifically seeks insights into spatial interactions and diffusion between the regional housing markets. House prices vary over space and time, but developments of house prices across regions may not be entirely independent of each other. As explained by Gong et al. (2016b), there are significant variations in regional house prices. However, house prices interrelate spatially over time, and it is paramount for governments to understand these interrelationships so as to formulate policies to regulate the overall functioning of the housing market.

Spatial interrelationships between regional house prices may take the form of a long-run convergence or a temporal diffusion mechanism. Long-run convergent

property markets equilibrate and remain integrated over a long period of time (Holmes and Grimes, 2008; Cook, 2005; Cotter et al., 2011). Temporal house price diffusion is also sometimes known in the literature as ripple or spillover effect (see Meen, 1999). This market phenomenon depicts the situation where house price shocks in one region is believed to propagate to house prices in other regions with a transitory or permanent effect (Balcilar et al., 2013; Canarella et al., 2012; Pollakowski and Ray, 1997). Empirical evidence in support of this temporal house price diffusion mechanism exists in the context of the US (Canarella et al., 2012; Holly et al., 2010; Pollakowski and Ray, 1997) and the UK (Meen, 1999, 1996; Holly et al., 2011). More recent results from China and other developing countries also lend support to the house price diffusion hypothesis (see Gong et al., 2016b; Lee and Chien, 2011; Nanda and Yeh, 2014; Balcilar et al., 2013). However, in most of these previous studies, the hypothesis is tested for a lead-lag relationship where it is assumed *a priori* that the diffusion will start from some economically "superior region".

In this paper, we shed light on the spatial and temporal house price diffusion in the case of the Netherlands. The focus is specifically as follows. First, we investigate if there is a spatial dependence of temporal house price volatilities and a diffusion pattern between provinces in the Netherlands. Secondly, we are interested in identifying from the data the provinces which may serve as the dominant sources of house price shocks. Lastly, we investigate if these spatio-temporal relationships vary over time.

We employ a graphical network approach for studying these spatio-temporal house price dynamics. Graphical modelling is a class of multivariate analysis that uses graphs consisting of nodes and edges to study the interaction and path dependence between variables. The nodes of this graph represent the variables while the edges (or links) denote their interactions and dependence structure (see Lauritzen, 1996; Eichler, 2007). The graphical modelling approach has become popular as a more natural way to discover hidden and complex interactions among multiple variables. It is applied mostly in the study of contagion and systemic risk analysis in the financial sector where there is complicated and non-linear relationships between variables (see Ahelegbey, 2016, for a more comprehensive review). Like most financial variables, one indeed expects a complex interrelationships between regional house prices which can easily be handled by the graphical network approach.

This paper specifically adopts the graphical method recently proposed by Ahelegbey et al. (2016a) called the Bayesian Graphical Vector Autoregression (BG-VAR). The BG-VAR is a data-driven approach where the directed edges of the network represent causal relationships. The empirical application in this paper uses quarterly data (1995:Q1 - 2016:Q1) on temporal house price volatilities for second-hand owner-occupied dwellings from the twelve provinces of the Netherlands. The results establish a temporal dependence and diffusion dynamics existing between the provincial housing markets. These spatial relationships, however, vary over time in terms of the degree of dependence and the centrally dominant sub-markets. In particular, between 1995Q1 and 2005Q2, Noord-Holland was most predominant, whereas the central regional housing market in the period 2005Q3–2016Q1 was Drenthe.

We organised the remaining sections of the paper as follows. A brief overview of the related literature is provided in Section 3.2. Section 3.3 describes the BG-VAR model.

The description of the data is presented in Section 3.4 while Section 3.5 discusses the empirical results. The entire paper is concluded in Section 3.6.

§ 3.2 Extant literature

Many scholars have been working on the spatio-temporal house price diffusion or the so-called ripple effect and a vast literature now exist. An extensive review of the literature is provided by Balcilar et al. (2013) and most recently by Nanda and Yeh (2014) and Gong et al. (2016b). We only provide a brief summary here. The study of this ripple effect hypothesis actually began from the UK when English researchers observed that house prices rise, during an upswing, first from the South-East (mostly London) and then spread out to other parts of the country (Giussani and Hadjimatheou, 1991; Meen, 1996, 1999). According to Pollakowski and Ray (1997) house price diffusion will not necessarily occur between neighbouring housing markets, but may require some form of economic interrelationship. Meen (1999) likewise shared the view of Pollakowski and Ray (1997), and noted that spatial dependence may not be necessary for explaining the ripple effect. Meen (1999) then suggested four probable mechanisms through which rising house prices from one region may later manifest in other parts of the UK. These channels according to the author include: migration, equity transfer, spatial arbitrage and spatial patterns in house price determinants. As also noted later by Canarella et al. (2012), migration particularly may lead to house price ripple effect if households relocate in response to changes in the spatial distribution in house prices.

Meen (1999) also provided an empirical framework for testing the ripple effect by assuming that regional house prices will react to shocks at different rates. The author's approach was equivalent to testing the stationarity of the regional to national house price ratios. Although Meen (1999) was unsuccessful in confirming the ripple effect with the Augmented Dickey-Fuller test, the author's empirical framework became the basis for other scholars who later found empirical evidence using more sophisticated stationarity test procedures. Cook (2003), for instance adopted the Threshold Autoregressive (TAR) and Momentum Threshold Autoregressive (MTAR) test procedures while Holmes and Grimes (2008) used a combination of unit root test and Principal Component Analysis (PCA) to confirm the spillover effect in the UK. Canarella et al. (2012) similarly studied the house price diffusion effect in the US by using a combination of the Generalised Least Squares (GLS) version of the Dickey-Fuller, non-linear unit root tests and other test procedures that control for structural breaks. Balcilar et al. (2013) also adopted a Bayesian and non-linear unit root tests, with and without structural breaks to investigate the ripple effect in the South African housing market. The Panel Seemingly Unrelated Regressions Augmented Dickey-Fuller (SURADF) has equally been employed by other scholars (e.g. Lee and Chien, 2011; Holmes, 2007).

Recently, tremendous effort, relying on the advances in the econometric literature, has also been channelled into refining the methodology for testing the ripple effect hypothesis beside the "Meen framework". Holly et al. (2011), for example proposed a dynamic modelling approach where they allowed shocks from the dominant region to propagate to other regions and then echo back. The authors found support for the ripple effect using this approach for the UK with London as the dominant region. Gong

et al. (2016b) adopted similar method in their study of ripple effect for 10 regions in the Pan-Pearl river of China. Nanda and Yeh (2014), in a related study also suggested using a dynamic panel-spatial model. Some studies equally advocated formulating a Spatial Vector Autoregressive (SPVAR) model and subsequently testing for Granger Causality (GC) and/or performing Impulse Response Analysis (IRA) to examine the ripple effect hypothesis. Brady (2014), for example captured the spatial diffusion between regional housing prices in the US with impulse response functions estimated from a Spatial Autoregressive (SAR) model.

Pinkse and Slade (2010) as well as Gibbons and Overman (2012), however, argued that the SAR model and many other spatial models (see LeSage and Pace, 2009; Florax and Folmer, 1992; Dubin, 1992) may suffer generally from mis-specification because the spatial weighting matrices which are central to those models are constructed in an ad-hoc manner. Other authors entirely avoid constructing the spatial weighting matrix by estimating traditional VAR to perform GC and IRA. For instance, Vansteenkiste and Hiebert (2011) adopted a global VAR model and IRA to study the house price spillover effects across countries in the euro area. Gupta and Miller (2012a), similarly formulated traditional VAR model after which they tested for GC and performed IRA to verify the spatial diffusion phenomenon between Los Angeles, Las Vegas, and Phoenix in the US.

The VAR based models, similarly suffer from mis-specification or over-parametrisation, which may render the impulse response function and GC test inaccurate (see Koop and Korobilis, 2010; Vega and Elhorst, 2013; George et al., 2008). To eliminate the problem of mis-specification and over-parametrisation, Ahelegbey et al. (2016a) recently proposed the Bayesian graphical network vector autoregressive (BG-VAR) method which provides a better approach to specify and estimate a parsimonious VAR model. The novelty of the BG-VAR is that, we can identify the temporal dependence structure between the variables without having to estimate the structural (VAR) parameters.

In addition, the method could be used to identify the direction of dependence between the variables and it is somewhat related to the concept of GC. The GC, however adopts a pairwise (or conditional pairwise) analysis to identify the dependence patterns without accounting for the structural uncertainties. On the other hand, the BG-VAR employs a Bayesian technique which incorporates necessary prior information to explore the structure and to apply model averaging. Ahelegbey (2016) provided empirical evidence that support the superior efficiency of the BG-VAR over the GC in producing dependence patterns that are more suitable for capturing complex interdependencies. Investigating the dependence structure between multiple time series with the BG-VAR model is generally more convenient for researchers and policy makers to understand directional or causal relationships.

§ 3.3 The Bayesian graphical vector autoregressive (BG-VAR) model

This section presents the formulation of the BG-VAR model adopted in this paper. Assume for a moment that temporal house price volatilities in one region is a result of earlier shock to house prices in other regions. We can formulate a vector autoregressive process of order p (VAR(p)) to capture these interdependencies. As mentioned earlier,

some authors study the spatial and temporal house price dynamics by testing for Granger causality (GC) and performing IRA from this underlying VAR model.

Let Y_t denote the vector of house price volatilities at the time t from n regions which are demeaned. We can write the VAR(p) process for Y_t following the equation

$$Y_t = \sum_{i=1}^{p} B_i Y_{t-i} + u_t = BX_t + u_t, \quad u_t \sim \mathcal{N}(\mathbf{0}, \Sigma_u) \tag{3.1}$$

where $t = p+1, \ldots, T$; p is the maximum lag order to be chosen and $X_t = (Y'_{t-1}, \ldots, Y'_{t-p})'$ is $np \times 1$ stacked matrices of the lagged regional house price volatilities. $B = (B_1, \ldots, B_p)$, where $B_i, 1 \leq i \leq p$ is an $n \times n$ matrix of coefficients, which determine the dependence of the house price volatilities on their lags.

The set of equations in (3.1) captures the structure of the interactions between the regional house price volatilities and Ahelegbey et al. (2016a) showed that the temporal dependencies between them could be inferred from B. For example, when the volatility of house prices in one region depends only on a subset but not on earlier shock to house prices in all the regions, there are components of B that become zero. In general, B_{ij} measures the anticipated effect of changes in the j-th predictor ($X_{j,t}$) on the house price development in the i-th region ($Y_{i,t}$).

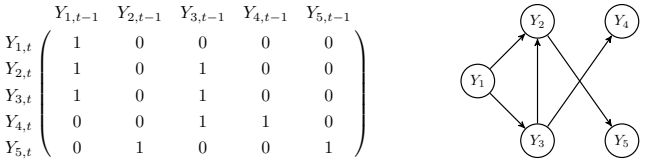
Ahelegbey et al. (2016a) demonstrated that the VAR model (3.1) can be operationalised as a graphical model using the relation $B = (G \circ \Phi)$, where G is a binary (0/1) matrix, Φ is a coefficients matrix, both of dimension $n \times np$, and $(\circ)$ is the element-by-element product. The elements of G represent the presence or absence of an edge (interaction) between volatility of house prices in pairs of regions. A one-to-one correspondence between B and Φ conditional on G can be identified. That is, $B_{ij} = \Phi_{ij} \neq 0$, if $G_{ij} = 1$; and $B_{ij} = 0$, if $G_{ij} = 0$.

As an example, consider an arbitrary five-dimensional VAR(1) with coefficients matrix

$$B = \begin{pmatrix} \beta_{11} & 0 & 0 & 0 & 0 \\ \beta_{21} & 0 & \beta_{23} & 0 & 0 \\ \beta_{31} & 0 & \beta_{33} & 0 & 0 \\ 0 & 0 & \beta_{43} & \beta_{44} & 0 \\ 0 & \beta_{52} & 0 & 0 & \beta_{55} \end{pmatrix} \tag{3.2}$$

where the non-zero elements of B are real numbers. The network that depicts the temporal dependence among the variables associated with (3.2) can be visualised in Figure 3.1. The nodes of this network are specifically the five variables: $Y_{1t}, Y_{2t}, Y_{3t}, Y_{4t}$ and Y_{5t}. Since $\beta_{21} \neq 0$, $Y_{1,t-1}$ has a significant impact on $Y_{2,t}$. This also means that an edge exists between Y_1 and Y_2 which is denoted as $Y_1 \to Y_2$. The edges of the network indicate the lagged dependencies between the variables without self lag effects, which are the indirect effects.

Elhorst (2014) and LeSage and Pace (2009) discussed the direct and the indirect (or spillover) effects between spatial variables. Figure 3.1 shows that the two effects may be easily distinguished with the BG-VAR approach. The direct effect are represented in the diagonal of the graph matrix G, while its off-diagonals describe the indirect interactions depicted by the Figure 3.1(b). For the diffusion dynamics, it suffices to estimate only the network structure captured by G. Let $D_t = (X'_t, Y'_t)'$ be a $d \times 1$



((a)) Graph matrix ((b)) Graph structure

FIGURE 3.1 Network matrix and diagram associated with the temporal dependence in the five-dimensional VAR(1) process in (3.2).

vector, where $d = n + np$ and assume $D_t \sim \mathcal{N}(\mathbf{0}, \Omega^{-1})$, where Ω is a $d \times d$ precision matrix. The joint distribution for all the variables in D_t can be summarised with a graphical model and represented by the pair $(G, \Omega) \in (\mathcal{G} \times \Theta)$. Here, G is a directed acyclic graph (DAG) of the relationships among the variables in D_t, Ω consists of the VAR model parameters, $\mathcal{G}$ and Θ are the graph and parameter space respectively. The triple (Ω, Σ_u, B) are mathematical related. Suppose $X_t \sim \mathcal{N}(0, \Sigma_{xx})$ and $Y_t|X_t \sim \mathcal{N}(BX_t, \Sigma_u)$, B and Σ_u can be obtained from the covariance matrix of D_t (i.e. $\Sigma = \Omega^{-1}$) by

$$B = \Sigma_{yx}\Sigma_{xx}^{-1}, \qquad \Sigma_u = \Sigma_{yy} - \Sigma_{yx}\Sigma_{xx}^{-1}\Sigma_{xy} \tag{3.3}$$

where Σ_{yx} is $n \times np$ covariances between Y_t and X_t, Σ_{xx} is $np \times np$ covariances among X_t and Σ_{yy} is $n \times n$ covariances among Y_t. Given B, Σ_u and Σ_{xx}, Ω can equally be obtained using the well-known Sherman-Morrison-Woodbury formula (Woodbury, 1950),

$$\Omega = \Sigma^{-1} = \begin{pmatrix} \Sigma_{xx}^{-1} + B'\Sigma_u^{-1}B & -B'\Sigma_u^{-1} \\ -\Sigma_u^{-1}B & \Sigma_u^{-1} \end{pmatrix}, \quad \text{where} \quad \Sigma = \begin{pmatrix} \Sigma_{xx} & \Sigma_{xy} \\ \Sigma_{yx} & \Sigma_{yy} \end{pmatrix} \tag{3.4}$$

By defining $B = (G \circ \Phi)$, equation (3.4) shows how Ω relates to G through B. The specification of the BG-VAR model is completed with the choice of a hierarchical prior on the lag order p, the graph structure G and the parameter Ω.

We now focus on the estimation procedure for the graph structure (G) associated with the temporal dependence between the regional house prices. In the Bayesian framework, the joint prior distribution of (p, G, Ω) is given by $Pr(p, G, \Omega) = Pr(p)Pr(G|p)Pr(\Omega|p, G)$. It is important to first select the optimal lag order for the VAR model. Following Ahelegbey et al. (2016b), we choose p in the range $0 < p_{\text{min}} < p_{\text{max}} < \infty$, for some lower bound p_{min} and upper bound p_{max}. More specifically, we assume p follows a discrete uniform prior on $\{p_{\text{min}}, \ldots, p_{\text{max}}\}$ with a distribution

$$Pr(p) = \frac{1}{p_{\text{max}} - p_{\text{min}} + 1} \tag{3.5}$$

Since we seek to estimate the regional market that is central in the spread of house price volatility from the data, it is more reasonable to assume a priori that any region is equally likely to play this role. This implies that the graph structure can be represented

as a product of local sub-graphs of each equation of the model and may be written as

$$Pr(G|p) = \prod_{i=1}^{n} Pr(\pi_i|p) \tag{3.6}$$

where $\pi_i = \{j = 1, \ldots, np : G_{ij} = 1\}$ is the set of price volatilities of the i-th equation predictors.

We formulate in what follows, the standard techniques for estimating G also described by Ahelegbey et al. (2016a,b). We assume for each edge G_{ij}, an independent Bernoulli trial with conditional prior probability

$$Pr(\pi_i|p, \gamma) = \gamma^{|\pi_i|}(1-\gamma)^{np-|\pi_i|} \tag{3.7}$$

where $|\pi_i|$ is the cardinality of π_i and $\gamma \in (0, 1)$ is the Bernoulli parameter. We use a uniform graph prior by choosing $\gamma = 0.5$ so that $Pr(\pi_i|p, \gamma = 0.5) = 2^{-np}$ and $Pr(G|p) \propto 1$.

Following standard Bayesian paradigm, we also assume that Ω conditional on p and a complete graph G is Wishart distributed, $\Omega \sim \mathcal{W}(\nu, \underline{S}^{-1})$, with density

$$Pr(\Omega|p, G) = \frac{1}{K_d(\nu, \underline{S})}|\Omega|^{\frac{(\nu-d-1)}{2}} \exp\Big\{-\frac{1}{2}\langle\Omega, \underline{S}\rangle\Big\} \tag{3.8}$$

where $\langle A, B\rangle = tr(A'B)$ is the trace inner product, ν is the degree of freedom, $\underline{S}$ is the prior sum of squared matrix and $K_d(\nu, \underline{S})$ is the normalizing constant. The likelihood of a random sample $\mathcal{D} = (D_1, \ldots, D_T)$ is multivariate Gaussian with density

$$Pr(\mathcal{D}|p, \Omega, G) = (2\pi)^{-\frac{1}{2}dT}|\Omega|^{\frac{1}{2}T} \exp\Big\{-\frac{1}{2}\langle\Omega, \hat{S}\rangle\Big\} \tag{3.9}$$

where $\hat{S} = \sum_{t=1}^{T} D_t D_t'$ is a $d \times d$ sample sum of squared matrix.

Given that G is unknown, a standard Bayesian approach for determining the graph structure is to integrate out Ω from (3.9) with respect to its prior given by

$$Pr(\mathcal{D}|p, G) = \int Pr(\mathcal{D}|p, \Omega, G)\, Pr(\Omega|p, G)d\Omega = \frac{K_d(\nu + T, \underline{S} + \hat{S})}{(2\pi)^{\frac{1}{2}dT}K_d(\nu, \underline{S})} \tag{3.10}$$

where $\underline{S} + \hat{S}$ is the posterior sum of squared matrix. The expression (3.10) is the marginal likelihood function expressed as ratio of the normalising constants of the Wishart posterior and prior. Following standard application, the marginal likelihood factorises into the product of local terms, each involving $Y_{i,t}$ and its set of selected predictors, $X_{\pi_i,t}$, given by

$$Pr(\mathcal{D}|p, G) = \prod_{i=1}^{n} Pr(\mathcal{D}|p, G_{i,\pi_i}) = \prod_{i=1}^{n} \frac{Pr(\mathcal{D}^{(i,\pi_i)}|p, G)}{Pr(\mathcal{D}^{(\pi_i)}|p, G)} \tag{3.11}$$

where $\mathcal{D}^{(i,\pi_i)}$ and $\mathcal{D}^{(\pi_i)}$ are sub-matrices of $\mathcal{D}$ consisting of $(Y_{i,t}, X_{\pi_i,t})$ and $X_{\pi_i,t}$ respectively. Let $w_i \in (\{i\} \cup \pi_i)$. The closed-form expression for the left-hand side of

(3.11) is given by

$$Pr(\mathcal{D}^{w_i}|p,G) = \frac{\pi^{-\frac{1}{2}T|w_i|}\nu^{\frac{1}{2}\nu|w_i|}}{(\nu+T)^{\frac{1}{2}(\nu+T)|w_i|}} \frac{|\underline{\Sigma}_{w_i}|^{\frac{1}{2}\nu}}{|\bar{\Sigma}_{w_i}|^{\frac{1}{2}(\nu+T)}} \prod_{s=1}^{|w_i|} \frac{\Gamma\left(\frac{\nu+T+1-s}{2}\right)}{\Gamma\left(\frac{\nu+1-s}{2}\right)} \tag{3.12}$$

where $|w_i|$ is the cardinality of w_i, $\underline{\Sigma}_{w_i}$ and $\bar{\Sigma}_{w_i}$ are the prior and posterior covariance matrices of $\mathcal{D}^{w_i}$.

Again, we follow standard practice and set $\underline{\Sigma}_{w_i} = I_{|w_i|}$, where $I_{|w_i|}$ is a $|w_i|$-dimensional identity matrix.[1] By definition, (3.12) consists of a component that is independent of $\bar{\Sigma}_{w_i}$. We can reduce the computational time by expressing this independent component as a function $Q_\nu(|w_i|,p,T)$ given by

$$Q_\nu(|w_i|,p,T) = \frac{\pi^{-\frac{1}{2}T|w_i|}\nu^{\frac{1}{2}\nu|w_i|}}{(\nu+T)^{\frac{1}{2}(\nu+T)|w_i|}} \prod_{s=1}^{|w_i|} \frac{\Gamma\left(\frac{\nu+T+1-s}{2}\right)}{\Gamma\left(\frac{\nu+1-s}{2}\right)} \tag{3.13}$$

Since for each equation, we have np number of explanatory variables, $|w_i|$ will be bounded below by 1 and above by $np+1$. Thus, we can set $\nu = np+2$. Given ν, T and p, $Q_\nu(|w_i|,p,T)$ does not directly depend on the variables in w_i but on $|w_i| \in \{1,\ldots,np+1\}$. Hence, (3.12) may be expressed as

$$Pr(\mathcal{D}^{w_i}|p,G) = Q_\nu(|w_i|,p,T)\ |\bar{\Sigma}_{w_i}|^{-\frac{1}{2}(\nu+T)} \tag{3.14}$$

The posterior covariance matrix of $\mathcal{D}$ is also given by

$$\bar{\Sigma} = \frac{1}{\nu+T}\left(\nu I_d + \sum_{t=1}^{T} D_t D_t'\right) \tag{3.15}$$

Thus, $\bar{\Sigma}_{w_i}$ in (3.14) can be obtained as a sub-matrix of $\bar{\Sigma}$ which corresponds to the elements in w_i. Pre-computing $\bar{\Sigma}$ and $Q_\nu(|w_i|,p,T)$ for $|w_i|$ given ν, T and p, before sampling the network matrix reduces the computational complexity and makes the algorithm efficient. The details of sampling the network structure is provided in the Appendix to Chapter 3.

§ 3.4 Description of data

This section gives a brief background to the regional housing market in the Netherlands and describes the data. The spatial units for our analysis include the twelve official Dutch provinces.[2] These are, namely Drenthe (DR), Flevoland (FL), Friesland (FR), Gelderland (GE), Groningen (GR), Limburg (LI), Noord-Brabant (NB), Noord-Holland (NH), Overijssel (OV), Zuid-Holland (ZH), Utrecht (UT) and Zeeland (ZE) (see map in Figure 3.2). According to Statistic Netherlands (CBS), Zuid-Holland is the largest in terms of GDP (141.758 billion Euros in 2014), followed by Noord-Holland (133.358

1 For any $n \times n$ identity matrix A, we have $|A| = 1$.

2 In this paper, we use region and province interchangeably.

FIGURE 3.2 Map of the twelve provinces of the Netherlands.

Source: d-maps.com

billion Euros in 2014). Zeeland is the smallest with estimated GDP of 11.429 billion Euros in 2014. The capital Amsterdam is hosted by Noord-Holland while the government seat (The Hague) is located in Zuid-Holland. The extant literature suggest a higher tendency of house price shocks to diffuse from some "mega economic districts" to peripheral regions (see Gong et al., 2016b; Holly et al., 2011). Thus, our initial expectation is that Noord-Holland or Zuid-Holland may be central in the house price diffusion mechanism in the Netherlands within certain periods.

We use quarterly house price indexes spanning the period 1995Q1 to 2016Q1 for second-hand owner-occupied dwellings in this paper. The data is obtained from Statistic Netherlands (CBS). CBS is the Dutch official agency which publishes statistics on housing and other sectors of the economy. The indexes are constructed adopting the sale price appraisal ratio (SPAR) method (see de Haan et al., 2009). By using official annual appraised values for the dwellings and chaining the ratios, CBS adjusts for appraisal bias in the SPAR index but is unable to control for quality changes. Given available house transaction data, CBS' SPAR index is the most reliable in the Netherlands (De Vries et al., 2009).

A simple plot of the house price indexes (Figure 3.3) shows a common trend in the growth of house prices in all the twelve regional markets before and after the GFC. The periods prior to 2009 show a relatively faster house price appreciation which may be attributed to many factors. For instance, the Dutch government promoted home ownership forcefully during those periods with the National Mortgage Guarantee scheme and through an income tax structure that offered generous rebates on the

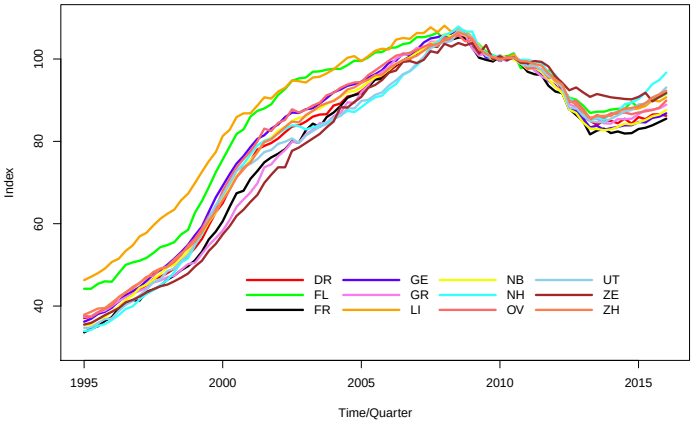


FIGURE 3.3 Dutch regional house price indexes.

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

mortgage interest rates (see, Toussaint and Elsinga, 2007; Boelhouwer et al., 2004; Elsinga, 2003; Boelhouwer, 2002). These incentive packages generally made it cheaper for individual households to purchase their own dwellings, which consequently led to increase in demand and rise in house prices before the crisis.

As in other countries, financial institutions in the Netherlands were also hit by the 2007-08 GFC. The impact of the crisis on house prices however started in the last quarter of 2008 as seen in Figure 3.3. Following the GFC, average house prices in the Netherlands declined by almost 25% between 2009 and 2013. Teulings (2014), attributed the collapse in the Dutch property values with the higher unemployment and redundancy rates during the meltdown. Other scholars however blamed the collapse on the Dutch financial institutions who tightened up mortgage accessibility and impeded new home buyers from the market (Elsinga et al., 2016; Boelhouwer, 2014; Bardhan et al., 2011). Since the beginning of 2014, there has been gradual recovery of Dutch house prices, somewhat faster in Zuid-Holland and Noord-Holland.

In this paper, we study the temporal diffusion pattern of house price volatilities in the Netherlands. We follow Martens and Van Dijk (2007) to define the house price volatilities for each region as the squared returns given by

$$SR_t = [100(\log I_t - \log I_{t-1})]^2 \tag{3.16}$$

where I_t is the house price index at the time t. Figure 3.4 summarises the temporal regional house price volatilities. It shows that house prices were more volatile in most regions from 1995 until the early 2000s, and gradually decline afterwards.

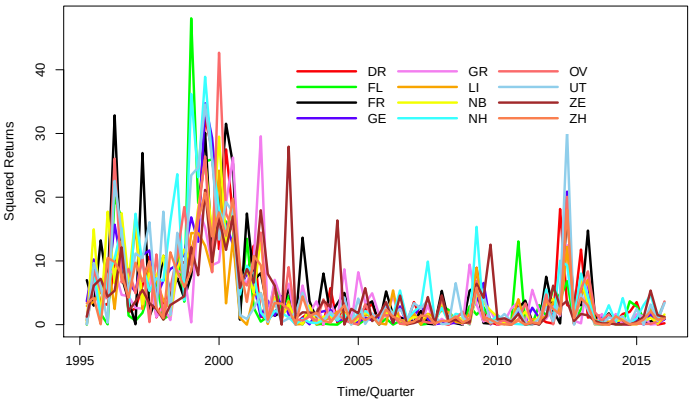


FIGURE 3.4 Regional house price volatilities.

§ 3.5 Spatio-temporal house price dynamics

We estimate the temporal dependencies from the network structure described in Section 3.3 using the (demeaned) regional house price volatilities. We set the minimum and maximum lag order to $p = 1$ and $p = 4$ respectively. The estimation first follow a twenty-quarter rolling window and the result is summarised with the network density to examine the extent of interdependencies between the regional house prices over time. The network density is a simple aggregate index for the degree of interdependence. It is defined for each estimation window as the percentage of the regions whose temporal house price volatilities are dependent on earlier price movements in other regions. More specifically, the network density is the number of identified edges in the network divided by the total possible edges. For n number of regions or variables, there are $n(n-1)$ possible edges indicating the indirect effects.

Figure 3.5 presents the network density associated with the temporal regional house price volatility interdependencies. The average network density over the study period is about 43%, which gives evidence of temporal interdependence and diffusion between the regional house price volatilities. Figure 3.5 also shows that the degree of interdependence varies over time. It was higher particularly between 1995 and 2005, then began to decrease until 2008, after which it has been on the rise again.

The above sub-periods somewhat coincide with recognisable stages in the development of house prices in the Netherlands. It is recognised by most Dutch researchers that the period 1995–2005 is one during which house prices increased legitimately because of the rise in household disposable income and government stimulation of the housing market (De Vries, 2010; Toussaint and Elsinga, 2007; Boelhouwer et al., 2004; Boelhouwer, 2002). On the other hand, some analysts argued that the Dutch house price development from 2005–2008 was mostly due to over-valuation and speculative investment activities which also precipitated the crisis that started in the last quarter of 2008 (Xu-Doeve, 2010; Aalbers, 2009a,b).

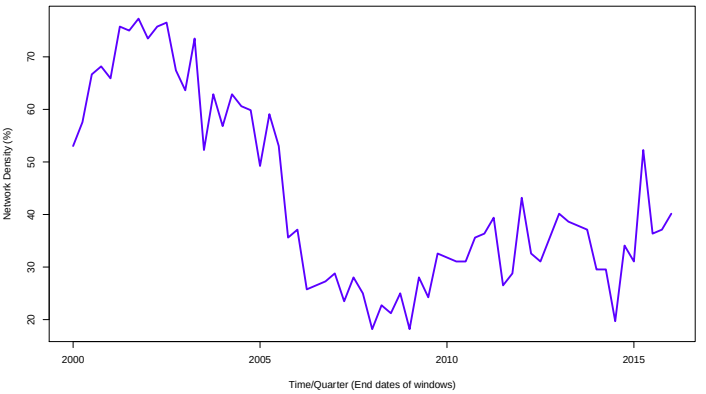


FIGURE 3.5 Network density estimated with rolling window over the period 1995Q2 – 2016Q1.

§ 3.5.1 Sub-period dynamics

To ascertain if the central regions in the house price diffusion dynamics vary with time, we study in details the network structure within sub-periods. It is appropriate to identify if there are structural shifts in the network density and delineate the sub-periods along them. A simple recurrent plot (Marwan et al., 2007) in Figure 3.6 shows a significant period of structural change in the network density, occurring between 2005 and 2006.[3] Using the sequential method of Bai and Perron (2003, 1998), we also test for the structural shift and the break date. The sequential test assumes no knowledge of the break date but requires that a model for the series and maximum likely breaks are specified. Following Brady (2014), we model the series for the network density as an AR(1) process. We allow up to 3 breaks, however the BIC suggests only one significant structural shift, occurring at 2005Q2. This confirms the recurrent plot also suggesting one structural shift.

We re-estimate the network structure for the two sub-periods: 1995Q1–2005Q2 and 2005Q3–2016Q1. The summary statistics and optimal lag order associated with the network structure for each specific sub-period are presented in Tables 3.1 and 3.2. The average path length, for example, represents the average graph-distance between all pair of nodes, where interconnected nodes have graph distance of 1. In general, the higher the graph distance the slower it takes house price shocks in one region to cascade systemically. Table 3.1 also indicates the total links and average degree which are important for the network analysis.

The interest here is to identify the regions with temporal house price volatilities that are predominately interdependent and their specific direction of interconnection with the others. These regions are interesting because they play important role in the transmission of house price shocks. In the network terminology, these regions are the

3 A recurrence plot is a way to visualise and study the dynamics of phase space by a two- dimensional plot (Marwan et al., 2007).

FIGURE 3.6 Recurrent plot indicating the patterns in the network density over time.

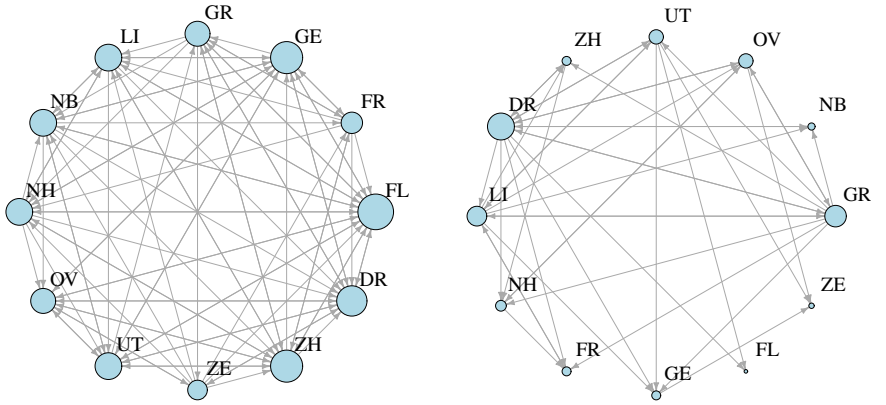
hub-centralities (see, Benzi et al., 2013). The network structures for the two sub-periods are presented in Figure 3.7. The figure shows the explicit nature and degree to which the regional house price volatilities are temporarily dependent on one another. For example, it indicates a direct temporal dependence of house price volatilities in Nord-Brabant on Noord-Holland between 1995Q1 and 2005Q2 but not during the period 2005Q3–2016Q1. As with Figure 3.5, Figure 3.7 similarly reveals that there is heavier dependency between the regional house prices before 2005 than it was afterwards. Again, this may indicate the shift in the developments of Dutch house prices.

TABLE 3.1 The network statistics for the sub-period graphs.

	Edges/Links	Density	Average Degree	Average Path Length
1995Q1–2005Q2	94	0.71	15.67	1.29
2005Q3–2016Q1	39	0.30	6.50	1.73

TABLE 3.2 Equation-specific lag order of each equation for the sub-periods.

Period	DR	FL	FR	GE	GR	LI	NB	NH	OV	UT	ZE	ZH
1995Q1–2005Q2	3	2	1	2	4	2	2	2	2	2	1	2
2005Q3–2016Q1	1	1	1	1	1	1	1	1	1	1	1	1



((a)) 1995Q1 – 2005Q2 ((b)) 2005Q3 – 2016Q1

FIGURE 3.7 Network diagrams showing the temporal dependence between house price volatilities of the 12 Dutch regional markets during sub-periods.

Note: The sizes of the nodes are proportional to the degrees (number of other regions to which the specified region at the node is connected to).

To determine the hub-centrality, we use the Katz measure (Katz, 1953). The Katz measure scores the centrality of a region by considering its direct and indirect interdependences with other regions. Table 3.3 presents the centralities and the ranks associated with the network structure in Figure 3.7 for each region. The table indicates Noord-Holland as the most central during the period 1995Q1–2015Q2, while Drenthe ranks the most central for the sub-period 2005Q3–2016Q1. As one of the largest economic regions (mainly due to influence of the national capital, Amsterdam), it is not surprising that Noord-Holland is central in the temporal house price diffusion pattern. Earlier studies (e.g. Holly et al., 2011; Giussani and Hadjimatheou, 1991) similarly found that house prices diffusion in the UK exists from the economic hub, London. On the other hand, the result of Table 3.3 shows that economically smaller regions such as Drenthe may equally be pivotal in diffusion of house prices during certain periods. Although it is unclear why smaller regions will be that central, suburbanisation and recent trend of urban to rural migration of certain class of people in the Netherlands, majority who are seniors, may play some role (see De Jong et al., 2016; Accetturo et al., 2014; Van Ommeren et al., 1999).

The network distance in Table 3.3 may be used to further examine the diffusion dynamics of temporal house price volatilities from the central regions. The network distance is by definition the length of the shortest path between two nodes in the network. A network distance of 1 denotes a direct interdependence, while a distance of 2 indicates the interdependence between two nodes that is mediated by another node. In tandem with this description, the results of Table 3.3 may be interpreted to mean that, temporal house price volatility from Noord-Holland in the period 1995Q1–2005Q2 had a direct causal relationship with the volatility of house prices in the other regions, except Friesland and Zeeland where this was mediated. Similarly, we find that temporal causal relationships exist between house price volatility in Drenthe and the rest of the regions during the period 2005Q3–2016Q1, except Zeeland for which this was mediated.

TABLE 3.3 Hub centrality, rank and distance associated with the network for the sub-periods.

	1995Q1 – 2005Q2			2005Q3 – 2016Q1		
	Centrality	Rank	Distance	Centrality	Rank	Distance
Drenthe	54.55	12	1	**23.65**	1	0
Flevoland	212.72	3	1	1.00	12	1
Friesland	139.46	9	2	1.78	9	1
Gelderland	136.25	10	1	1.66	10	1
Groningen	163.18	6	1	17.59	2	1
Limburg	179.52	5	1	11.68	3	1
Noord-Brabant	212.98	2	1	1.80	8	1
Noord-Holland	**228.85**	1	0	2.96	6	1
Overijssel	122.96	11	1	5.25	5	1
Utrecht	142.55	8	1	7.18	4	1
Zeeland	151.88	7	2	1.00	11	2
Zuid-Holland	207.51	4	1	1.80	7	1

The bold values indicate the hubs.

§ 3.6 Summary and concluding remarks

In an effort to revive the housing markets that have collapsed in many countries following the 2007–2008 Global Financial Crisis (GFC), there is an ongoing research agenda that seeks understanding into the spatio-temporal dynamics of house prices. This paper makes three main contributions to this new research area. Firstly, the paper studied the spatio-temporal house price dynamics in the unique context of the Netherlands, which is first of its kind. Here, the paper specifically asked if there is temporal spatial dependence of house prices in the Netherlands. It then investigated the diffusion pattern and identified the specific regions where temporal house price volatilities are likely to spread.

For the second contribution, the paper demonstrated the usefulness of graphical and network techniques in analysing the spatio-temporal house price dynamics. Particularly, the paper adopted the newly proposed Bayesian graphical vector autoregression (BG-VAR) model which is in general more efficient in identifying dependence patterns between multiple variables than the traditional concept of Granger Causality (see Ahelegbey et al., 2016a). As a third contribution, the paper proposed a simple data driven techniques to identify the regional housing sub-market where diffusion of temporal house price volatilities may predominately start. This approach deviates from previous studies which assumed *a priori* some "bigger cities" as most central in investigating the house price diffusion process (e.g. Holly et al., 2011). The potential selection bias is avoided in our approach because the central region can be easily inferred from the network using statistical measures for the centrality.

In the empirical analysis, the paper used temporal volatilities constructed from quarterly house price indexes for owner-occupied dwelling between 1995Q1 and 2016Q1. The results, based on the BG-VAR model and various network statistics, support a temporal dependence and diffusion of house prices in the Netherlands. We also observed that the degree of temporal interdependence varies over time. Especially, we found that the Dutch regional house prices were highly interdependent between 1995 and 2005. After 2005, the degree of interdependence weakened until 2008 and again increased from 2008 to 2016 (Figure 3.5). We performed formal empirical break tests, which suggest that a structural shift in the temporal dependence actually exists

at 2005Q2 (see Figure 3.6). The break may reflect some experts' believe of Dutch housing investments shifting to more speculative activities which also precipitated the severe decline of house prices after 2008 (see Xu-Doeve, 2010; Aalbers, 2009a).

Studying in more detail the resulting sub-periods 1995Q1–2005Q2 and 2005Q3–2016Q1, we identified Noord-Holland and Drenthe as the respective regional housing markets that are most central in a temporal diffusion of house price volatility. One key lesson from our findings is that, contrary to the extant literature (e.g. Meen, 1999; Holly et al., 2011; Gong et al., 2016b) which posit that temporal house price volatility spread from some economically "mega city", there exists the possibility that the diffusion may equally start from an "economically smaller" region (like Drenthe in the Dutch case under study here). The results of the paper also suggest that the central region where the house price diffusion predominantly starts may change over time depending on the economic conditions.

Previous literature also suggest that temporal house price volatility diffuse from the central region and slowly through to the remote peripheral areas. We analyse this diffusion pattern in this paper with the network distance. The network distance yields literally the number of regions to which temporal house price volatilities may diffuse having started from the central region. This however augments the graphical aids provided by the results of the BG-VAR detailed in the main text. For the Netherlands, we identified that the diffusion trajectory is limited to at most 2 regions, following a maximum network distance of 2 in the respective sub-periods studied.

In sum, the BG-VAR provides an effective approach for analysing the complex spatial interactions between the regional house prices. It builds on the traditional VAR model by adopting an efficient identification strategy which avoids estimation of the structural parameters. The method also could easily distinguish the direct and indirect interaction between spatial variables as discussed by LeSage and Pace (2009). By transforming the conventional spatial (autoregressive) models into the structural VAR framework, the BG-VAR may equally be applicable. Furthermore, because the method avoids estimation of the structural parameters, the BG-VAR promises a better approach to avoid the ad-hoc and mis-specification of the spatial weighting matrix inherent in most spatial analysis (see e.g. Gibbons and Overman, 2012; Pinkse and Slade, 2010). We leave this however for further investigation and future research.

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.

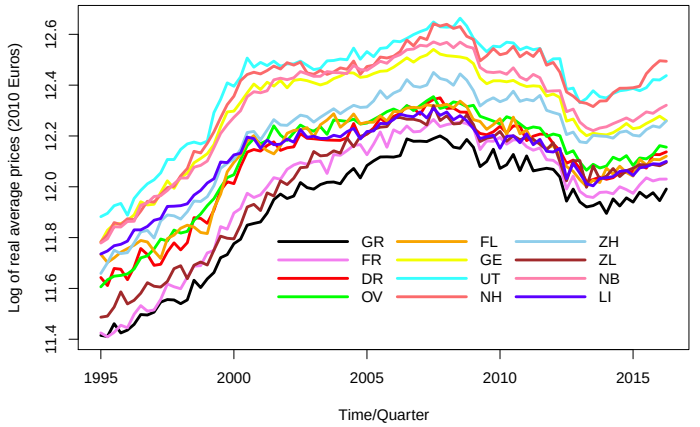

FIGURE 4.1 Regional real average house prices in the Netherlands (1996q1-2016q2).

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.

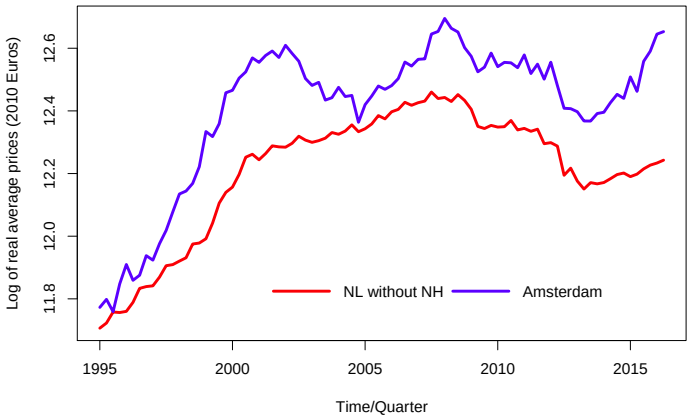

FIGURE 4.2 Quarterly regional average prices of owner-occupied dwellings (1996q1-2016q2).

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^i_t, 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

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

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: Δy_{it}, Δx_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

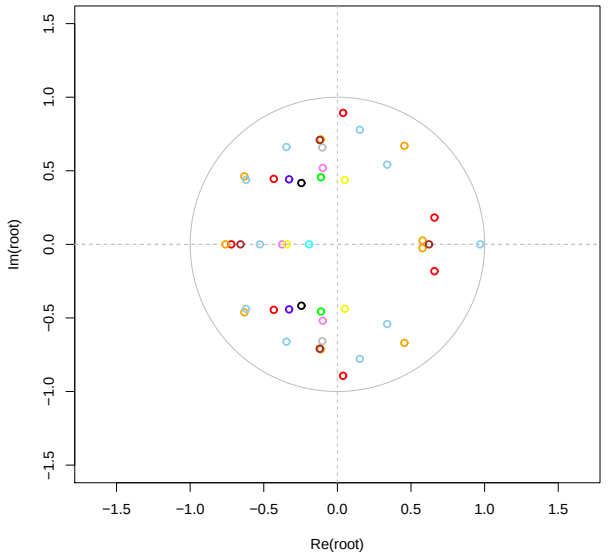

FIGURE 4.3 Inverse roots for AR characteristics equations.

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.

5 Risks and interrelationships of subdistrict house prices: the case of Amsterdam

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Abstract

This paper uses individual house transaction data from 1995 to 2014 in Amsterdam to explore the risks and interrelationships of the subdistrict house prices. Simple indicators suggest that house prices grow faster and are more risky in the central business district and its immediate surrounding areas than in the peripherals. Furthermore, we observe an over time decreasing inter-variations between the subdistrict house price growth rates, whereas we find a lead-lag and house price causal flow from the more central to the peripheral subdistricts.

Keywords: Hedonic index House prices Lead–lag effect Property price risk Subdistricts Amsterdam

§ 5.1 Introduction

House price developments have significant wealth-effect on households because of the large outlays involved in residential property investments. In 2009, Statistics Netherlands (CBS) estimated a total of 738,449 million euros wealth in residential properties for the Netherlands. By 2012, however, the total wealth had declined to 721,018 million euros (2.36%), showing a considerable amount of financial risks involved in residential property investment. Such risks are inherent in the dynamics of house prices, which need a better understanding particularly after the 2007-08 Global Financial Crisis (GFC).

In this paper, the aim is to compute indicators that characterise the risks of residential house prices specifically at the lower-level districts and to study the interrelationships between these subdistrict house prices. While the price risks reveal unique characteristics of the house price development in each subdistrict, the interrelationships show how the house price development in a subdistrict is connected to the growth in the other subdistricts. These analyses at the lower-level districts may unveil important residential asset wealth distribution that is not available at the aggregate national or provincial level. Such information may be of interest to stakeholders, including statistical agencies, households, institutional investors and

policy makers who control the overall functioning of the city-wide housing market. We obtain dataset for individual house transactions between 1995 and 2014, which enables us to analyse the case of the city of Amsterdam.

The residential property market of Amsterdam, which is also the capital city, is an interesting case to study in the Netherlands. Residential properties are usually more expensive in Amsterdam than in the other cities, which may be due to the higher demand for the capital where many employment opportunities and social amenities exist. Over time, the development pattern of Amsterdam house prices also differ considerably from other locations. Following the GFC, for example, house prices in Amsterdam declined more sharply but also recovered quicker than in other major Dutch cities, such as The Hague, Rotterdam and Utrecht.

To begin the analysis, customised house price indexes are created for the lower-level districts using the time dummy hedonic method. We next estimate simple statistics from the indexes to characterize and to compare the risks of house prices in the subdistricts. Finally, we study two aspects of the interrelationships between the house prices: (1) the inter-variation between the subdistrict house price returns (or growth rates), and (2) the lead-lag relationships between the subdistrict house prices.

The paper adopts risk metrics that include specifically the standard deviation, semi-deviation, and the 'decline severity'. The standard deviation is a measure of the dispersion of the temporal (period-to-period) house price growth rates from the average, while the semi-deviation is a version of the standard deviation that considers the average deviation of only values below the mean. The semi-deviation is one of the commonly used downside risk measures for investment analysis in the mainstream finance literature, but it is surprisingly applied seldom in the housing context (see Wolski, 2013; Foo and Eng, 2000; Grootveld and Hallerbach, 1999). The 'decline severity' is similar to the semi-deviation but captures the variation of returns which actually fall below zero.

The lead-lag relationships between the subdistrict house prices are studied using the Granger causality technique, while a version of the semi-deviation, which we refer to in this paper as the 'inter-district deviation' is used to study the inter-variation between the growth rates. The inter-district deviation is defined as the variation of the annual house price growth rate in one subdistrict from the growth rate across all the subdistricts. In the course of life, Dutch households usually purchase a property in a less desirable location with the intention of moving to a more desirable area when there is increase in disposable income (Banks et al., 2015; Droes et al., 2010; Sinai and Souleles, 2003). This tendency, however, could be affected by the extent of variations in the growth of house prices across the various locations. The inter-district deviation captures these locational house price differences.

The rest of the paper is structured as follows. The method and construction of the metrics are specified in Section 5.3, following a brief overview of the literature in Section 5.2. The data is described in Section 5.4. Section 5.5 discusses the empirical estimates of the metrics and analyses the interrelationships between the subdistrict house prices. Section 5.6 summarises the results and concludes the entire paper.

§ 5.2 Overview of the literature

This paper focuses mainly on residential property price risks and the interrelationship between the house price developments. The property price risk is here referred to 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 the balance sheet of households and other significant parts of the economy (Dolde and Tirtiroglu, 2002; Duca et al., 2010). The 2007-08 GFC especially has lent some credence to the notion that stress in the financial sector may ensue from collapse in real estate prices (Aalbers, 2009b; Baker, 2008).

Many authors use the volatility defined by the standard deviation to measure the property price risk in the literature (e.g. Ross and Zisler, 1991; Miller and Pandher, 2008; Dolde and Tirtiroglu, 2002). However, it is well-known that this measure accounts 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 on a portfolio held over a short period of time, given a certain confidence level (Crouhy et al., 2006).

Although widely used in the 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; Yamai and Yoshiba, 2002; Szegö, 2002).[1] 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 (Hull, 2006).

This article aims to compare house price risks in smaller subdistrict markets using summary statistics. Simple summary statistics may be informative for the individual households and institutions that must make decision on housing investments in a particular subdistrict. We use three metrics (the standard deviation, semi-deviation and decline severity), which are based on localised price indexes constructed for each of the lower-level-districts. The indexes are created with the time dummy hedonic method (TDHM). The TDHM is a widely used approach that is based on the idea that house prices can be described by their physical and locational attributes (Rosen, 1974; Malpezzi et al., 2003). Our dataset contains details on these physical and locational features which enable application of the TDHM in this paper.

The procedure for the TDHM mainly involves a regression of time dummy variables and the characteristics on the logged property sale prices (see de Haan and Diewert, 2013; Hill, 2013). This regression equation can easily be estimated by the method of ordinary least squares (OLS) and the estimated coefficients could then be converted into a

1 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.

constant quality price indexes (time dummy hedonic price indexes). The indexes uniquely reflect the development of house prices in each of the subdistricts. Nonetheless, significant interrelationships may also exist between these subdistrict house prices. For instance, due to economic activities, such as migration and equity transfer, shocks to property prices may spread from one location to the other places with a transitory or permanent impact (Meen, 1999; Holly et al., 2011).

The phenomenon in which house price shocks spread over their influence from one region to another, is often referred to as the ripple or spillover effect in the literature, and was first observed by researchers in the UK (Giussani and Hadjimatheou, 1991; MacDonald and Taylor, 1993; Meen, 1999). Later, research in other countries also supported the ripple effect hypothesis. Empirical studies by Berg (2002), for example, using second-hand family houses in Sweden found evidence supporting the ripple effect existing from Stockholm to other regions. In the US, Canarella et al. (2012) investigated the spatial interrelationships between house prices and concluded on a ripple effect potentially existing from the east and west coast metropolitan areas to the rest of the US. Buyst and Helgers (2013), who investigated the case of Belgium, also found that house price shocks are more likely to spread from Antwerp to other parts of the country. Comparable results were found in China by Gong et al. (2016b) and for South Africa by Balcilar et al. (2013).

In the Netherlands, however, there is a dearth in the literature regarding the spatial interrelationships between house prices. This paper contributes to the subject by studying the lead-lag effect between the lower-level-district house prices of Amsterdam using the Granger causality technique. The concept of Granger causality (GC), popularized in the literature by Granger (1969), is one of the simple empirical methods that has been used widely for testing the lead-lag effect and the ripple effect between regional house prices. It is has been applied by, for example, Giussani and Hadjimatheou (1991) and recently by Gong et al. (2016b), who studied the ripple effect between regional house prices.

§ 5.3 Empirical method

A time dummy hedonic house price index is first constructed for each subdistrict. Statistics Netherlands designate fifteen subdistricts in Amsterdam for official statistical purposes, which are also adopted in this paper. 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 time dummy hedonic model (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:

$$\ln p_n^t = \beta_0 + \sum_{\tau=1}^{T} \delta^\tau D_n^\tau + \sum_{k=1}^{K} \beta_k z_{nk}^t + \varepsilon_n^t \qquad (5.1)$$

where p_n^t is the price of the n^{th} 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. $T > 1$ is the length of the sample period. By omitting one of the dummy variables (usually the base period), equation (5.1) may be estimated on the pooled data by the method of OLS and the index tracking the growth rate from time 0 to τ is simply obtained with the exponentiation $\pi^\tau = \exp(\hat{\delta}^\tau)$. Here, $\hat{\delta}^\tau$ denotes the estimate of δ^τ.

§ 5.3.1 Risk indicators

For each of the subdistrict (i say), we follow the above procedure to estimate the house price index from 1995 to 2014, using 1995 as the base year. After that, the standard deviation and the semi-deviation measuring the house price risks are constructed as the square root of the quantities, σ_i^2 and γ_i^2 respectively defined by;

$$\begin{aligned} \sigma_i^2 &= (T-1)^{-1} \sum_{t=1}^{T} \left(d_t^i - \mu_i \right)^2 \\ \gamma_i^2 &= (T-1)^{-1} \sum_{t=1}^{T} \left(\min(d_t^i - \mu_i, 0) \right)^2 \end{aligned} \tag{5.2}$$

where, $\mu^i = T^{-1} \sum_{t=1}^{T} d_t^i$ is the mean house price return in the subdistrict i. The (temporal) house price returns are defined as $d_t^i = \pi_i^t / \pi_i^{t-1} - 1$. The semi-deviation considers only the returns below the mean, which makes it a downside risk metric that has a more appealing connotation for risk than the standard deviation.[2]

Similarly, we define the 'decline severity' as the average over the growth rates that are actually below zero. This is specifically written as the square root of δ_i^2, where

$$\delta_i^2 = (T-1)^{-1} \sum_{t=1}^{T} \left(\min(d_t^i, 0) \right)^2 \tag{5.3}$$

Because δ_i^2 considers only the returns below zero, the 'decline severity' may accurately capture the true losses than the semi-deviation which includes returns below the mean that do not necessarily represent losses.

§ 5.3.2 Subdistrict house price interrelationships

Two aspects of the interrelationships between subdistrict house prices (the inter-variation between growth rates and the lead-lag effects) are considered in this paper. We study the inter-variation between the subdistrict house price growth rates, using the "inter-district" deviation. The inter-district deviation gives indication of how far house prices in a particular subdistrict are growing below the rates in the other

2 For a real number x, the function $\min(x, 0)$ equals x, if $x < 0$ and 0 otherwise.

subdistricts. It is expressly defined as the square root of ϕ_i^2, where

$$\phi_i^2 = [(L-1)(T-1)]^{-1} \sum_{\substack{j=1 \\ j \neq i}}^{L-1} \sum_{t=1}^{T} \Big(\min(d_t^i - d_t^j, 0) \Big)^2 \tag{5.4}$$

$L > 1$ is the total number of subdistricts. The definition of ϕ_i^2 is a version of the semi-variance statistically expressed as the squared deviations of the house price growth rates d_t^j in the subdistricts j that fall above the rate d_t^i in the district i. It may be considered as the premium for a house move within the municipality. For housing related government compensation of a sort, the inter-district deviation may also give indication of the discrepancy between the housing worth of households which would determine the benefit in each subdistricts.

To study the lead-lag effects between the growth rate of subdistrict house prices, the pairwise Granger causality (GC) method is adopted. Let x_t^i and x_t^j be the growth rates from the respective subdistricts i and j. The empirical procedure for the pairwise GC test is to first estimate the regression equations:

$$\begin{aligned} x_t^i &= \alpha_0 + \sum_{k=1}^{p} \alpha_{1k} x_{t-k}^i + \sum_{k=1}^{p} \beta_{1k} x_{t-k}^j + \epsilon_{1t} \\ x_t^j &= \beta_0 + \sum_{k=1}^{p} \alpha_{2k} x_{t-k}^j + \sum_{k=1}^{p} \beta_{2k} x_{t-k}^i + \epsilon_{2t} \end{aligned} \tag{5.5}$$

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

§ 5.4 Description of data

The analysis in this paper uses dataset on individual sale transactions in Amsterdam between 1983 and 2014. This dataset is obtained from the realtor organisation NVM.[3] Information on about 150,000 transactions was received in total. The NVM's coverage of sales information in the Netherlands has been improving over the years. The average coverage per year is generally about 75%. However, we discovered that the NVM data had no information on the dwelling characteristics for a large portion of the sales reported prior to 1995. Since these records are needed to construct the time dummy hedonic indexes, all observations before 1995 were discarded.

3 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.

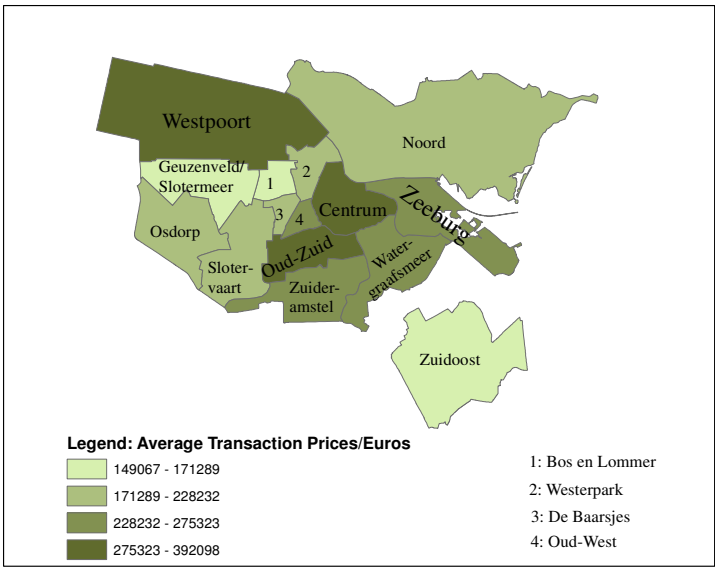


FIGURE 5.1 Local districts and neighbourhoods in the city of Amsterdam.

Source: CBS, NVM
Note: Average transaction prices are based on NVM data from 1995 to 2014.

For the rest of the dataset, we sought to construct house price indexes for existing dwellings and we therefore removed newly build homes, which totalled 4,169. A more detailed data cleaning was carried out following Diewert (2010), who estimated various hedonic house prices indexes using similar dataset. Specifically, observations with missing transaction prices (these are 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 million (74), and those below €10,000 (404).

The records with extremely small house sizes[4] (below 20m^2) in addition to the observations with unavailable structure sizes (3642 in total) were excluded as well. Furthermore, we deleted 5 observations for which the property type was unavailable or unknown. The remaining data, constituting a total sample size of 116,446 was finally divided into the fifteen statistical subdistricts of Amsterdam.

Figure 5.1 and Table 5.1 present the summary statistics for the remaining data. A brief look at the figure and the table indicates that during the study period, houses 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 €300,000. In addition to the locational attributes, there is

4 Properties with extremely small sizes (below 20m^2) rarely exist in the Netherlands.

TABLE 5.1 Summary statistics for transactions from 1995 to 2014.

Subdistrict	Total observations	Mean price (euros)	Standard deviation	Average usable area (M^2)	Average age (decades)
Centrum	16 805	344 293.0	238 061.9	97.0	5.85
Westpoort	0 041	392 098.4	174 284.3	87.8	0.54
Westerpark	5 958	228 231.9	126 395.0	69.9	5.75
Oud-West	7 633	275 323.4	184 124.0	80.4	6.79
Zeeburg	7 628	266 334.1	142 666.7	88.7	2.80
Bos en Lommer	5 009	171 289.3	81 045.08	69.0	5.87
De Baarsjes	6 547	202 730.7	102 998.6	71.8	6.52
Noord	8 521	193 182.5	111 130.2	89.9	3.94
Geuzenveld en Slotermeer	3 720	164 187.6	79 909.1	83.7	3.62
Osdorp	5 518	194 725.1	110 606.0	97.6	2.63
Slotervaart en Overtoomse Veld	4 565	225 467.8	123 070.2	101.0	2.20
Zuid-Oost	6 842	149 067.1	72 615.4	86.3	2.33
Watergraafsmeer	8 409	258 422.4	142 885.8	87.2	5.46
Oud-Zuid	18 830	348 942.8	278 432.5	96.8	6.73
Zuideramstel	10 420	272 807.0	185 531.9	93.8	5.07
Whole of Amsterdam	116 446	261 512.6	193 972.7	88.9	5.07

Source: Authors' computations based on NVM data.

significant disparity in the average disposable income of local residents, which may contribute to house price variations between the sub-districts (see Amsterdam, 2013).

The larger population also significantly affects house price developments in Amsterdam.[5] In 2013, for example, there was a housing deficit of almost 31,370 due to the larger number of households. The estimated number of households was about 431,370, while the total housing stock stood at about 400,000 in 2013 (Amsterdam, 2013). The housing deficit in Amsterdam is generally persistent and eventually has a considerable impact on house prices (see van de Minne, 2015).

§ 5.5 Empirical estimation and results

§ 5.5.1 Subdistrict Indexes

The localised house price indexes were constructed for fourteen of the Amsterdam sub-districts using the TDHM. Westpoort was omitted because there were only few observations which did not cover the entire study period.[6] The implementation of the TDHM first requires that choice be made about which dwelling characteristics to include in the regression equation (5.1). We begin with several characteristics and then exclude those features that were statistically insignificant across the fourteen districts using the p-values. The final regression uses the log transaction prices as dependent variable and only seven explanatory variables, most of which are categorised into the several groups described in Table A5.1.

Including the time dummies (the base period 1995 omitted for identifiability of the model), the adjusted R-squared showing the proportion of variation in log transaction

5 The population growth between 1990 and 2013 for Amsterdam was about 6.5% according to the CBS.

6 The lower observations in Westpoort is because the district is relatively new and the majority of the houses were built recently.

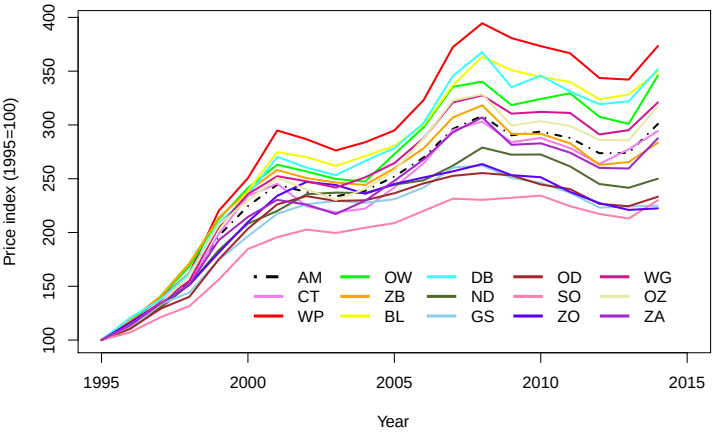


FIGURE 5.2 The city-wide Amsterdam and the local residential property prices indexes compared.

Note: AM = Amsterdam, CT = Centrum, WP = Westerpark, OW = Oud-West, ZB = Zeeburg, BL = Bos en Lommer, DB = De Baarsjes, ND = Noord, GS = Geuzenveld en Slotermeer, OD =Osdorp, SO = Slotervaart en Overtoomse Veld, ZO = Zuid-Oost, WG = Watergraafsmeer, OZ = Oud-Zuid, ZA =Zuideramstel.
Source: Author's estimate from NVM data

prices explained across the 14 districts ranges from 80.33% to about 90.41%. The same factors in addition to the location (district) dummies indicating the districts of transaction explain nearly 84.24% of the variation in log sale prices across the whole Amsterdam. The regression result for the entire Amsterdam is presented in Table A5.2.

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 total usable area, the number of rooms and the number of 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.

The age coefficient is negatively signed, which might appear counter-intuitive at first sight. However, older dwellings tend to be more expensive because many Dutch people prefer them, especially when they are located along monumental streets and close to museums or other public areas. A further look at Table 5.1 and Figure 5.1 indeed reveals that except Westpoort, most of the subdistricts closer to the central area of the city where properties are more expensive also have comparatively older dwellings.

The house prices indexes are constructed by the exponentiation of the estimated year dummy coefficients as described in Section 5.3. Figure 5.2 compares the indexes from the 14 districts with the city-wide Amsterdam price index. The plot reveals significant differences in the house price developments across the the Amsterdam subdistricts. Compared to the citywide trend, house prices are generally higher and more volatile in Westerpark, Oud-West, Bos en Lommer and De Baarsjes. A few of the subdistricts

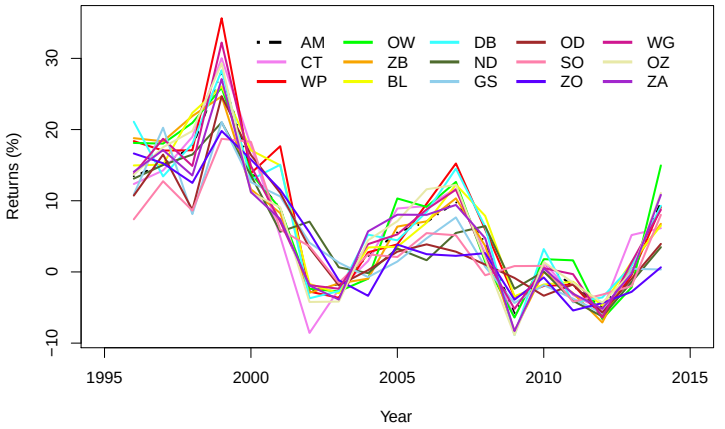


FIGURE 5.3 Temporal house price returns.

Note: AM = Amsterdam, CT = Centrum, WP = Westerpark, OW = Oud-West, ZB = Zeeburg, BL = Bos en Lommer, DB = De Baarsjes, ND = Noord, GS = Geuzenveld en Slotermeer, OD =Osdorp, SO = Slotervaart en Overtoomse Veld, ZO = Zuid-Oost, WG = Watergraafsmeer, OZ = Oud-Zuid, ZA =Zuideramstel.
Source: Author's estimate from NVM data

(Centrum, Zeeburg and Zuidamstel) closely mimic the city-wide house price trend especially after 2005, whereas subdistricts, such as Slotervaart en Overtoomse Veld, Osdorp, Geuzenveld en Slotermeer and Zuid-Oost, that are on peripheral have lower and more stable house prices. As in Figure 5.1, it is observable here too that those subdistricts that are closer to the city centre tend to have higher house prices over time.

§ 5.5.2 House price returns and risks

This subsection reports on the returns and risks of house price for the subdistricts. The temporal returns (d_t^i) are displayed in Figure 5.3. The risk measures here include the standard deviation, the semi-deviation and the decline severity, which are first computed aggregately over the entire study period and then over a rolling window of five years to discern the risk development pattern over time.

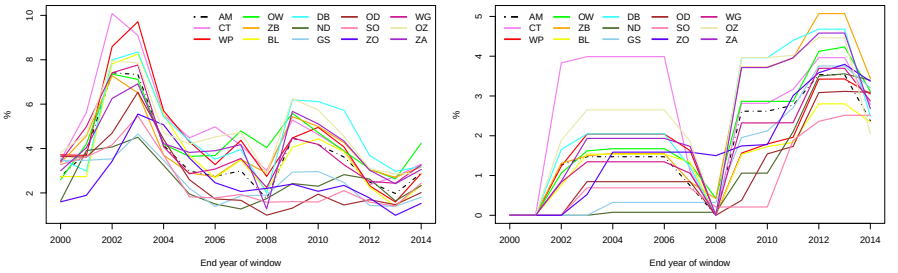
The aggregate result displayed in Table 5.2 shows that the annual house price growth rate is higher (greater than 7%) in Westerpark, Oud-West, Bos en Lommer and De Baarsjes, while this is relatively lower (less than 5%) in Osdorp, Zuid-Oost, Slotervaart en O. Veld and Geuz. en Slotermeer. Similarly, the standard deviation, semi-deviation and the decline severity all suggest that houses prices are of higher risk in Westerpark, Oud-West, De Baarsjes, Oud-zuid, centrum and Zeeburg than in the other subdistricts, which are more on the peripheral of the city.

Figure 5.4 displays the subsdistrict risk developments overtime. The figure shows significant differences in the risk level between the subsdistricts. The pattern overtime, however do not vary much. For all subdistricts, the semi-deviation shows that house prices risk increases from 1995 until 2003 after which it became fairly stable. The decline severity, on the other hand, indicates that the house price risk was relatively stable for all subdistricts but increased sharply after 2008.

TABLE 5.2 Average returns and risks of subdistrict house prices (1995 to 2014).

Subdistrict	Average return	Standard deviation	Semi-deviation	Decline severity	Rank of riskiness
Centrum	6.2686	9.8478	6.2498	**2.8847**	5
Westerpark	**7.6770**	**10.852**	**6.6735**	2.0471	1
Oud-West	7.1739	9.8267	6.5296	2.3352	2
Zeeburg	6.0465	9.6737	6.1424	2.7209	6
Bos en Lommer	7.1811	9.2690	5.8561	1.6393	7
De Baarsjes	7.2679	9.8317	6.4933	2.6208	3
Noord	5.1919	7.5457	4.6599	1.8257	11
Geuzenveld en Slotermeer	4.6212	7.7383	4.6024	1.9330	12
Osdorp	4.8312	7.9343	4.4694	1.6561	13
Slotervaart en Overtoomse Veld	4.6719	6.5636	3.9181	1.3419	14
Zuid-Oost	4.5900	8.1308	4.9299	2.1108	10
Watergraafsmeer	6.7140	9.5101	5.7046	2.0178	9
Oud-Zuid	6.6843	9.7729	6.3639	2.6630	4
Zuideramstel	6.0611	8.8373	5.8506	2.5516	8
Whole of Amsterdam	6.3069	8.8324	5.5124	1.9649	—

Mean return and risk figures are in percentages, with the maximum indicated in bold. The ranking is according to the semi-deviation.

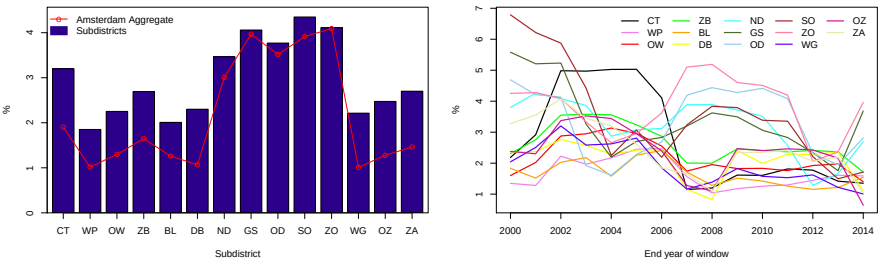


((a)) Semi-deviation ((b)) Decline-severity

FIGURE 5.4 Pattern of subdistrict house price risk over time using a 5-year rolling window.

Note: AM = Amsterdam, CT = Centrum, WP = Westerpark, OW = Oud-West, ZB = Zeeburg, BL = Bos en Lommer, DB = De Baarsjes, ND = Noord, GS = Geuzenveld en Slotermeer, OD =Osdorp, SO = Slotervaart en Overtoomse Veld, ZO = Zuid-Oost, WG = Watergraafsmeer, OZ = Oud-Zuid, ZA =Zuideramstel.

In 2007-08, the GFC had a dramatic and negative impact on house prices and this is captured well by the decline severity measure. Following the crisis, house prices fell in Amsterdam by almost 12.56% between 2008 and 2013 (see Figure 5.2 & 5.3). Figure 5.4(b), however, shows that the impact of the GFC varied significantly across the Amsterdam subdistricts. The impact appears severer especially in Oud-zuid, Oud-West, Zuideramstel, centrum and De Baarsjes, where house price returns below zero is higher between 2008 and 2103 (Figure 5.4(b)). Although the semi-deviation and decline severity tend to have comparable risk values after 2008, the decline severity may be more accurate because it actually considers returns which are below zero. The semi-deviation, on the other hand, uses values below the average return that in principle may not indicate actual losses.



((a)) Entire period ((b)) Five year rolling window

FIGURE 5.5 Amsterdam inter subdistrict house price deviations.

Note: CT = Centrum, WP = Westerpark, OW = Oud-West, ZB = Zeeburg, BL = Bos en Lommer, DB = De Baarsjes, ND = Noord, GS = Geuzenveld en Slotermeer, OD =Osdorp, SO = Slotervaart en Overtoomse Veld, ZO = Zuid-Oost, WG = Watergraafsmeer, OZ = Oud-Zuid, ZA =Zuideramstel.

§ 5.5.3 Subdistrict house price interrelationships

Inter-variation

The inter-variation is used to measure the extent to which a particular subdistrict house price growth (or return) fall below the city wide values. The inter-city deviation (equation 5.4) is used to quantify the inter-variations. The metric is computed first using the average of the indicated subdistrict deviation below the Amsterdam aggregated city-wide return series and then using the average deviation below the individual temporal returns of all the subdistricts. The former is depicted in red line and the latter in the blue bars of Figure 5.5(a). The figure indicates that subdistricts, including Noord, Geuzenveld en Slotermeer, Osdorp, Slotervaart en Overtoomse Veld and Zuid-Oost, where house prices are lower (see Figure 5.2) generally have larger variation of house price returns below the average. Similarly, Oud-West, De Baarsjes, Oud-Zuid and Watergraafsmeer, among other subdistricts, with relatively expensive houses tend to exhibit lower return deviation below the city-wide average. For most subdistricts, the pattern over time (Figure 5.5(b)) shows a slightly decreasing trend before 2008, while there are no significant changes afterwards.

Lead-lag effect

The subdistrict house price returns may also exhibit lead-lag effects, besides the significant inter-variations that exit between them. The lead-lag effect is confirmed in this paper using the Granger causality (GC) approach. In implementing the GC test, it is important that the house price return series are statistically stationary. The commonly used ADF (Dickey and Fuller, 1979) and KPSS (Kwiatkowski et al., 1992) tests both confirm that the house price return series are stationary at sufficient statistical significant levels (see table A5.3).

Table 5.3 summarises the results of the pairwise GC test, where the null hypothesis is that the subdistricts on the row do not Granger cause those on the columns. At the 5% statistical significance level, the results show considerable lead-lag effects between the subdistricts, with growth of house prices in any subdistrict being Granger caused

by at least one other subdistrict prices. Westpark house price returns, for example, is Granger caused by as many as 9 other subdistricts. Geuzenveld en Slotermeer and Osdorp are equally Granger-caused by 8 and 7 other subdistricts respectively.

The pattern of lead-lag effects appears spatially complicated with the Granger causality not necessarily existing between subdistricts that border each other. However, it is observable that the causal flow occurs most from the more central subdistricts and close environs, including Zeeburg, Centrum and Oud-Zuid. Chen et al. (2011) and Gong et al. (2016a) similarly found that house price lead-lag effect and causal flow occur predominantly from the central to the peripheral districts. Meen (1999) suggests this kind of house price spatial interrelationship might occur through socio-economic activities such as internal migration and equity transfer (see also Pollakowski and Ray, 1997).

§ 5.6 Concluding remarks

The 2007-08 Global Financial Crisis (GFC) has given greater impetus to research seeking understanding into the dynamics and risks of house prices. Using dataset from Amsterdam on individual house transactions, this paper has explored summary statistics to measure the house prices risks and investigated the interrelationships between the subdistrict house prices. The summary statistics adopted are, namely, the standard deviation, semi-deviation and the decline severity, which is a variant of the semi-deviation. The interrelationships considered include the inter-variation between the subdistrict house price returns and the lead-lag effects, which are studied within the Granger causality framework.

The key obeservations and conclusions of the paper could be summarised as the following. (1) House prices are generally more expensive and grow faster at the more central subdistricts and the immediate surroundings than in the peripherals. (2) There is an over time decreasing trend in the inter-variations between the subdistrict house price returns. The inter-variations are especially higher before the GFC, while they are lower and fairly constant afterwards. (3) The lead-lag relationships and house price causal flow occur most from the central to the peripheral subdistricts and this is similar to earlier empirical results by Gong et al. (2016a) and Chen et al. (2011).

In application, the risk metrics used in this paper may be of interest to statistical agencies. The metrics reveal important trends that are consistent generally with the Dutch house price development cycles. The decline severity especially is promising as a publishable risk metric for the housing market. It measures the variation of the temporal house price returns that are actually below zero and seems to capture the higher property price risk after the GFC more accurately than the other indicators (see Figure 5.4). The results of the paper also provide useful information for policy regulations and for housing investors. For housing related government compensation, for example, the inter-district deviation may indicate the discrepancy between the housing worth of households which would determine the benefit for households in each subdistricts. The results indicating the risk distributions across the subdistricts and the interrelationships between the subdistrict house prices may equally guide investors to choose desirable locations for their investments.

TABLE 5.3 Pairwise Granger causality test results.

Subdistrict	CT	WP	OW	ZB	BL	DB	ND	GS	OD	SO	ZO	WG	OZ	ZA
CT		14.37(1)	1.889(4)	1.192(4)	5.832(1)	9.565(1)	1.440(1)	3.649(4)	8.302(1)	1.918(4)	4.685(1)	3.760(1)	0.762(1)	3.243(1)
		0.000***	0.177	0.364	0.022**	0.004***	0.240	0.036**	0.007***	0.172	0.039**	0.062*	0.390	0.082*
WP	1.662(1)		0.224(2)	5.752(1)	0.830(1)	0.010(1)	1.449(1)	1.509(4)	2.042(1)	1.569(4)	1.722(1)	2.808(4)	3.433(2)	2.888(2)
	0.207		0.801	0.023**	0.370	0.922	0.238	0.261	0.163	0.245	0.199	0.074*	0.049	0.075*
OW	0.570(4)	0.689(2)		0.514(1)	1.859(2)	6.944(1)	2.796(1)	3.137(4)	7.799(1)	2.291(2)	4.369(1)	3.149(1)	0.456(1)	2.042(1)
	0.689	0.017**		0.479	0.178	0.013**	0.104	0.055*	0.009***	0.123	0.045**	0.0861*	0.505	0.163
ZB	2.110(4)	25.74(1)	3.541(1)		10.00(1)	14.34(1)	8.057(1)	12.98(1)	17.42(1)	0.888(4)	6.939(1)	0.308(4)	2.145(1)	6.693(1)
	0.142	0.000***	0.070*		0.004***	0.001***	0.008***	0.001***	0.000***	0.500	0.013**	0.867	0.153	0.015**
BL	0.398(1)	9.470(1)	0.362(2)	2.689(1)		2.429(1)	3.148(1)	1.716(4)	2.727(4)	1.452(4)	6.059(1)	1.146(2)	0.396(1)	0.300(1)
	0.533	0.004***	0.700	0.112		0.130	0.086*	0.211	0.080	0.277	0.020**	0.335	0.534	0.588
DB	0.814(1)	2.213(1)	0.142(1)	4.213(1)	0.008(1)		2.293(1)	4.587(1)	6.319(1)	5.086(1)	2.309(1)	1.174(2)	3.376(2)	4.318(2)
	0.374	0.147	0.709	0.049**	0.929		0.140	0.040**	0.018**	0.032**	0.139	0.326	0.051*	0.025**
ND	0.060(1)	3.068(1)	0.006(1)	0.383(1)	0.866(1)	1.506(1)		5.552(1)	8.180(1)	6.798(1)	1.295(1)	0.718(1)	0.018(1)	0.214(3)
	0.808	0.090*	0.938	0.541	0.360	0.229		0.025**	0.008***	0.014**	0.264	0.403	0.896	0.885
GS	1.242(4)	6.490(4)	1.593(4)	0.397(1)	7.669(4)	0.751(1)	0.817(1)		0.011(1)	1.442(1)	0.008(1)	3.056(4)	0.254(1)	2.787(4)
	0.345	0.005***	0.239	0.534	0.002***	0.393	0.373		0.917	0.239	0.929	0.060*	0.618	0.075*
OD	0.587(1)	0.091(1)	0.143(1)	0.643(1)	11.27(4)	0.553(1)	0.009	1.002(1)		7.248(3)	5.997(4)	0.816(1)	0.454(1)	0.365(1)
	0.450	0.765	0.708	0.429	0.000***	0.463	0.927	0.325		0.002***	0.007***	0.374	0.505	0.550
SO	10.68(4)	8.302(4)	1.396(2)	5.084(4)	30.38(4)	2.046(1)	0.000	1.520(1)	3.546(3)		3.067(4)	4.409(4)	0.034(1)	0.003(1)
	0.000***	0.002***	0.267	0.012**	0.000***	0.162	0.991	0.227	0.035**		0.059*	0.0201**	0.854	0.955
ZO	0.091(1)	1.290(1)	0.080(1)	0.426(1)	0.206(1)	0.605(1)	0.275(1)	10.87(1)	0.581(4)	4.736(4)		0.190(1)	0.009	0.002(1)
	0.764	0.265	0.779	0.519	0.653	0.443	0.604	0.002***	0.682	0.016**		0.666	0.926	0.966
WG	0.102(1)	3.850(4)	0.074(1)	1.198(4)	1.796(2)	4.091(2)	1.003(1)	3.919(4)	3.355(1)	2.005(4)	2.956(1)		0.525(1)	0.148(1)
	0.752	0.031**	0.788	0.361	0.188	0.030**	0.325	0.029**	0.077*	0.158	0.096		0.474	0.703
OZ	0.458(1)	9.413(2)	0.752(1)	0.104(1)	4.026(1)	6.962(2)	3.618(1)	4.472(1)	6.549(1)	7.744(1)	4.864(1)	4.039(1)		3.340(1)
	0.503	0.000***	0.393	0.749	0.054*	0.004***	0.067	0.043**	0.016**	0.009***	0.035**	0.054*		0.078*
ZA	0.005(1)	5.858(2)	0.157(1)	0.692(1)	1.371(1)	8.045(2)	0.391(3)	8.309(4)	3.991(1)	6.031(1)	2.361(1)	0.275(1)	0.921(1)	
	0.960	0.008***	0.695	0.412	0.251	0.002***	0.760	0.002***	0.055*	0.020**	0.135	0.604	0.345	

The null hypothesis is that the subdistricts on the row do not Granger cause those on the columns. Test regression is estimated with intercept. The lag p is determined by BIC and indicated in parenthesis. The Wald statistics are reported with the p-values reported under it. $*$, $**$ and $***$ denote statistical significance at the 10, 5 and 1% respectively.

For further investigation, however, it might be insightful to consider other empirical methods and the application of a more complex economic model to investigate the interrelationships between the subdistrict house prices. As Meen (1999) suggests, spatial interrelationship between house prices might occur through socio-economic activities, including internal migration. The internal migration dynamics may be considered explicitly in the economic model.

6 Home-value insurance and idiosyncratic risks of residential property prices

Under review

Abstract

The recent Global Financial Crisis has reawakened home-owners to the need for protecting their home-equities from possible future house price decline. This paper re-examines the Shiller and Weiss (1999) home-value insurance scheme and proposes a modification that eliminates a large proportion of the idiosyncratic sale price risks of residential properties. Using data between 1995 and 2014 for Amsterdam, the proposed insurance policy shows a higher pay-out efficiency, a higher loss coverage and a greater pay-out probability than the original Shiller and Weiss (1999) scheme. The new home-value insurance policy thus provides better protection for the property sale price risks.

Keywords Home-ownership, Home-value insurance, Idiosyncratic risk, Sale price risk

§ 6.1 Introduction

Home-ownership has increasingly become the preferred housing tenure for most European households and in many other countries. In 2015, Eurostat estimated the European average home-ownership rate at about 70%, with the range between 51.8% in Germany and 96.5% in Romania. Research has revealed several benefits that motivate households into the home-ownership sector. Besides the esteemed social status, most household prefer home-ownership over renting because they believe it fosters family autonomy, provides environment for better child development, allows the flexibility to adapt the physical structure of the residential dwelling and has tax advantages (Andrews and Sánchez, 2011; Doling and Elsinga, 2006; Elsinga, 2003; Haurin et al., 2002). Households are also motivated by the welfare benefits of home-ownership, since it may serve as source of extra income and hedge against higher housing costs in old age (Toussaint and Elsinga, 2009; Haffner, 2008; Elsinga and Mandič, 2010).

Home-ownership, however, involves considerable risks. Primarily, households that acquire residential properties with mortgage loans will be faced with the risk of defaulting on the repayments, which may in turn lead to foreclosure. Furthermore, the high volatility of house prices exposes home-owners to negative equity and sale price risk. In negative equity, the value of the residential property is below the mortgage

amount owed to the financial institutions and this to an extent constrains household mobility and consumption (Valletta, 2013; Dröes and Hassink, 2013; Chan, 2001). Sale price risk constitutes the possible loss from selling the property below the purchase price, which may be quite substantial. In the Netherlands, for instance, households that bought houses in the year 2007 and 2008, lost almost 21% on the value of their homes by the end of 2013 as a result of the large decrease in house prices caused by the Global Financial Crisis (GFC).

Home-value insurance is important for reducing the property sale price risk and to protect the accumulated home-equity which potentially yields the welfare benefits (see Doling and Ronald, 2010; Haffner, 2008). A section of the housing literature has proposed using housing futures and other forms of derivatives as possible home-value insurance schemes that may hedge the property sale price risk (Case Jr et al., 1993; Shiller, 2003; Shiller and Weiss, 1999). In their seminal paper, Case Jr et al. (1993) specifically suggested an insurance scheme that pays out benefit to home-owners according to the decline in a reference property price index. While the practical implementation of home-value insurance policies have been less successful, broadly owing to issues of illiquidity (see Swindler, 2012), the Case Jr et al. (1993) home-value protection scheme (Case-Shiller-Weiss or CSW hereafter) has intrinsic deficiencies that make it unattractive for the majority of home-owners (see Sommervoll and Wood, 2011).

Characteristically, the CWS policy pays home-owners who incurred losses only if the underlying index indicated a decline in house prices. Thus, the home-owners are not covered against the possible adverse idiosyncratic price changes. Strangely, however, this policy would pay benefit to an home-owner who incurred no loss on selling the residential property if the underlying index indicates a decline in house prices. Sommervoll and Wood (2011) and Sommervoll and de Haan (2014), in a more detailed empirical analyses conducted for the entire Netherlands and for the Australian metropolitan area of Melbourne, showed that the CSW policy actually has a very low loss coverage. This means that majority of the policy holding home-owners that sold properties at a loss would receive nothing or less than the actual loss. Their analyses further established that the CWS policy has low pay-out efficiency and target efficiency, which relate to the probability at which a policy holder incurring a loss would receive benefit from the scheme.

This paper proposes logical modifications to the CWS home-value protection scheme that limit the forgoing deficiencies. It suggests pay-out schemes that are based on aggregate measures of the underlying index and the more reasonable constriction that pay-out are made to only those actually incurring loss on the property sales. The proposed scheme is analysed and compared with the original CSW policy using detailed transaction data between 1995 and 2014 in Amsterdam. The results suggest that the modified scheme provides better cover for the sale price risk.

The rest of the paper is in sections. An overview of the related literature is presented in Section 6.2. Section 6.3 describes the modified CSW home-value protection scheme. Section 6.4 contains the descriptions of the data, while Section 6.5 discusses the empirical analyses for the whole Amsterdam and the results for the various property

types that detail the differences between the idiosyncratic risks associated with these housing market segments. The paper is concluded in Section 6.6.

§ 6.2 Previous literature

This paper relates to the broader house price dynamics literature. The persistence of house prices and their characteristic high volatility in which the price path swings up and down to form a boom and burst cycle are well documented (see e.g. Agnello et al., 2015; Abraham and Hendershott, 1996; Muellbauer and Murphy, 1997; Droes et al., 2010). As one of the essential lessons from the GFC, this fluctuating nature of house prices may also present a source of risk for home-owners and for the stability of the larger economy (Agnello and Schuknecht, 2011; Aalbers, 2015; Case and Shiller, 2003; Baker, 2008; Stephens, 2006).

Several scholars have studied the fundamental factors which drive the developments of house prices (see, e.g. Abraham and Hendershott, 1996; Case and Shiller, 1988; Malpezzi, 1999; De Vries, 2010; DiPasquale, 1999; Himmelberg et al., 2005). Boelhouwer et al. (2004) classified these fundamentals into four groups, namely factors of economic development (e.g. income, interest rates), demographic factors (population growth, etc.), institutional policy (e.g. fiscal tax structure, land regulations) and speculative or psychological behaviour of home-buyers.

The psychological behaviour of home-owners relates to their expectations of future house prices, which tend to affect current property price developments (Case and Shiller, 2003; Flood and Hodrick, 1990). While house prices would maintain a stable long-run relationship with fundamentals, the speculative and psychological effect of household behaviours are noted for contributing to the short-term fluctuations (Case and Shiller, 1988; Flood and Hodrick, 1990; Case and Shiller, 2003; Shiller et al., 2014). A section of the literature, however identifies that these temporal house price fluctuations arising from certain regions may spread over their influence to an entire country, with a transitory or permanent effect. This market phenomenon is often referred to as the ripple or spillover effect (see Meen, 1999; Gong et al., 2016b; Teye and Ahelegbey, 2017).

Sinai and Souleles (2005) and Droes et al. (2010) argued that owning a home presently may serve as a hedge against uncertainties of house prices and higher rents in the future. This is because of the potential of accumulating substantial housing equity which may be used to purchase another home later during the course of life. Home-owners may also derive cash benefits from the future sale of their properties. However, the uncertainties with the future sale prices create the possibility that the home-owner may incur a loss on the investment capital.

Case Jr et al. (1993) proposed hedging against the future sale price in order to insure the home-owner against any future financial burden. To that effect, these authors also suggested index-based derivatives and other forms of housing insurance schemes (see also Shiller and Weiss, 1999; Shiller, 2003). Following Case Jr et al. (1993), some real estate researchers have studied in details the nature of risk associated with house prices, while others have investigated the pricing and applicability of the proposed derivatives (see Sommervoll and de Haan, 2014, for a historic discussion of home-value insurance policies). Iacoviello and Ortalo-Magne (2003), for example,

investigated the hedging benefits of real estate properties in London, whereas Van Bragt et al. (2015) explored the risk-neutral valuation framework as pricing method for these insurance products.

In a more detailed analysis, Peng and Thibodeau (2013, 2017), studied the idiosyncratic risks of neighbourhood house prices. Adopting a cross-sectional regression analysis, these authors examined if the neighbourhood characteristics of residential properties may explain variations in the idiosyncratic risks. In their research, Peng and Thibodeau (2013, 2017) found that idiosyncratic house price risk increases proportionately with the neighbourhood median household income and house price volatility. Their results, however established that higher risk neighbourhoods are not necessarily rewarded with higher price appreciations.

Dröes and Hassink (2013), similarly conducted an empirical study by decomposing the total house price risk into an idiosyncratic and a market component. Their research, which is based on transaction data from the Netherlands concluded that the idiosyncratic risks of individual residential properties are large but tend to be averaged away using aggregated market indexes in measuring the property price risk. The finding of Dröes and Hassink (2013) thus suggests that an index-based home-value insurance cannot provide a complete cover for the sale price risk of residential properties.

In separate related studies, Sommervoll and Wood (2011) and Sommervoll and de Haan (2014) investigated the amount of risk that the index-based insurance scheme would cover practically. The authors estimated for the different application areas (Melbourne and Netherlands) that the home-value insurance scheme, based on an underlying property price index, would only cover up to 50% of the sale price risk, leaving a large part of the idiosyncratic risks uninsured. In the contribution of this paper, we suggest logical modification to the original Case Jr et al. (1993) index-based home-value insurance that provides a hedge potentially for a larger proportion of the sale price risk. The modification is based on aggregate statistics of the underlying index, which to our knowledge has not been analysed in the housing literature. Our analysis suggests that the modified scheme provides up to 70% loss coverage.

In general, however, there are problems that currently hamper the implementation of home-value insurance scheme. Such challenges include low trading volumes, issues with moral hazards and adverse selection problem as well as the appropriate pricing method of the scheme (see Case Jr et al., 1993). The low trading volume may result from less patronage from the home-owners, perhaps due to the little awareness and the general belief that house prices would continue to rise (Shiller et al., 2014). With the recent display of high volatility in house prices and following the GFC, home-owners are more likely to be aware of the house price risk and to seek protection against their home equities.

On the other hand, the assurance of receiving pay-outs from the insurance policy has intrinsic moral hazard. For instance, the home-owner may develop the attitude of abandoning important maintenance of the residential properties, knowing that any drop in the value of the property would be covered by the issuance policy. The adverse selection problem arises when home-owners purposefully choose deteriorating neighbourhoods, knowing that they would receive insurance pay-outs or when the underwriting insurance institutions subjectively pick which neighbourhood not to grant

insurance. As Case Jr et al. (1993) argued, imposing deductibles and stricter government involvement may check the excesses with moral hazards and the adverse selection problem (see also, Shiller, 2003).

§ 6.3 The modified CSW insurance scheme

Shiller (2003) is of the firm opinion that households could reduce risk through an appropriate risk-sharing mechanism. The CSW is one of such schemes that enables home-owners to share their housing risks with more advanced portfolio managers. More specifically, the CSW insurance policy is an index-based home-value protection scheme that pays benefit to holders that is proportional to the decline captured by the reference residential property price index (RPPI).

For residential property j, in a designated housing market H, let the transaction prices at the times s and t, with $0 \leq s < t$, be $p^H_{j,s}$ and $p^H_{j,t}$ respectively. For the same market H, let I^H_s and I^H_t be the reference index numbers tracking the price levels in the periods s and t. The pay-out of the CSW scheme to the home-owner of the property j holding the policy is given as

$$\pi^H_{j,t-s} = \max\left[\left(I^H_s - I^H_t\right)p^H_{j,s}/I^H_s, 0\right] \tag{6.1}$$

The expression (6.1) implies that the home-owner receives pay-out benefit if the RPPI for the housing market H indicates a decline, i.e, if $I^H_s > I^H_t$. However, if $I^H_s < I^H_t$, while $p^H_{j,s} > p^H_{j,t}$, the policy holder receives nothing. Following Sommervoll and de Haan (2014), consider an example where the initial price of the property, $p^H_{j,s}$ = €100,000 and the subsequent price, $p^H_{j,t}$ = €90,000. Assume furthermore that the RPPI indicates a market decline of properties by 5%. Then, the home-owner suffers a loss of €10,000 but will receive only €5,000 if (s)he holds a CSW policy. Again, assuming the RPPI instead indicates a price appreciation of 5%, the home-owner receives nothing at all although the property is sold at a loss of €10,000.

From the home-owner's perceptive, it makes more sense to receive the 5% market increase after selling at such loss. This paper proposes a modified home-value insurance policy that caters for such scenario, where pay-out is advanced to those suffering loss proportionally to the house price appreciations or depreciation. This modification could be realised using a pay-out scheme that is based on an aggregate measure of the reference RPPI to ensures that any accumulated home-equity over time does not completely erode away by a sudden drop in property prices. We define the pay-out for the modified CSW (MCSW, hereafter) insurance policy as

$$\pi^H_{j,t-s} = |\delta^H_{t-s}|p^H_{j,s}\mathbb{1}_{\left(p^H_{j,s} > p^H_{j,t}\right)} \tag{6.2}$$

where δ^H_{t-s} is some aggregate measure of the reference RPPI and $\mathbb{1}_{(.)}$ is the indicator function. Unlike the CSW scheme, the expression (6.2) means the holder of the MCSW

policy receives pay-out only if the property is sold less the purchase price (i.e., if $p^H_{j,s} > p^H_{j,t}$).

The aggregate measure δ^H_{t-s} may take several forms. We analyse four of such measures in this paper, when

1. δ^H_{t-s} is the market house price change between the times s and t,
2. δ^H_{t-s} is the average market house price change between s and t,
3. δ^H_{t-s} is the average market house price change between the time t of the resale of the property and a year prior to the resale, and
4. δ^H_{t-s} is the market house price change between the time of resale t and a year prior to t.

The market price change is as measured by the reference RPPI. The averages for 2 & 3 are obtained over the period-to-period price changes within the indicated period. We label these MCSW schemes respectively as MCSW1, $\cdots$, MCSW4.

The MCSW1 scheme is a CSW policy that pays the holder incurring loss benefit that is equal to the market price appreciation or decline indicated by the HPPI. The pay-out for the MCSW2 policy is the absolute value of the (quarterly) average house price growth between the time of purchase and time of resale. The pay-outs for MCSW3 and MCSW4 are respectively the same as MCSW1 and MCSW2 but their aggregation reference period is between the time of resale (t) and a year prior to t (i.e $t-4$).[1]

Sommervoll and Wood (2011) proposed three statistical measures (pay-out efficiency, loss coverage, target efficiency) for investigating the efficiency of any index-based home-value insurance policy. They defined the pay-out efficiency (PE) as the proportion of all pay-outs received by home-owner incurring a loss. The Loss coverage (LC), is the most important for the home-owners. It expresses the proportion of losses the insurance policy covers. The target efficiency (TE) indicates the probability that a policy holder will receive a pay-out. More specifically, the TE is the proportion of home-owners receiving pay-outs out of the entire policy holders incurring a loss (see also Sommervoll and de Haan, 2014).

In principle, the closer the values of these measures get to one, the better the policy from the perceptive of the home-owners. By construction, the PE for the MCSW scheme is one, since any home-owner suffering a loss will receive pay-out, unless, as it rarely happens, the reference index indicates no market appreciation nor decline. On the other hand, the PE for the CSW may be less than one. Furthermore, the TE for the MCSW is one by construction, while TE for the CSW may be less than one. The PE and TE thus shows that the MCSW is practically more efficient than CSW. However, the MCSW will equally not cover all the losses for the policy holder. Following Sommervoll and de Haan (2014), we call these residuals losses as idiosyncratic risks and we examine how they vary between the different property classes.

1 If the holding period is less than a year, $t-4$ is simply replaced by s.

§ 6.4 Data description

The dataset for the analysis covers about 75% of all property transactions in Amsterdam between 1995 and 2014 obtained from the Dutch National Association of Property Brokers. Out of 150,000 raw data, we extracted 116,446 transaction sales following a thorough data clean-up procedure detailed by Teye et al. (2017). For the purposes of the current paper, we further extracted 22,393 repeated sale transactions consisting of 18,029 individual residential properties. The properties fall into one of the six categories indicated by the Dutch National Association of Property Brokers, including terraced houses, town houses, corner houses, semi-detached houses, detached houses and apartments.

The descriptive statistics for the repeated transactions are shown in Table 6.1. The table indicates that apartment blocks form the majority of housing stock in Amsterdam. Detached and terraced houses are also common, but town and semi-detached houses are less popular. The average price change (return) between first and second sale is about 36.90%. Detached and semi-detached houses appear to yield higher nominal returns than apartment blocks and terraced houses. The average holding period between two repeated sales runs up to 20.24 quarters. The data also reveals that about 17.86% of property transactions over the period 1995-2014 ended in losses. The losses appear to be linked with shorter holding periods, which is not surprising, because property prices typically appreciate above their initial levels over longer time period.

Figure 6.1 sheds light on the distribution of the house transactions over the holding period. It shows that a larger proportion of properties that resold within two quarters incur losses than gains. This may indicate an inherent higher probability of selling at loss within shorter holding periods as the proportion of losses declines sharply for longer holding periods. Interestingly, the proportion of transactions involved in a gain does not increase linearly with the holding period. From the figure, the percentage of resold properties with nominal gains could be seen to increase between the 8^{th} and 26^{th} quarters of holding and then declines for longer holding periods.

The location and individual characteristics of the property contribute to its selling price. In addition, the selling price would be largely determined by the economic and housing market conditions. Home-owners are more likely to profit from selling properties during market booms than in the downturns. Table 6.2 shows that the proportion of

TABLE 6.1 Summary statistics for repeated house transactions between 1995 and 2014

House type	Number of resales	Number of dwellings	Average % price change	Average holding period	% resales with loss	% resales with gain
All	22,393	18,029	36.90	20.24	17.86	79.44
Terraced house	1,928	1,638	42.07	21.11	16.44	80.08
Town house	30	26	26.51	18.70	13.33	73.33
Corner house	527	453	34.70	21.62	17.65	78.37
Semi-detached house	164	139	55.84	24.38	10.98	83.54
Detached house	1,181	156	74.38	21.78	14.92	81.22
Apartment	19,563	15,617	35.95	20.07	18.10	79.36

The price change is the difference between the first and second transaction prices. Holding period is the number of quarters between the repeated transactions.

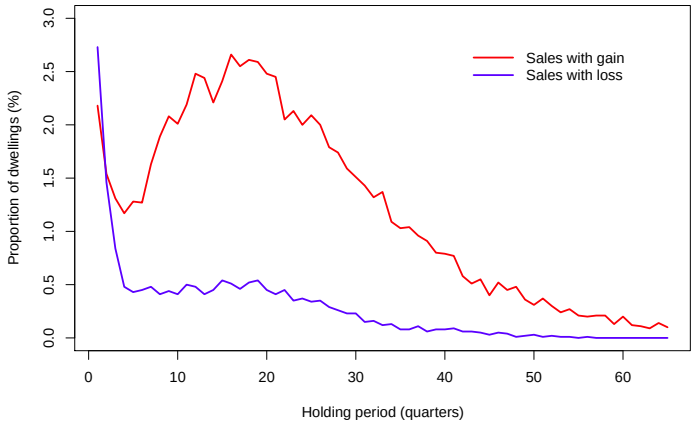


FIGURE 6.1 Distribution of sales over the holding periods

TABLE 6.2 Over time distribution of property transactions between 1995 and 2014

Year	Number of resales	Number of resales with loss	Average price (euros)	Average holding period	Average holding time if loss	% resales with loss	% resales with gain
1995	45	19	86,785	1.53	1.42	42.22	46.67
1996	116	19	111,925	3.23	2.26	16.38	80.17
1997	213	38	124,901	4.82	2.39	17.84	78.40
1998	313	41	154,136	6.92	2.46	13.10	81.79
1999	455	29	193,791	8.83	2.38	6.37	90.77
2000	610	63	217,538	9.78	1.73	10.33	86.39
2001	890	78	241,025	11.29	2.10	8.76	88.99
2002	1,046	163	227,565	13.18	3.94	15.58	81.84
2003	1,091	214	227,119	14.92	5.89	19.62	77.91
2004	1,094	160	233,414	17.01	9.36	14.63	82.18
2005	1,413	147	265,628	19.26	10.86	10.40	87.83
2006	1,615	129	258,092	19.91	8.76	7.99	89.47
2007	1,865	121	308,011	20.19	8.07	6.49	91.96
2008	1,903	145	306,762	21.37	8.78	7.62	91.01
2009	1,656	226	284,309	21.38	9.69	13.65	83.51
2010	1,641	323	293,130	23.19	11.20	19.68	77.27
2011	1,582	412	274,803	24.80	15.65	26.04	71.74
2012	1,593	609	263,713	25.22	18.62	38.23	57.19
2013	1,389	575	284,312	26.23	20.31	41.40	54.64
2014	1,863	488	293,925	28.97	23.10	26.19	71.18

The number of sales indicates total dwellings reselling in the reference year, which is a subject of sales in the same or in previous years. Average price is computed for all repeated transactions in the reference year. Holding period is in quarters.

properties sold at loss declined significantly during the housing boom between 2005 and 2008 in Amsterdam. On the other hand, in the course of the market downturn between 2002 and 2005, and following the GFC (2008-2013), the table indicates that the average transaction price fell, while the number of losses from the repeated property transactions grew comparatively higher within those periods. Particularly, we can find the proportion of properties that sold with nominal loss rising from 7.62% in 2008 to 41.40% by 2013 (Table 6.2). Over this same period, the nationwide house

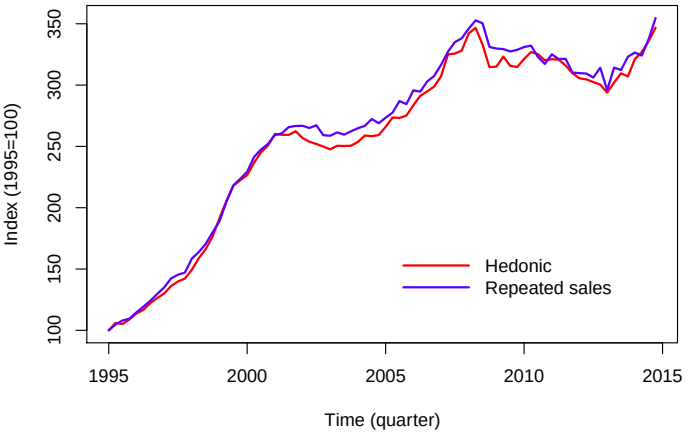


FIGURE 6.2 Amsterdam quarterly hedonic and repeated sales indexes.

price decline has been estimated at about 21%. A CSW or MCSW insurance scheme would cover part of these losses which we investigate in this paper.

§ 6.5 Empirical results

Since the CSW and MCSW are index-based schemes, the reference RPPI plays an important part in the analysis. This paper uses both the hedonic and the repeated sale indexes. The hedonic index method assumes that the transaction price is linked with the (shadow) prices of enjoying the locational features and individual characteristics of the residential property (see Hill, 2013; Rosen, 1974). By controlling for the period of transaction, the hedonic index is estimated using ordinary least squares (see de Haan and Diewert, 2013).

The repeated sales approach first proposed by Bailey et al. (1963), estimates the house index by considering properties that sold twice or more. This method involves regressing the consecutive price differences on the set of dummies that specifies the transaction periods. The two price index methods are widely used and one may be preferred over the other depending on the purpose and the availability of data (see de Haan and Diewert, 2013; Case and Shiller, 1987). The two methods are both adopted here however to cast light on the pay-out and efficiency of MCSW scheme.

Figure 6.2 shows the two indexes, which essentially capture an identical trend in the house price movements but vary on the price level at certain periods. The hedonic price index is lower mostly after the Amsterdam housing market downturn in 2002. In principle, the variations in the price levels depicted by the two indexes may similarly manifest in the corresponding pay-outs of the CSW or MCSW policy.

Table 6.3 displays the pay-out efficiency, target efficiency and the loss coverage for the CSW and MCSW schemes. The table shows, as already mentioned that the MCSW

TABLE 6.3 Pay-out efficiency, target efficiency and average loss coverage for CSW and MCSW schemes.

Policy	Pay-out efficiency		Target efficiency		Loss coverage	
	Hedonic index	Repeated sales index	Hedonic index	Repeated sales index	Hedonic index	Repeated sales index
CSW	0.53	0.55	0.45	0.44	0.13	0.15
MCSW1	1.00	1.00	1.00	1.00	0.51	0.51
MCSW2	1.00	1.00	1.00	1.00	0.06	0.06
MCSW3	1.00	1.00	1.00	1.00	0.09	0.08
MCSW4	1.00	1.00	1.00	1.00	0.27	0.25

Pay-out efficiency is the proportion of all pay-outs to home-owners inuring a loss. Target efficiency is the percentage of home-owners receiving pay-outs for a loss among all sales with losses. Loss coverage is the fraction of total losses covered by the combine pay-outs from the home-value insurance protection scheme. The reference indexes are computed for the entire Amsterdam.

schemes have optimal pay-out and target efficiencies both which are approximate to one. This is so because Figure 6.2 clearly shows that the price change between any two point in time is nonzero. The CSW policy, however has pay-out efficient ranging from 53% to 55%, and target efficiency of 44%-45%. By implication, there is almost 55% to 56% probability that a CSW policy holders incurring loss would receive no pay-outs.

On average, none of the home-value protection schemes provides a complete loss coverage. Table 6.3 indicates that the MCSW1 scheme has the highest loss coverage of about 51%. The MCSW1 scheme advances pay-outs to holders proportional to the decline or increase detected in the reference index between the time of purchase and resale. The MCSW2 and MCSW3 schemes give 6%-9% loss coverage, which is lower than the original CWS with a potential loss coverage between 13% to 15%. Interestingly, the MCSW4 which considers the growth rate only in the immediate past year yields a substantial loss coverage of 25% to 27%. Similar to the MCSW1 scheme, the MCSW4 policy holder has better protection than the home-owner with the CSW home-value product. The residual risk, however remains large with either the MCSW1 or MCSW4 scheme since the losses are not fully covered.

The residual risks may practically be considered as the idiosyncratic price risks not shared by the entire markets (see Sommervoll and Wood, 2011). To estimate these idiosyncratic risks more precisely, Sommervoll and de Haan (2014) suggested using customised indexes for smaller housing submarkets that share some common characteristics. Housing submarkets may reveal unique systematic features that are different from the larger city or nation-wide market. These submarkets could be spatial aggregations or other interesting forms of market segmentations.

In a related study, Teye et al. (2017) analysed the idiosyncratic risks for the spatially segmented Amsterdam housing submarkets. For this paper, we consider the segmentation of the Amsterdam residential housing market into the three property classes: small apartments (bedroom up to 3), large apartments (bed rooms more than 3) and houses. Houses, include terraced houses, town houses, corner houses, semi-detached houses and detached houses. The houses are combined into one submarket, partly because there are few resales to enable the construction of separate repeated sales indexes for each (see Section 6.4). The smaller and larger apartment markets may differ on their demand base. Smaller apartments may be patronised more by lower-income groups, smaller-sized families and first-time home-buyers.

TABLE 6.4 Loss coverage for CSW and MCSW schemes.

Policy	Small apartments		Large apartments		Houses	
	Hedonic index	Repeated sales index	Hedonic index	Repeated sales index	Hedonic index	Repeated sales index
CSW	0.15	0.18	0.17	0.19	0.15	0.14
MCSW1	0.67	0.66	0.70	0.68	0.53	0.55
MCSW2	0.07	0.07	0.10	0.10	0.07	0.07
MCSW3	0.10	0.10	0.13	0.12	0.10	0.10
MCSW4	0.33	0.30	0.37	0.34	0.28	0.30

Pay-out efficiency is the proportion of all pay-outs to home-owners inuring a loss. Target efficiency is the percentage of home-owners receiving pay-outs for a loss among all sales with losses. Loss coverage is the fraction of total losses covered by the combine pay-outs from the home-value insurance protection scheme. The reference indexes are computed separately for the indicated housing submarket.

Bigger-sized apartments, on the other hand, may greatly appeal to larger-sized families and middle-income earners.

Table 6.4 presents the loss coverage for the three submarkets. As expected, the loss coverage (and hence the idiosyncratic price risk) varies significantly for the housing submarkets. The CSW insurance policy, for example, estimates the loss coverage at 15%-18%, 17%-19% and 14%-15% for small apartments, large apartments and houses respectively. The table equally shows consistently that each of the insurance policies (CSW or MCSW) has enhance loss coverage for larger apartments than smaller apartments and houses. Interestingly, we can observe here again that the MCSW1 and MCSW4 policies have higher loss coverage than the CSW scheme. The MCSW1 scheme especially provides substantial loss coverage of up to 66%-67%, 68%-70% and 53%-55% for small apartments, large apartments and houses respectively.

By implication, the table shows that the idiosyncratic or residual risks will be larger for houses, followed by smaller apartments than larger apartments. Moreover, this residual risk depends on which home-value protection scheme is adopted. The results, however show that home-owners of any property type would be better protected against the idiosyncratic risks using the MCSW1 and MCSW4 scheme. It is also noteworthy that the loss coverage is slightly higher with the hedonic index than the repeated sale index. In most cases, the loss coverage from the hedonic index is up to 2% higher than repeated sale index as reference (see Table 6.3 & 6.4).

§ 6.6 Concluding remarks

The high volatility of residential property prices in recent times once again places an urgent need for home-owners to protect their home-value equities. This paper has re-examined the index-based home-value protection scheme to discover the amount of market risk that it potentially eliminates and the extent of idiosyncratic risks present for different categories of residential properties. The index-based home-value insurance policy (CSW) first proposed by Case Jr et al. (1993) advances pay-outs to its holders based on the market decline indicated by the reference index. The idiosyncratic risks constitute the individual property price decreases that are not caused by market forces and thus uncovered by the CSW scheme.

Using transaction data from Amsterdam spanning the period 1995 to 2014, the analysis confirms earlier results by Sommervoll and Wood (2011) and Sommervoll and

de Haan (2014) that the CSW scheme is less efficient and has extremely low loss coverage. In particular, our results, based on the hedonic and repeated sales indexes, show that the CSW scheme has less than 45% target efficiency, which defines the probability that a home-owner selling a property at a loss will receive pay-outs. The average loss coverage is between 13% to 15%, which leaves a large proportion of idiosyncratic risks uncovered.

A logical modifications to the CSW scheme in this paper however shows that the efficiency and loss coverage could be enhanced significantly. By using a pay-out scheme that is based on aggregate measures of the index and restricting the pay-out to only properties which sold at loss, the modified version has approximately 100% target efficiency and the loss coverage may be enhanced up to 51% (see Table 6.3).

Our results further show that by segmenting the Amsterdam housing market into submarkets that share common characteristics, the loss coverage of the modified CSW scheme may be better improved. With the market segmented into three: small apartments, large apartments and houses, we observed that the modified CSW scheme achieves respective loss coverage equal to 66%-67%, 68%-70% and 53%-55%. The paper contains other modifications with equally higher loss coverages.

In summary, the lesson is that, segmenting the market into more homogeneous submarkets leads to better protection from the modified CSW scheme and a reduction in the residual risks, although the original scheme may perform poorly. The challenge however is that, segmenting the market into extremely finer/thinner submarkets immensely reduces the number of (repeated) transaction sales which poses problem for constructing a reliable index for such thin submarkets. Francke (2010), Francke and De Vos (2000) and Schwann (1998), for example, proposed methods for constructing house prices indexes in thin markets. In a future research, such methods could be applied in combinations with different markets segmentations to study the efficiency and loss coverage of the CSW scheme and its modified versions.

Our analysis does not include the pricing of the modified CSW home-value protection schemes and the additional financial burden to home-ownership. The pricing of these schemes may be one of the important issues to clarify in a future research for their practical implementations.

In a future research, it might also be insightful to consider the general behaviour of home-owners to housing equity insurance. While household decision about selling residential property may depend on several factors, the assurance of receiving insurance pay-outs might influence them to postpone the sales or opt for unreasonable prices. Such behaviour could negatively affect any housing equity insurance scheme and would be interesting to investigate further.

The above also relates to the issue of moral hazard or what is sometimes referred to as agency problem where home-owners neglect important maintenance in anticipation of receiving insurance pay-outs. As suggested by Case Jr et al. (1993), one of the possible ways to check this moral hazard is for the underwriting companies to impose some minimum maintenance requirement for obtaining pay-outs. This maintenance requirement can be practically implemented as a fix percentage deductible from the insurance pay-out.

7 General conclusion

Since the 2007-2008 Global Financial Crisis (GFC), a great deal of research has been conducted in various countries into the dynamics and risks associated with house prices in an attempt to find innovative ways of reducing these risks and resuscitating a depressed housing market. This dissertation contributes to that literature by providing comprehensive analyses of the spatial diffusion and risks associated with house prices in the Netherlands. It also studies the efficiency and loss coverage of home-value insurance in the context of the Dutch housing market and suggests modifications to the index-based insurance scheme that would minimise the residual idiosyncratic risks for home-owners. The dissertation innovatively adopts empirical methods that combine standard statistical analyses with more complex and recent econometric models.

The contributions of the dissertation are presented in five main chapters. Four of these chapters have already been published separately in international journals and one is under review. Chapter 2 provided a general overview of the Dutch housing market and the risks involved in home-ownership. Chapters 3, 4 and 5 were devoted to the diffusion mechanism of house prices in the Netherlands. Chapter 5 also dealt in part with house price risks, while Chapter 6 focused on the house price risks and home-value insurance. Each chapter has provided a detailed conclusion on each aspect of the research questions addressed in this dissertation. This concluding chapter summarises the main findings of the dissertation as a whole. The limitations of the analyses are discussed, together with potential applications for its findings and directions for further research.

§ 7.1 Main findings

§ 7.1.1 Diffusion

Housing researchers define the "diffusion" or "ripple effect" as a housing market phenomenon whereby house price movements in one region spread to house prices in other parts of a country, with a transitory or permanent impact (Meen, 1999; Giussani and Hadjimatheou, 1991). The diffusion mechanism of house prices in the Netherlands is covered in Chapters 3, 4 and 5 of the dissertation. Chapter 3addresses the following research question:

> *To what extent does house price diffusion exist in the Netherlands? Which regions predominate in the house prices diffusion mechanism? How does the diffusion mechanism vary over time?*

A graphical network method was adopted to address these questions. The graphical network is a relatively new econometric approach to modelling the complex and hidden interrelations between multivariate time series variables. The method used in this dissertation specifically applies the Bayesian graphical vector autoregression (BG-VAR) model of Ahelegbey et al. (2016a), which combines graphical techniques and vector autoregression models. The advantage of this approach is that both the region that predominantly drives diffusion and the direction of diffusion can be deduced from the graph. Network statistics can also be computed to reveal the characteristics of the diffusion mechanism (see Section 3.5).

The empirical analysis used the twelve provinces/regions of the Netherlands as the spatial units and their respective house price indexes from 1995 to 2016 provided by Statistics Netherlands. The results show existing diffusion pattern of house prices in the Netherlands, which varies over the sample period. The diffusion pattern seems to have been more intense from 1995 to 2005 and weaker from 2005 until 2008, after which the diffusion again began to intensify (Figure 3.5).

A formal empirical test identifies a structural break at 2005Q2 (see Figure 3.6), which delineates a period of sustained house price appreciation in the Netherlands from the so-called bubble period, consisting of the pre- and post-crisis periods. A more detailed study of the sub-periods 1995Q1–2005Q2 and 2005Q3–2016Q1 identifies Noord-Holland and Drenthe respectively as the regional housing markets that predominate in house price diffusion. The result for Noord-Holland, which is one of the more economically significant Dutch provinces, is unsurprising. Similar findings in the UK and other countries also suggest that major economic regions are more influential in house price diffusion (Meen, 1999; Holly et al., 2011; Gong et al., 2016b). It is interesting, however, that Drenthe, one of the smaller regions, has also played a central role in the house price diffusion mechanism during certain periods in the Netherlands.

Chapter 4 focuses on house price diffusion from the Dutch capital Amsterdam, which is located within the province of Noord-Holland. Amsterdam's housing market is one of the largest and most dynamic in the Netherlands. The chapter specifically looks at the extent to which house price movements in Amsterdam drive house prices in other regions of the Netherlands, and it confirms the existence of house price diffusion from economically more significant regions, as existing literature from other countries has suggested.

In methodological terms, a section of the existing literature argues that the diffusion of house prices manifests itself as a lead-lag or long-run effect (see Giussani and Hadjimatheou, 1991; MacDonald and Taylor, 1993). Adopting this paradigm, the lead-lag and long-run effects are examined using the Toda-Yamamoto Granger (Toda and Yamamoto, 1995) aand the ARDL bounds co-integration techniques (Pesaran et al., 2001), both of which allow the use of stationary and non-stationary time series in the analyses. The real Amsterdam and regional house price indexes between 1995 and 2016 were used for the analyses, while controlling for common house price fundamentals.

The results of the Granger causality analysis confirm that a lead-lag effect exists in house prices from Amsterdam to all regions of the Netherlands except for Zeeland. The co-integration test concludes that a pairwise long-convergence exists between Amsterdam house prices and only six regions, including Friesland, Groningen,

Limburg, Overijssel, and Utrecht. The commutative evidence thus suggests the existence of house price diffusion from Amsterdam to all Dutch regions except Zeeland (a small region that is located some distance away from Amsterdam). This result is unsurprising; it corroborates findings in the UK, for example, where house price movements in the South-East, mainly London, are found to diffuse to other parts of the country (MacDonald and Taylor, 1993; Giussani and Hadjimatheou, 1991).

Chapter 5 analyses the house price diffusion pattern within Amsterdam itself. The Amsterdam housing market is spatially divided into fifteen districts and hedonic house price indexes were created for each of these districts using individual transaction data between 1995 and 2014, supplied by the Dutch National Association of Real Estate Agents (NVM). The empirical method adopts simple pairwise Granger causality analysis (Granger, 1980), without controlling for the common fundamentals. The result does not show a clear diffusion pattern, but there appears a predominant causal flow emanating from areas within the central business districts out to more peripheral areas. Empirical analyses in other countries have shown a similar unidirectional causal flow of house prices from main cities to surrounding peripheral areas (see Gong et al., 2016a; Chen et al., 2011).

§ 7.1.2 House price risk

The analysis of house price risks is partly covered in chapters 5 and Chapter 6. Chapter 5 is specifically concerned with the spatial distribution of house price risks and over-time variations in house prices. The empirical methodology adopts simple descriptive statistics for the hedonic indexes created for the different districts, which form the spatial units. The statistics generally show that the house price risk is higher in the central business districts than in peripheral areas. Similarly, decreasing variation between the central business districts and the peripheral area is observed over time.

Chapter 6 addresses two issues: the residual idiosyncratic risks of house prices, and the efficiency and loss coverage of index-based home-value insurance schemes. The empirical approach to residual idiosyncratic risks uses the home-value approach of Sommervoll and Wood (2011). Assuming that each property is covered by a home-value insurance policy with a pay-out, which is proportional to the decline in a reference house price index, the residual idiosyncratic risks are the losses that would not be covered by the insurance policy (Sommervoll and de Haan, 2014; Sommervoll and Wood, 2011). The analysis was carried out for different property types, using individual transaction data as in Chapter 6. The results show that the residual idiosyncratic risks are largest for houses, followed by smaller apartments (number of bedrooms up to 3) and larger apartments (number of bedrooms greater than 3).

The analysis of index-based home-value insurance using the same data reveals a 45% target efficiency, which defines the probability that a home-owner selling a property at a loss will receive pay-outs. The average loss coverage is estimated at between 13% to 15%, which means a large proportion of idiosyncratic risks are not covered by index-based home-value insurance policy. Earlier results by Sommervoll and de Haan (2014) and Sommervoll and Wood (2011), also revealed very low loss coverage for home-value insurance policy.

Chapter 6 also proposes modifications to the index-based home-value insurance scheme which would lead to much higher efficiency and loss coverage. The modification uses a pay-out scheme based on aggregate measures of the index and restricts the pay-out to properties sold at a loss. In the analysis, the modified version has approximately 100% target efficiency and the loss coverage is enhanced to 51%. The results also show that loss-coverage may be improved to 54%-70% when the market is segmented into more homogeneous sub-markets. Loss coverage and efficiency do not differ much between the reference hedonic and repeated sale house price indexes used in the analysis.

§ 7.2 Reflections

This dissertation covers important aspects of the diffusion mechanism of house prices and house price risk in the Netherlands. There were three specific objectives; firstly, to discover the diffusion mechanism of house prices in the Netherlands and the role played by the capital city, Amsterdam; secondly, to examine the spatial distribution of house price risks; and thirdly, to investigate the efficiency of the index-based home-value insurance for protecting home-owners against house price risks in the Dutch context.

The innovative empirical methods used were based on standard statistical analysis and more recent and complex econometric models. However, as with any scientific research, there are methodological and data limitations that require further consideration. Here, the methodological and data limitations of the empirical analyses are summarised. Possible ways to address these limitations in a further research are also discussed.

§ 7.2.1 Methodological limitations

There are methodological weaknesses with the analyses of the house price diffusion and risks. The empirical analyses of the house price diffusion mechanism adopt econometric techniques. The econometric approaches here basically investigate the interrelationships between regional house prices, without including the variables that drive the diffusion mechanism. Meen (1999) argues that the diffusion of house prices may be driven by economic activity, such as migration, equity transfer, and spatial arbitrage. The econometric applications in this dissertation, however, do not include these variables, which limits the economic explanations behind the diffusion process specifically in the Netherlands.

In Chapter 3, the empirical methods adopt a Bayesian graphical method. This method, ideally, allows for prior information regarding the spatial interactions to be incorporated into the analysis. However, the estimation is more complex for an arbitrary prior distribution and it is currently estimable for a uniform prior distribution, which stipulates that each region is equally likely to influence others. The uniform prior may be more restrictive. However, the results of the analysis tend to corroborate earlier results in other countries, where house price diffusion is found to emanate from certain major urban areas.

Chapter 3 also lacks a control for house price fundamental determinants, which constitutes another methodological weakness. Omitting these house price fundamental determinants may confound the spatial interrelations between house prices (Duranton et al., 2015; Lütkepohl, 2005). In Chapter 4, an attempt is made to control for these fundamentals. However, only the national fundamentals are used rather than regional/provincial-level fundamental house price determinants, which would be more suitable. The part of Chapter 5 which addresses house price interrelationships also lacks control for the district-level fundamental house price determinants.

In the study of the spatial distribution of house price risks in Chapter 5, the methodology adopts simple summary statistics, from which conclusions are drawn through ocular observation. A more rigorous empirical analysis involving the testing of a hypothesis could be implemented. The current approach, however, is exploratory and provides results that may serve as a guide for the more detailed empirical testing of hypotheses.

Chapter 6, which examines residual idiosyncratic risks, relies on the assumption that each property is covered by home-value insurance policy that pays benefits based on a reference house price index. In principle, such an insurance policy does not exist in the Netherlands and the assumption is therefore entirely hypothetical. Nevertheless, the assumption provides a way of investigating the efficiency and loss coverage of the index-based home-value insurance policy for possible future implementation.

The efficiency and loss coverage of the hypothetical insurance policy analysed in Chapter 6 also depend heavily on the level of aggregation for which the reference index is created. Aggregation at a smaller and more homogeneous level is more appropriate for such an analysis. The aggregation in Chapter 6, however, combines all houses together, which may not lead to a homogeneous group.

Furthermore, a complete analysis of residual idiosyncratic house price risk, such as in Chapter 6, should consider the outstanding mortgage loan in addition to the sale value of a property. This would give a broader picture of the residual risks, while also accounting for the total home-value equity. Outstanding loans were not considered in the analysis.

§ 7.2.2 Data limitations

Data plays an important role and determines the validity of results in any empirical research. Most of the methodological weaknesses of the analyses in this dissertation are inherent in the data limitation. More specifically, the omission of the house price fundamental determinants in the analyses of the house price diffusion mechanism in Chapters 3, 4, and 5 is due to the lack of data on these variables at the provincial and district levels. Where these do exist, the frequency and length were too limited for the time series applications adopted in the empirical analyses.

The aggregation of all houses into one class for the analyses of the residual idiosyncratic risks, efficiency and loss coverage of the index-based home-value insurance policy, is specifically due to the lack of sufficient (repeated sale) data to enable house price indexes to be separately and reliably created for each type of house.

House prices indexes generally suffer from noise and are less reliable when only a few transaction data are available.

The lack of repeated transaction data for each house is, however, partly due to the data source. The Dutch Organisation for Real Estate Agents (NVM), which supplied the data, does not cover transaction sales for all properties. The coverage for the NVM data does not generally extend beyond 75% of all transactions, and this also introduces a selection or sampling bias that may affect the results of the analyses.

As stated earlier, one extremely important element for the risk analysis and the efficiency and loss coverage of the home-value insurance, is the outstanding mortgage loan data. This kind of data is highly confidential in the Netherlands and unfortunately was not accessible for this research, despite the several requests to officials of the national mortgage guarantee (NHG), which collects such data.

§ 7.2.3 Suggestions for future research

In future research, it would be essential to collect data on the fundamental house price determinants at the regional and district levels. This would allow an empirical investigation of house price diffusion, eliminating possible confounding effects of house price fundamentals. In addition, future research of the diffusion mechanism could consider an economic model, for which the driving factors suggested by Meen (1999) are explicitly modelled (see discussions in Section 4.5).

Methodologically, the Bayesian graphical autoregressive (BG-VAR) approach is a promising effective way to study the diffusion mechanism. The method effectively combines the traditional VAR model with a more efficient identification strategy, thereby avoiding the complications when estimating structural parameters in a typical spatial analysis. It can also easily differentiates between direct and indirect interaction between spatial variables. In effect, the BG-VAR method may make it possible to avoid the estimation of the structural parameters, which involves an ad-hoc and often inaccurate specification of the spatial weighting matrix in spatial analysis (see e.g. Gibbons and Overman, 2012; Pinkse and Slade, 2010). This could be done by transforming the conventional spatial (autoregressive) model into the structural VAR framework, and then applying the BG-VAR. Future research could investigate this issue further. Additionally, the current application of the BG-VAR, which assumes a uniform prior distribution for the interaction between the spatial variables, could be relaxed in a future research.

In relation to the spatial distribution of house price risk in Chapter 5, the current treatment is exploratory in nature, using simple statistics and ocular observation. In future research, a more detailed empirical investigation involving hypothesis testing could be adopted. For example, using the summary statistics, the variation of the house price risk with respect to the distance of designated local areas or the individual residential properties from the central business district could be tested. However, this would require the collection of more detailed geographical data on the properties (see Gong et al., 2016a).

In the current analysis of the residual idiosyncratic house price risk, a comparison is made between the sale price of the residential property and its purchase price only. For further investigation, it would be important to consider the outstanding mortgage

loan. This would enable overall housing equity to be taken into account. Furthermore, because residential properties are highly heterogeneous, it may be useful to consider a smaller and more homogeneous level of aggregation for the properties, possibly at the neighbourhood or post-code level. However, these smaller housing markets may be very thin and would require appropriate indexes methodology as suggested by, for example Francke (2010) or Schwann (1998).

§ 7.3 Applications of the research findings

The tremendous effort that the existing literature has channelled into understanding the dynamics and risks of house prices has partly been in order to find ways of resuscitating the depressed housing market following the 2007-08 GFC and innovative ways of reducing significant housing risks. Despite the methodological and data limitations, the research findings in this dissertation are applicable in several ways for governments, households, commercial investors and financial institutions, who are actors in the housing market.

§ 7.3.1 Governments

To stimulate the national housing market, the interrelations between the regional markets play an important role, determining whether a basket of regionally interrelated policies or a single national policy framework is appropriate (see Gong et al., 2016b; Cotter et al., 2011). A single policy framework would be more appropriate for a well-integrated and convergent market (Bekaert and Harvey, 2003; Pukthuanthong and Roll, 2009). However, where diffusion occurs predominantly from a certain region, policy regulations could be focused on that market, with the effects then trickling down to other regions. In Chapters 3, 4 and 5, the findings suggest that there is a house price diffusion mechanism in the Netherlands, predominantly existing from Amsterdam or the wider province of Noord-Holland. Policy makers attempting to stimulate the Dutch market as a whole may be able to focus regulations on the housing market in Amsterdam or Noord-Holland, from where the effect would be likely to spread to the rest of the country.

The centrality of the Amsterdam or Noord-Holland market also means that any overheating is likely to spread throughout the country. Therefore, by treating the Amsterdam or Noord-Holland housing market as systemically important, policies markers are likely to mitigate the spill-over effects of price volatilities, which may adversely impact on the entire Dutch housing market (Stephens, 2006; Harrington, 2009; Castro and Ferrari, 2014).

§ 7.3.2 Households and commercial investors

For households and commercial investors, it might be more important to know the areas and type of houses that are associated with higher risks and better returns. The results from Chapter 5 suggest that house prices have greater growth potential and involve higher risk as we move from peripheral areas to the central business districts. Such a finding could help households and commercial investors to make home investment choices based on their appetite for risk. Moreover, Chapter 6 indicates that idiosyncratic risks are higher for houses, followed by smaller apartments (number of

bedrooms up to 3) and larger apartments (number of bedrooms greater than 3). This result is also relevant to the decisions made by households and commercial investors.

Of course, it would also be of great interest, particularly for households, to know the best form of home-value insurance to protect their housing equity, and this would also yield many welfare benefits. The analysis of Chapter 6 shows that the current index-based home-value insurance scheme has very low loss coverage (see Sommervoll and Wood, 2011; Sommervoll and de Haan, 2014). The suggested modification is promising, but such products still require better insights into its pricing.

§ 7.3.3 Financial institutions

Like the households and commercial investors, financial institutions and particularly lenders, would benefit from better knowledge of which locations and types of residential properties are associated with higher risks and better returns. This would enable them to improve the pricing of mortgage loans and other housing-related products. For instance, reverse mortgages, which are equity release products that enable older home-owners to convert their home equity into cash, have recently been growing in popularity. Lenders could significantly reduce the risks of these products if they knew which housing market segments are more likely to appreciate and yield the lump sum advanced to home-owners. On the other hand, these lenders may also be interested in purchasing index-based home-value insurance from insurers to protect the value of the collateral involved in such reverse mortgages.

The wider interest of insurance companies lies in the proposed home-value insurance product in Chapter 6, which promises higher loss-coverage. Beside the lenders, most households may wish to purchase such products as means of protecting their equity. However, the insurance companies need to investigate the practicalities of the scheme in relation to pricing and issues of moral hazard discussed in Chapter 6 (see Case Jr et al., 1993; Shiller, 2003).

§ 7.3.4 Statistical agencies

Like Statistics Netherlands, many statistical agencies are interested in publishing indices that summarise important information on the housing market. One such indicator in the results of the empirical analyses in this dissertation is network density (Figure 3.5), which could also be referred to as the spill-over index. The network density is basically a simple aggregate index which crudely represents the extent of interdependencies between the growth in regional house prices over time. It is similar to the Granger causality index proposed by Billio et al. (2012), which estimates the interconnectedness between the returns of financial institutions. Such indexes are useful for monitoring contagion among financial institutions and identifying periods of overheating, which may lead to a systemic breakdown (see Ahelegbey, 2016).

It can be seen from Figure 3.5 that the degree of interdependence between regional house price growth varies over time; it was particularly high between 1995 and 2005, before decreasing until 2008, after which it again started to rise. These periods correspond to important and recognisable stages in the development of Dutch house prices (De Vries, 2010; Xu-Doeve, 2010; Toussaint and Elsinga, 2007), and the figure reveals the potential for house price diffusion during these periods. The periods

2005-2008 and 2008-2016 are interesting as they coincide with the pre- and post-GFC periods. Network density could also be created by statistical agencies at the city level to show the degree of diffusion and interdependence between different local housing markets.

In relation to house price risk, it would be useful for statistical agencies to periodically publish simple statistics for smaller district, neighbourhood and postcode levels. One possible indicator could take the form of the standard deviation or the semi-deviation and decline-severity adopted in this dissertation (see Section 5.3 for the mathematical definitions). The semi-deviation and decline-severity consider, respectively, only the returns below the average and zero; thus, they generally do not overestimate house price risk as with the standard deviation (see Table 5.2 and Figure 5.4). Semi-deviation and decline-severity indicators could also be published for different house types. Such information would be useful for households and other housing market players.

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Appendix to Chapter 3

The sampling of the graph structure in this paper follows the procedure described by Ahelegbey et al. (2016b). The method is summarised here for completeness. First, for a given lag order p, the initialisation of the Markov chain Monte Carlo (MCMC) is ran in two steps.

1. Set G^0 to $n \times np$ null matrix. This is the case when each equation has no predictor(s).

2. For each equation $i = 1, \ldots, n$; test each $X_j \in X$, $j = 1, \ldots, np$ as a potential predictor of Y_i. If $Pr(Y_i|X_j, p) > Pr(Y_i|p)$, then set $G^0_{i,j} = 1$, otherwise $G^0_{i,j} = 0$.

These steps provide a good starting point for implementing the algorithm for sampling the network structure. The authors suggest to use the Gibbs sampling algorithm which proceeds at each m-th iteration as follows:

1. Denote with $G^{(m-1)}$, the current network matrix and find $\pi_i^{(m-1)}$, the set of indexes of the non-zero elements of the i-th row of $G^{(m-1)}$.

2. Find $X_{\pi_i}^{(m-1)}$, the vector of elements in X whose indexes corresponds to $\pi_i^{(m-1)}$.

3. Draw an index k from the set of indexes of possible predictors, say $X_k \in X$.

4. Set $G^* = G^{(m-1)}$ and add/remove edge between Y_i and X_k, i.e., $G^{(*)}_{ik} = 1 - G^{(m-1)}_{ik}$.

5. Find $\pi_i^{(*)}$, the set of indexes of the non-zero elements of the i-th row of $G^{(*)}$ and $X_{\pi_i}^{(*)}$, the vector of elements in X whose indexes corresponds to $\pi_i^{(*)}$.

6. Compute $Pr(Y_i|X_{\pi_i}^{(m-1)}, p)$ and $Pr(Y_i|X_{\pi_i}^{(*)}|p)$, and $R_\alpha = \dfrac{Pr(Y_i|X_{\pi_i}^{(*)}, p)}{Pr(Y_i|X_{\pi_i}^{(m-1)}, p)}$.

7. Sample $u \sim \mathcal{U}_{[0,1]}$ from a uniform distribution. If $u < \min\{1, R_\alpha\}$, set $G^{(m)} = G^{(*)}$, otherwise set $G^{(m)} = G^{(m-1)}$.

The above steps are implemented for a total of M iterations and averaged over the sampled graphs. The posterior probability of an edge is then estimated by $\hat{e}_{ij} = \frac{1}{M}\sum_{m=1}^{M} G_{ij}^{(m)}$, where $G_{ij}^{(m)}$ is the edge from $X_{j,t}$ to $Y_{i,t}$ in the network matrix G at the m-th iteration. See Ahelegbey et al. (2016a) for details on the convergence diagnostics of the MCMC chain. For simplicity, we estimate $\hat{G}_{ij}$ such that $\hat{G}_{ij} = 1$, if $\hat{e}_{ij} > 0.5$, and zero otherwise.

We construct a temporal network structure by transforming the estimate matrix $\hat{G}$ to an adjacency (square binary) matrix of a directed graph. Following the labelling of our network matrix as shown in Figure 3.1, the edges in the adjacency matrix indicate a direct link from a column label to a row label. For example $A_{ij} = 1$ means $Y_j \to Y_i$. Let A be an $n \times n$ null matrix. We construct the adjacency matrix following the steps below.

1. For $i \neq j = 1, \ldots, n$, denote with y_j, the set of indexes of $Y_{j,t-1}, \ldots, Y_{j,t-p} \in X_t$
2. Find $V_{i,y_j} = \hat{G}_{i,v_j}$, the vector of edges on the i-th row and the y_j columns of $\hat{G}$
3. If $\sum V_{i,y_j} \neq 0$ then set $A_{ij} = 1$, otherwise $A_{ij} = 0$

The main diagonal of A are therefore represented by zeros. The above is similar to testing, $H_0 : B_{1,ij} = \ldots = B_{p,ij} = 0$ against H_A : Not H_0, $\forall i, j = \{1, \ldots, n\}, i \neq j$.

Appendix to Chapter 5

TABLE A5.1 Definition of explanatory variables in the time dummy hedonic model.

Characteristics	Description	Variable type	Measurement unit
M2	total usable floor area in square meters	continuous	positive real number
NKAMERS	number of rooms	continuous	positive integer
NVERDIEP	number of floors	continuous	positive integer
AGE	the age of the building in decades	continuous	non-negative integer
VERW	system of heating	categorical	$0, \cdots, 3$
ONBI	maintenance level inside the property	categorical	$1, \cdots, 9$
HOUSETYPE	type of house	categorical	$2, \cdots, 7$
LOC	the district in which property is located	categorical	$0, \cdots, 14$

Source: Extract from NVM data. Type of heating system: no heating system, gas/stove heating, central boiler heating and air condition/solar heating. Maintenance level: bad, poor to moderate, moderate, moderate to reasonable, reasonable, reasonable to good, good, good to excellent and excellent. Properties classes: terraced house, town house, corner house, semi-detached house, detached house and apartment. The location of the properties was categorised into 15 as specified in Table 5.1.

TABLE A5.2 Hedonic regression estimates for the whole of Amsterdam.

Variable	Estimate	Std. Error	t-value	Pr(> |t|)
Intercept	1.070e+01	1.540e-02	695.003	< 2e-16 ***
1996	1.265e-01	6.013e-03	21.041	< 2e-16 ***
1997	2.801e-01	5.757e-03	48.653	< 2e-16 ***
1998	4.333e-01	5.715e-03	75.808	< 2e-16 ***
1999	6.706e-01	5.558e-03	120.655	< 2e-16 ***
2000	8.053e-01	5.452e-03	147.715	< 2e-16 ***
2001	8.916e-01	5.325e-03	167.431	< 2e-16 ***
2002	8.765e-01	5.241e-03	167.243	< 2e-16 ***
2003	8.510e-01	5.216e-03	163.143	< 2e-16 ***
2004	8.706e-01	5.204e-03	167.305	< 2e-16 ***
2005	9.261e-01	5.067e-03	182.765	< 2e-16 ***
2006	9.989e-01	5.020e-03	199.008	< 2e-16 ***
2007	1.092e+00	4.996e-03	218.572	< 2e-16 ***
2008	1.126e+00	5.004e-03	225.033	< 2e-16 ***
2009	1.066e+00	5.085e-03	209.665	< 2e-16 ***
2010	1.069e+00	5.116e-03	208.968	< 2e-16 ***
2011	1.046e+00	5.116e-03	204.451	< 2e-16 ***
2012	9.919e-01	5.148e-03	192.660	< 2e-16 ***
2013	9.922e-01	5.222e-03	189.997	< 2e-16 ***
2014	1.077e+00	5.136e-03	209.756	< 2e-16 ***
M2	7.818e-03	2.517e-05	310.600	< 2e-16 ***
NKAMERS	1.949e-02	7.371e-04	26.440	< 2e-16 ***
AGE	-2.881e-03	3.135e-04	-9.190	< 2e-16 ***
NVERDIEP	1.064e-02	1.223e-03	8.702	< 2e-16 ***
VERW1	-6.645e-02	3.651e-03	-18.203	< 2e-16 ***
VERW2	5.185e-02	2.794e-03	18.559	< 2e-16 ***
VERW3	1.019e-01	4.924e-02	2.070	0.038471 *
ONBI2	1.059e-03	3.139e-02	0.034	0.973078
ONBI3	2.847e-02	1.483e-02	1.919	0.054992 .
ONBI4	3.401e-02	1.772e-02	1.919	0.054934 .
ONBI5	5.142e-02	1.411e-02	3.643	0.000269 ***
ONBI6	7.189e-02	1.452e-02	4.952	7.36e-07 ***
ONBI7	1.594e-01	1.396e-02	11.413	< 2e-16 ***
ONBI8	2.596e-01	1.447e-02	17.946	< 2e-16 ***
ONBI9	2.730e-01	1.403e-02	19.465	< 2e-16 ***
Town house	9.764e-02	1.349e-02	7.236	4.65e-13 ***
Corner house	7.207e-02	4.735e-03	15.219	< 2e-16 ***
Semi-detached house	2.391e-01	7.828e-03	30.545	< 2e-16 ***
Detached house	2.633e-01	7.059e-03	37.293	< 2e-16 ***
Apartment	-2.646e-02	2.912e-03	-9.087	< 2e-16 ***
Loc36301	6.941e-02	3.442e-02	2.017	0.043736 *
Loc36302	-2.047e-01	3.384e-03	-60.477	< 2e-16 ***
Loc36303	-1.101e-01	3.096e-03	-35.572	< 2e-16 ***
Loc36304	-2.625e-01	3.212e-03	-81.723	< 2e-16 ***
Loc36305	-4.052e-01	3.640e-03	-111.322	< 2e-16 ***
Loc36306	-2.735e-01	3.286e-03	-83.230	< 2e-16 ***
Loc36307	-5.498e-01	3.174e-03	-173.192	< 2e-16 ***
Loc36308	-5.697e-01	4.154e-03	-137.140	< 2e-16 ***
Loc36309	-5.753e-01	3.623e-03	-158.809	< 2e-16 ***
Loc36310	-4.531e-01	3.930e-03	-115.297	< 2e-16 ***
Loc36311	-7.026e-01	3.456e-03	-203.322	< 2e-16 ***
Loc36312	-2.098e-01	2.987e-03	-70.246	< 2e-16 ***
Loc36313	-4.562e-02	2.398e-03	-19.022	< 2e-16 ***
Loc36314	-1.973e-01	2.828e-03	-69.765	< 2e-16 ***

1996-2014 are the year dummies, while 1995 is omitted for identifiability. Residual standard error: 0.2198 on 115235 degrees of freedom, Multiple R-squared: 0.8425, Adjusted R-squared: 0.8424, F-statistic: 1.163e+04 on 53 and 115235 DF, p-value: < 2.2e-16. Signif. codes: 0.05 '·', 0.01 '*', 0.001 '**', 0 '***'.

TABLE A5.3 Stationarity test for house price return series.

	ADF		KPSS	
Series	Test-statistics	P-value	Test-statistics	P-value
CT	-2.42 (1)	0.15	0.42 (1)	0.07^{*}
WP	-1.73 (1)	0.40	0.56 (1)	0.03^{**}
OW	-2.25 (1)	0.20	0.49 (1)	0.04^{**}
ZB	-1.92 (1)	0.32	0.60 (1)	0.02^{**}
BL	-1.93 (1)	0.31	0.58 (1)	0.02^{***}
DB	-1.83 (1)	0.36	0.56 (1)	0.03^{**}
ND	-1.64 (1)	0.44	0.75 (1)	$< 0.01^{***}$
GS	-1.74 (1)	0.39	0.78 (1)	$< 0.01^{***}$
OD	-1.58 (1)	0.47	0.70 (1)	$< 0.01^{***}$
SO	-1.89 (1)	0.33	0.58 (1)	0.02^{**}
ZO	-1.53 (1)	0.49	0.82 (1)	0.01^{***}
WG	-2.02 (1)	0.28	0.53 (1)	0.04^{**}
OZ	-2.12 (1)	0.24	0.47 (1)	0.05^{**}
ZA	-1.99 (1)	0.29	0.52 (1)	0.04^{**}

The test regression is estimated separately for each time series with an intercept. Due to the limited sample size, the augmented lag in the ADF procedure is set to one (indicated in the parenthesis). One indicated in parenthesis for the KPSS test is the Newey-West estimator of the bandwidth parameter. The null hypothesis for ADF is that the series contains unit root, while the KPSS null states that the series is stationary. $*$, $**$ and $***$ denote statistical significance at the 10, 5 and 1% respectively.

Curriculum vitae

Alfred L. Teye was born in Odortorm-Poliwa, a little village in the eastern region of Ghana, to Mr. & Mrs. E. T. Lartey on April 20, 1984. He had his secondary school education at the Akro Secondary Technical School in Odumase Krobo, between 2000 and 2002. In 2007, he obtained his combined bachelor's degree in Mathematics and Computer Science, with first-class honours, from the University of Ghana. After graduating from the University of Ghana, he was appointed a teaching assistant at the Department of Mathematics in the same university, where he served for the one year compulsory national service. He was offered the prestigious Huygen Scholarship by Nuffic in 2008 to study his Msc in Stochastics and Financial Mathematics at the University of Amsterdam, which he completed with cum-laude in 2010. Thereafter, he held a one year graduate research position at the Vrije Universiteit Amsterdam and after few years away from academia he started his PhD in 2014 at the Delft Technical University, where he has been working on the diffusion and risks of residential house prices in the Netherlands. During the PhD, Alfred has co-authored several journal articles and working papers.

Publications as chapters of this dissertation

1. **Teye, A. L.**, de Haan, J., Elsinga, M.J., Bondinuba, F. K. and Gbadegesin, J.T. (2017). "Risks in Homeownership: A Perspective on the Netherlands". *International Journal of Housing Markets and Analysis,* vol. 10(4), pp. 472-488.
2. **Teye, A. L.** and Ahelegbey, D.F. (2017). "Detecting Spatial and Temporal House Price Diffusion in the Netherlands: A Bayesian Network Approach". *Regional Science and Urban Economics,* vol. 65(4), pp. 56–64.
3. **Teye, A. L.**, Knoppel, M., de Haan, J. and Elsinga, M.J. (2017). "Ripple Effects between Amsterdam and Regional House Prices in the Netherlands". *Journal of European Real Estate Research,* vol. 10(3), Vol. 10(3), pp.331-345.
4. **Teye, A. L.**, de Haan, J. and Elsinga, M.J. (2017). "Risks and interrelationships of subdistrict house prices: the case of Amsterdam". *Journal of Housing and the Built Environment,*
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Other publications

6. Bondinuba, F. K., Hedidor, D., Sadique, A. M., **Teye A. L.** (2017). "De/Motivations of Housing Microfinance Delivery in Ghana". *Journal of Property Management,* Vol. 35(5), pp.528-544.
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