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House Price Dynamics

The role of credit, demographics and depreciation

This dissertation outlines multiple important issues related to house price dynamics and its determinants. This dissertation focusses on changing determinants of house prices in the long-run (Chapter 2), the effect of credit conditions on house prices (Chapter 3), the effect of demographic growth and decline on house prices (Chapter 4) and finally the effect of depreciation on house prices (Chapter 5). Even though we limited ourselves to the housing market in the Netherlands, the findings might be relevant for other sectors in the real estate market or even any other market that is characterized by (heavy) supply constraints.

Alexander van de Minne received his master's degree in Engineering from the Delft Institute of Technology. Thereafter he started his PhD in finance at the University of Amsterdam. In 2012 Alex won the ***'Best Doctoral Paper'*** presented at the ERES annual conference in Eindhoven, the Netherlands. His joint research with Marc Francke on land price indices was awarded ***'Best Dutch real estate research of 2013'*** by the VOGON and PropertyNL. Alex has taught Finance to first year bachelor students and principles of real estate to third year bachelor students at the University of Amsterdam. As of October 2015, he is working as a Postdoctoral Research Fellow on MIT center for Real Estate, sponsored by Real Capital Analytics.

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House Price Dynamics

Alexander van de Minne



House Price Dynamics

The role of credit, demographics and depreciation

HOUSE PRICE DYNAMICS

THE ROLE OF CREDIT, DEMOGRAPHICS AND DEPRECIATION

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HOUSE PRICE DYNAMICS

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aan de Universiteit van Amsterdam
op gezag van de Rector Magnificus
prof. dr. D.C. van den Boom
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FACULTEIT ECONOMIE EN BEDRIJFSKUNDE

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Chapter 1

Introduction

1.1 House Price Risk

It is (still) widely perceived that housing is a solid investment. Indeed, multiple studies show that house prices have more or less tripled in most industrialized countries from the 1980s until 2008 (Adams and Füss 2010; Andrews, Sánchez, and Johansson 2011). By now, housing equity accounts for the largest share of household wealth in most countries. In this regard it should come as no surprise that policymakers actively promoted home-ownership by subsidies (like interest rate deductibility in the United States) and by imposing less stringent controls on financial intermediaries, allowing for more households to obtain a mortgage. Mortgage market innovations by financial intermediaries also drastically increased the supply of (cheap) mortgage credit. This resulted in higher home-ownership rates around the world. For example, in the United States (US), home-ownership rates went from 64% in the 1980s to almost 70% in 2007 (Mian and Sufi 2014). In the same period home-ownership rates in the Netherlands went from approximately 48% to 58% (De Vries 2010). The easy access to mortgage credit also increased household mortgage debt. Between 1985 and 2007, the share of household mortgage debt as a proportion of the total value of housing in the US increased substantially from 30% to 50% (Bokhari 2012). This fraction increased from roughly 40% to 65% for Dutch household in that same period. Interestingly, there is also evidence that the (cheap) access to mortgage credit itself resulted in house price increases (Gerlach and Peng 2005; Mian and Sufi 2014).

However, there are also risks involved in home-ownership (and subsequent mortgage debt) on both the household and macroeconomic level. High levels of mortgage debt increases the propensity at which households default on their mortgages when house prices go down (Foote, Gerardi, and Willen 2008; Elul et al. 2010) and there is evidence that the high leverage rates in the US was the primary driver of the recession in 2007 – 2008 (Mian and Sufi 2014). Especially low-income households, with virtually no home equity, stopped to consume altogether after house prices went down and - as a result - the entire economy went into recession. In the US alone, $5.5 trillion of housing wealth vaporized in a single year. This is equal to an average (real)

house price decline of 26%. Other countries saw similar contractions in housing wealth, like Ireland and Spain, with similar macroeconomic effects. House price declines in the Netherlands have been more gradual.[1] For the period 2008 – 2012 total real house price declines are on a comparable level with the US.

The aim of this dissertation is to provide an analysis on house price dynamics and its (changing) determinants. This dissertation focusses on the effects of the supply of credit on the mortgage market, demographic growth and decline, and the effect of depreciation on house prices in the Netherlands.

1.2 Overview of the Dissertation

The set-up of this dissertation is as follows. In Chapter 2 it is shown that the determinants of house prices change over time, using a rolling error correction model. This study utilized a unique long-run historical macro database from the year 1825 onwards for Amsterdam. The results indicate that the determinants of house prices are not fixed, but change over time and reflect the economic state of affairs in each different era. At the beginning of the sample population growth, construction costs and housing supply are the most important house price determinants. One of the main determinants at the end of the sample are interest rates and the Gross Domestic Product per capita, reflecting the maturing of the mortgage markets and subsequent easy access to (cheap) mortgage credit.

Chapter 3 deals with the effect of mortgage markets on house prices in more detail for the Netherlands between 1995 and 2012. This study deals with two related topics. Firstly, Chapter 3 introduces a new methodology to construct an index for the supply of credit on the mortgage market, denoted the *credit conditions index*. Subsequently, this index is used in an equation for house prices to determine its effect on house prices. It is shown that the supply of credit on the mortgage market has been an important determinant of house prices.

In Chapter 4 it is shown that demographic decline has a disproportional large negative effect on house prices, using municipality level (panel) data. The effect of demographic growth on house prices depends on the local supply constraints. Population growth hardly affects house prices in municipalities with little supply constraints in the long-run. On the other hand, population increases in a municipality with high supply constraints *is* accompanied with higher house prices.

Chapter 5 introduces a methodology to decompose house prices in its structure value and

[1] This might have been caused by the high mortgage debt rates in the Netherlands for international standards: It is not uncommon to have a mortgage debt higher than the value of the home (see Chapter 3 as well) in the Netherlands. As a result many Dutch households can only sell their home *if* they can sell their home for an above market-price (also note that the Dutch mortgage market is recourse, Francke and Schilder 2014). Thus price decreases are slow and the market becomes less liquid (Genesove and Mayer 1997; Genesove and Mayer 2001; De Wit and Van der Klaauw 2013). Indeed, average time of sale increased and the number of transaction decreased dramatically in this period (De Wit, Englund, and Francke 2013).

land value. With this model we are able to measure the effect of depreciation on structure values. The effect of depreciation on structures is larger than most previous studies indicate. Maintaining a home well reduces the rate of depreciation considerably. It is also shown that land prices have been more volatile than structure prices. Interesting is that the indices are barely correlated.

Finally, Chapter 6 provides an overview of the main findings of all the chapters in this dissertation.

Chapter 2

The Time-Varying Determinants of House Prices in the Long-Run

Abstract[1]

The determinants of house prices change over time. This Chapter documents these changes using long-run historical data from Amsterdam from the year 1825 onwards. Because many houses in Amsterdam have survived until this day, we can construct a long-run repeat sales index and examine its determinants. We find that in the early beginnings of our transactions dataset population growth, construction costs and new housing supply are the most important determinants of house price dynamics. After 1900 income starts to play a role and, with the development of the mortgage market, interest rates as well. Directly after World War II population and investment in housing are key determinants of house prices, which likely reflects the baby boom generation and post-war reconstruction plans. Our results imply that the determinants of house prices are not fixed but change over time and reflect the economic state of affairs in each different era.

2.1 Introduction

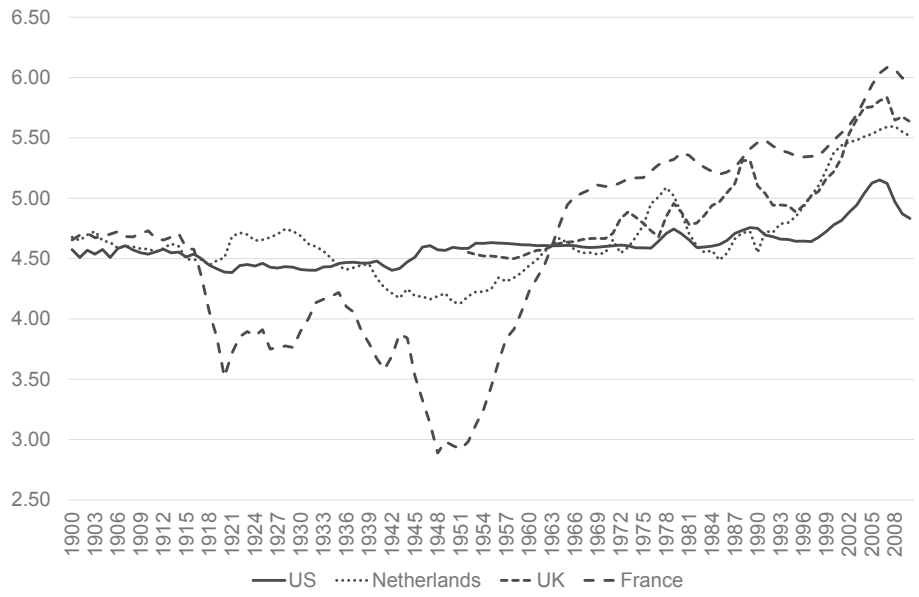
In Europe, housing accounts for 40% – 60% of total household wealth and it is roughly 20% for the average household in the United States (Statistics Netherlands and US Bureau of Economic Analysis and Statistics, respectively). It should, therefore, not come as a surprise that economists and policy makers are highly interested in the fundamental determinants of house prices.

Between the mid-1980s and 2008 real house prices more or less doubled in most industrialized countries (De Wit, Englund, and Francke 2013). From a historical perspective, however, this is a relatively new phenomenon. Figure 2.1, for example, shows historical real log house price indices for the US, UK, France, and the Netherlands. Annual real house price appreciation is

[1]This chapter is based on Dröes and Van de Minne (2015).

close to zero, or in some cases even declining (France), during most of the 20th century. Total real house price appreciation (averaged across the four countries) between 1900 and 1985 is 20% (on average 0.23% per year) while real house price appreciation for the period 1985 - 2010 is five times as large, about 107% (on average 7.15% per year). To understand these different growth rates, it is essential to understand how the fundamental determinants of house prices, and their impact, have changed over time.

Figure 2.1: Log real house price indices for a selection of countries, 1900 – 2012.



Notes: The indices start at 1900, except for the UK which starts at 1952. The base year is 1963. The index for the US is taken from Freddie Mac (for the period 1975 – 2014) and is augmented by the historic data from Robert Shiller. The UK data is taken from Nationwide and for France from CGEDD. The house price data for France goes back to 1936. House price data from Paris was used to extend this time series. House prices for the Netherlands are based on our own calculations (see Section 2.2). Both the UK and UK indices are based on the 'standard' Case and Shiller (1987) repeat sales methodology. The French price index is based on (weighted) median sales prices. For the Netherlands, see Appendix A.1.1.

This Chapter examines the time-varying determinants of long-run, historical, house prices. We use almost 200 years of house price data (1825–2012) from Amsterdam, the Netherlands. We focus on seven major determinant of house prices: investment in housing (proxied by housing supply), construction costs, Gross Domestic Product (GDP) per capita, the opportunity cost of capital (interest rates), labor force, unemployment, and population growth. We use a rolling (window) error correction model (R-ECM) with changing covariates to examine the cointegrating relationships between house prices and its determinant and show how these relationships have changed over time. Even though it is widely acknowledged that house price

determinants differ across markets, this study examines the changes in house price determinants in a single housing market over a long period of time.

We find that the long-run cointegrating relationships change over time. Population growth, construction costs and housing supply were the main drivers of house prices in the 19th century. Our results show that the cointegrating relationships changed from more construction cost driven to more income and - especially in the end of the sample - interest rate driven variables. Mortgage market innovations and financial liberalization allowed financial intermediaries to advance higher levels of credit to consumers from the 1970s onwards (Fernandez-Corugedo and Muellbauer 2006). Conjoined with declining interest rates this resulted in more affordable housing and subsequent increases in house prices. Moreover, the size of the effects are also time varying. For example, the effect of GDP on house prices was substantial lower during the period 1900 - 1970 than in the period 1970 - 2012. Finally, we find that directly after World War II population growth and investment in housing are the main drivers of house prices. This likely reflects the baby boom generation and post-war reconstruction plans. Population also had a large impact on house prices in Amsterdam during the 1970s. This is mainly due to the large scale deurbanisation taking place in that time period.[2]

Even though we are not the first to analyse changing patterns in long-run house price time series (most notably see, Ambrose, Eichholtz, and Lindenthal 2013; Ngene, Lambert, and Darrat 2014), we are the first to use additional data to analyse which fundamental house price determinants are important in which era.[3] This helps us to address several important questions about house price dynamics. First, our results can explain some of the discrepancies in the literature about the determinants of house prices. A stylized example is the study by Englund and Ioannides (1997) versus that of Adams and Füss (2010). Both use the same OECD database and both regress house prices on a proxy for economic activity and interest rates for 15 OECD countries. However, the effect of interest rates on house prices according to Adams and Füss (2010) is a multitude of that found by Englund and Ioannides (1997). This can be explained by the fact that the study of Englund and Ioannides (1997) uses data from 1970 - 1992 and the study of Adams and Füss (2010) is based on a different time period, 1975 - 2009. Generally speaking, during the 1970s and 1980s the loan-to-value caps were a lot stricter and access to credit was relatively limited. Thus, it should come as no surprise that the effect of interest rates on house prices was lower in the pre-1990s era.

Second, ignoring changing cointegrating relationships of house prices over time can very

[2]It were actually the babyboomers who had families by that time that left Amsterdam for more open / green areas directly neighboring Amsterdam.

[3]Both Ambrose, Eichholtz, and Lindenthal (2013) and Ngene, Lambert, and Darrat (2014) do not look directly at which variables affect house prices before and after a break. More specifically, Ambrose, Eichholtz, and Lindenthal (2013) explore the rent-price ratio on the same Herengracht as the yardstick for fundamental valuation for two sub-periods (1650 – 1915 and 1916 – 2005) and Ngene, Lambert, and Darrat (2014) analyse structural breaks in long memory or fractional integration using an ARFIMA model between 1991 and 2014 in the US. Ambrose, Eichholtz, and Lindenthal (2013) assume that interest rates and rents 'capture' all fundamentals such as economic development, demographics, wars, etc.

easily result in house price increases to be incorrectly interpreted as a bubble (Ngene, Lambert, and Darrat 2014). In the literature it is quite standard to measure bubbles using an error correction approach. Whenever prices are above (below) equilibrium houses are overvalued (undervalued). However, the equilibrium relation (and thus the deviation from it) depends on which variables are included. In fact, a number of academic studies conducted in the early 2000s suggested that the U.S. housing market was experiencing the characteristics of a house price bubble (see Ambrose, Eichholtz, and Lindenthal 2013). However, Case and Shiller (2003) compared U.S. house price growth with income growth since 1985 and concluded that income growth could explain nearly all of the house price increase for over 40 states. In addition, McCarthy and Peach (2004) found little evidence supporting a bubble in the U.S. housing market after adjusting housing prices to account for the effects of interest rate changes. In our study, we will cope with such issues by allowing the cointegrating relationships to change over time.

The remainder of this Chapter is structured as follows. Section 2.2 provides a discussion on the historical context of the Amsterdam housing market and Section 2.3 describes the data used in this study. Section 2.4 contains the methodology to examine the time-varying determinants of house prices. In Section 2.5 we report the results and Section 2.6 concludes.

2.2 House Prices and the Historical Context of the Amsterdam Housing Market

To examine the long-run determinants of house prices, we start with constructing a price index for the Amsterdam housing market. We are not particularly interested in individual transaction prices, but in the price developments over time and the macro-economic determinants that can explain those changes. We used two sources to construct the long-run house price index. For the period 1825 - 1972 we exploit the same data as is used by Eichholtz (1997). The dataset covers all transactions of dwellings on the Herengracht from 1628 to 1972 (see Appendix A.1).

The Herengracht is one of the central canals in Amsterdam that was constructed between 1585 and 1660. By 1680, most of the canal lots were developed. The population and radius of Amsterdam grew only slowly in our analyzed period, and during most of this time the Herengracht remained a mix of residential properties and offices (Geltner et al. 2014). Only in the beginning and in the mid of the 20$^{\text{th}}$ century did Amsterdam see a sudden expansion of its metropolitan area size.[4] One particular complication with this type of historical data is that at some periods in time there are not many or even no sales (see Appendix A.1). In addition, it may also take a long period of time between transactions of the same house. This is something

[4]In the 1930s an extensive construction plan ('plan Zuid') was executed and supervised by the famous Dutch architect Berlage. After the Second World War, and with help of the Marshall-plan, Amsterdam expended to both the West and East.

we explicitly have to take into account when constructing the house price index.

Since most of the dwellings on the Herengracht have survived until this day, we can use a repeat sales approach to construct a 'constant quality' house price index. As is typical for repeat sales models, our method does not control for capital expenditures (including large scale renovations) and depreciation, resulting in a under- or overestimation of the price index, respectively (Harding, Rosenthal, and Sirmans 2007). Especially in our case, with almost 200 years of data, many structures will have been altered completely. However, the most important characteristics of the properties remain the same: Location, land size and property type.[5] Moreover, pairs with an (absolute) average return of 50% per year were omitted from the data. These 'abnormal' returns are probably caused by large scale changes to the property between sales.[6] Also, in our specific application, we will only look at 30-year windows (see Section 2.4). The effect of (occasional) renovations on a house price index is less over 30-year windows than over the entire 200 years. Therefore, we expect that the repeat sales index will still be a good approximation of house price appreciation even in the long-run and we will use the index as basis for our analysis.

For this research, we have used a structural time series approach to estimate a local linear trend (i.e. house price index) model using the repeat sales methodology described by Francke (2010), instead of the more standard dummy variable approach (as made popular by Bailey, Muth, and Nourse 1963). This approach has the following benefits. Firstly, the model is tailor made for thin markets and is able to cope with the often large time between sales (which can be decades in our case). Secondly, because we estimate a stochastic (local linear) trend to construct a house price index, the resulting price index should be less sensitive to (short-run) outliers and more sensitive to macro-economic (long-run) shocks. A detailed description of the construction of the house price index is available in Appendix A.1.1 and A.1.2.

Figure 2.2 contains the estimated real (log) price index from 1825 until 1973.[7] We have extended the price index for the period 1973 – 2012 by using the Herengracht Index (HGI) as published on the website of Eichholtz.[8] This index is based on a more traditional, Case and Shiller (1987), Repeat Sales methodology as described in Eichholtz (1997). The price index used in the analysis is deflated using the Consumer Price Index (CPI) which is directly available

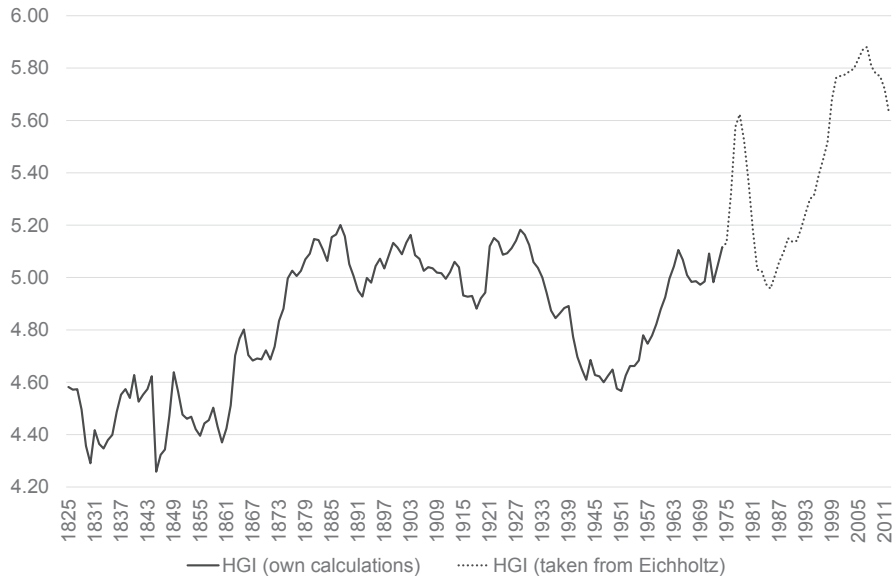
[5]Especially in large cities (like Amsterdam), it is known that the location is an important price determinant as the land value takes up a large proportion of the total house price value (Glaeser, Gyourko, and Saiz 2008).

[6] An alternative approach can be found in Goetzmann and Spiegel (1995). The model by Goetzmann and Spiegel (1995) is an extension of the model by Case and Shiller (1987). Around the time of sale they expect that households who either sell or buy the property will make improvements to the structure and surroundings. This causes an increase in the value of the property which is independent of time. Therefore, they propose to add a non-temporal return to the model at the time of sale.

[7]We have estimated the price index using data starting from the 17$^{\text{th}}$ century onwards to increase the accuracy of our estimates. The analysis in the remainder of this study, however, is based on the price index from 1825 onwards since the explanatory macro factors are only available as of 1825.

[8] We did not have access to the underlying micro data for this time period. Alternatively, we also used data from the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM) as robustness check. However, the results and conclusions remain the same.

Figure 2.2: Log real house price index (1825 – 2012) and its sources.



Notes: Price index of the Herengracht (HGI) is based on the Herengracht micro data before 1977, using the Bayesian Repeat Sales model described in Appendix A.1.1 and A.1.2. After 1977 we use the HGI as publicized on the website of Eichholtz.

from the website of Statistics Netherlands. The CPI is the only deflator available to us for the entire time period.

Some of the explanatory variables in this research will be Amsterdam specific. Other explanatory variables, like GDP per capita, and unemployment rates, are on a (Dutch) aggregate level since this data is not available to us for Amsterdam for such a long time period. We are comfortable making the assumption that these macro variables will still affect Amsterdam house prices, as the Dutch economy is heavily intertwined since the Renaissance (Geltner et al. 2014). In addition, in case of the construction costs and interest rates, there is no reason to believe that there is a (large) difference between the nationwide and Amsterdam specific time series. In that regard, it is also important to note that the Netherlands is comparable in terms of population and land size to a large Metropolitan Statistical Area (Dröes and Hassink 2013). The Netherlands has a clear urban core (of which Amsterdam is part of) and a surrounding periphery, which accords with the definition of a MSA.[9]

2.3 Data and the Determinants of House Prices

In long-run equilibrium, new building developments are determined by production costs and the costs of land. When prices go up, because of an increase in demand and a temporary shortage of houses, there is an incentive to construct new houses (Francke, Vujić, and Vos 2009). The supply of these houses will bring the house prices down to a new equilibrium (DiPasquale and Wheaton 1994). Since we are interested in this long-run equilibrium, house prices should be examined by a macroeconomic housing model where supply and demand factors are both considered. In this study we focus on the following fundamental determinants of house prices: Housing supply, construction costs, Gross Domestic Product (GDP) per capita, the opportunity cost of capital, population growth, unemployment rate, and the working age population as percentage of total population. These variables are typical in studies which focus on explaining (long-run) house prices, see Table 2.1.[10] Unfortunately, there are no time series on the (non-housing) wealth of households for the total studied time period in the Netherlands. The opportunity cost of capital is a combination of interest rates and user costs. In this Section, we discuss why these determinants are important, the different data sources that have been used, and the descriptive statistics.

Table 2.2 contains the data sources used in this Chapter. Most of the macro-economic factors are available from Statistics Netherlands (CBS). The interest rates, used to compute the opportunity cost of capital, are taken from the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM) and Homer and Sylla (2005). As mentioned, house prices are

[9] The Netherlands is comparable in terms of population with large Metropolitan Statistical Areas (MSAs) such as the New York MSA and has the same GDP as the Los Angeles MSA.

[10] In this case *long-run* means the estimates of the long-run equation in error correction models. All studies mentioned in Table 2.1 used an error correction framework.

Table 2.1: House price determinants according to a selected number of studies.

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
Construction costs		✓	✓			✓		✓	
Housing or land supply		✓	✓	✓	✓				
GDP / income	✓	✓	✓	✓	✓	✓	✓	✓	
Wealth		✓			✓				
Interest rates / User costs	✓	✓		✓	✓	✓	✓	✓	✓
Population	✓	✓	✓		✓	✓			
Country	US	UK/US	US	US	US	NL	NL	OECD	NL
Frequency	Y	Q	Y	Y	Y	Q	Y	Q	Y
Sample start	1979	1969	1979	1982	1981	1975	1965	1975	1650
Sample end	1996	1996	1995	2004	2003	2002	2009	2007	2005

I = Malpezzi (1999), **II** = Meen (2002), **III** = Capozza et al. (2002), **IV** = McCarthy and Peach (2004), **V** = Verbruggen et al. (2005), **VI** = Gallin (2006), **VII** = Francke, Vujić, and Vos (2009), **VIII** = Adams and Füss (2010). **IX** = Ambrose, Eichholtz, and Lindenthal (2013).
US = United States, **NL** = the Netherlands, **UK** = the United Kingdom, **OECD** = the countries participating in the Organisation for Economic Co-operation and Development.
Y = Yearly, **Q** = Quarterly.

obtained from Eichholtz (1997). House prices, construction costs, and GDP are index values. Housing supply is measured as the number of houses in Amsterdam.[11] The labor force share, the opportunity cost of capital, and employment are in percentages. Population is the total number of inhabitants in Amsterdam. Table 2.2 also contains a broad classification of the macro-economic factors into (housing) demand and supply factors (including their expected sign). Table 2.3 and 2.4 reports the descriptive statistics of the macro-economic factors respectively in levels and in log first-differences (i.e. percentage differences). All time series (except population, housing supply, labor force and unemployment) are deflated using the CPI. The time series (figures) in log-levels are given in Appendix A.1.3. We will discuss the expected impact of the macro-economic factors on house prices in the remainder of this Section.

Real GDP per capita is seen as a proxy for economic activity and/or income (Englund and Ioannides 1997). An increase in income is expected to have a positive effect on housing demand and, consequently, house prices. GDP has been increasing over time, on average, by 2.8 percent each year (see Table 2.4). Note that GDP is missing for the First and Second World War periods (see Appendix A.1.3).

Population growth is another typical demand-side variable. Between 1825 and 1970 population of Amsterdam steadily grew from less than $200,000$ to almost $870,000$ inhabitants (see Table 2.3). If supply, at least in the short-run, is fixed due to the time it takes to construct buildings (Harter-Dreiman 2004) or legislation and lack of available space (Hilber and Vermeulen 2012), an increase in population is expected to have a positive effect on house prices.

[11] Homes built outside of Amsterdam can also affect house prices inside Amsterdam. We therefore also tested the effect of housing supply in the Netherlands on our price index. The results remain comparable. However, using Amsterdam specific housing supply increases the total number of cointegrating relationships.

Table 2.2: Data sources: Macro-economic variables and house prices.

Variable	**Aggregation**	**Source**	**Unit**	**Type of determinant**	**Expected sign**
House price index	Amsterdam	Eichholtz (1997), CBS	index		
Housing supply	Amsterdam	OIS	units	Supply	-
Construction costs	Ams./Neth.	CBS, Neha	index	Supply	+
GDP per capita	Netherlands	CBS	index	Demand	+
Labor-Force	Netherlands	CBS	%	Demand	+
Opp. cost of capital	Netherlands	NVM, Homer and Sylla (2005)	%	Dem./Sup.	-/+
Unemployment	Netherlands	CBS	%	Demand	-
Population ($\times 1,000$)	Amsterdam	OIS	total	Demand	+
Consumer Price index	Netherlands	CBS	index		

CBS = Statistics Netherlands, Neha = Dutch Historical Archives, OIS = Research, Information and Statistics, City of Amsterdam and NVM = the Dutch Association of Realtors.

Table 2.3: Descriptive statistics (real, levels): Macro-economic variables and house prices.

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Skewn.**	**Kurt.**	**P-value**
House price index	150.79	62.18	70.70	358.04	1.55	5.35	0.352
Housing supply ($\times 1,000$)	188.12	103.01	80.00	397.46	0.56	1.93	0.999
Construction costs	171.08	101.27	64.83	405.14	0.77	2.18	0.038
GDP per capita	6,257	11,888	97.00	45,569	2.07	6.20	0.579
Labor-Force	40.27%	2.17%	36.75%	47.59%	1.28	5.52	0.116
Opp. cost of capital	6.12%	2.59%	1.00%	12.79%	5.11	2.84	0.000
Unemployment	4.80%	2.90%	0.80%	17.40%	2.10	8.88	0.233
Population ($\times 1,000$)	556.54	237.81	192.33	872.43	-0.30	1.49	0.707
Consumer Price index	693.89	953.05	96.00	4,572.00	1.68	4.44	0.939
Number of observations			187				
Sample period			1825-2012				

Note. The reported P-values are the significance levels at which you can reject the null hypothesis of a unit root (Augmented Dickey Fuller test). All ADF tests were done with a constant and a trend. Critical values are taken from MacKinnon (2010). The test is conducted on the log of the variable.
The lag lengths differ per variable and are based on the Akaike Information Criterion.

Table 2.4: Descriptive statistics (real, ln first differences): Macro-economic variables and house prices.

Variable	Mean	Std. Dev.	Min.	Max.	Skewn.	Kurt.	P-value
House prices	0.006	0.070	-0.365	0.258	-0.492	7.358	0.000
Housing supply	0.009	0.011	-0.020	0.080	1.510	11.717	0.002
Construction costs	0.006	0.067	-0.338	0.278	-0.254	7.732	0.000
GDP per capita	0.028	0.057	-0.190	0.187	-0.318	3.899	0.000
Labor-Force	0.001	0.006	-0.017	0.022	0.528	4.780	0.324
Opp. cost of capital	-0.005	0.284	-0.847	0.999	0.142	5.066	0.000
Unemployment	0.001	0.207	-1.211	0.606	-0.813	9.969	0.000
Population ($\times 1,000$)	0.008	0.015	-0.068	0.080	-0.034	9.890	0.000
Consumer Price index	0.019	0.058	-0.145	0.360	0.739	9.094	0.000
Number of observations			186				
Sample period			1826-2012				

Note. The reported P-values are the significance levels at which you can reject the null hypothesis of a unit root (Augmented Dickey Fuller test). All ADF tests were done with a constant and a trend. Critical values are taken from MacKinnon (2010).
The lag lengths differ per variable and are based on the Akaike Information Criterion.

Between 1970 and 1985 the population of Amsterdam shrunk with almost $200,000$ inhabitants due to large scale deurbanisation in that period. Glaeser and Gyourko (2005) found that population decline has a disproportionate effect on house prices, because the durability of housing means that it can take decades for negative urban shocks to be fully reflected in housing supply levels. During the 1990s and 2000s the population of Amsterdam grew to almost $800,000$. Alternatively, working age population as percentage of total population might also have a positive effect on house prices (Case and Shiller 2003). In essence, having a job is a precondition for owning a house. It typically, conjointly with income, determines house price dynamics (see also Chan 2001). The working age is defined as the percentage of population aged between 20 and 65. The percentage working age population to total population during the period 1825–2012 has been between 36 to 47 percent (see Table 2.3). We only have data on the percentage working age population on a Dutch aggregate level.

Several studies also show that unemployment negatively affects house prices (see for example De Wit, Englund, and Francke 2013; Adams and Füss 2010; Abraham and Hendershott 1996). On average unemployment levels have been relatively low in the Netherlands (4.8%, see Table 2.3). However, in the 1930s - during the Great Depression - unemployment peaked at 17%.

The 5-year-annuity (nominal) mortgage interest rate, from 1973 onwards, is taken from the NVM. We use an index of the long-term Dutch government bond yields to proxy for the (mortgage) rates before this period (taken from Homer and Sylla 2005). Subsequently, the real opportunity cost of capital is calculated by (see Williams 2009):

$$OCC_t = (N_t - \mathrm{E}\big[\Delta cpi_t\big]) + 2\%, \tag{2.1}$$

where N_t is the nominal rate and cpi_t the log of the CPI in year t. As is usual when computing the opportunity cost of capital we take the expected inflation instead of inflation itself, by using a simple (7-year) Moving Average filter. We add 2% to measure (imputed) rental returns minus maintenance expenditures and other costs. During the 19$^{\text{th}}$ century inflation was at times extreme. The time series of the opportunity cost of capital is very volatile (see Table 2.4). Only after the Second World War does the opportunity costs of capital seem to stabilize. We introduce a (lower bound) opportunity cost of capital cap of 1%, since we want to circumvent taking the log of a negative value and generally to filter out extreme values. This happened in 9 (consecutive) periods, with 5 of them being during the Second World War. The extremely low opportunity cost of capital in the 1970s is not surprising given the high inflation during this period (oil crises). The opportunity cost of capital can be interpreted as a demand and a supply-side factor. In particular, higher out-of-pocket costs (in case of increasing oppurtunity cost of capital) will decrease the demand for housing resulting in decreasing house prices (Schilder 2012). Alternatively, a higher interest rate may also have a negative effect on the ability of construction companies to obtain a loan, which decreases the supply of new housing and, consequently, increases house prices (DiPasquale and Wheaton 1994; Capozza et al. 2002). The effect of the real interest rate is, therefore, mainly an empirical question.

The value of a property can be interpreted as the value of land plus the value of the structure (Bourassa et al. 2011). The construction cost of a property measures the replacement value of a structure and, therefore, is typically capitalized into house prices (see Case and Shiller 1990; Davis and Palumbo 2008). Furthermore, any given positive economic shock will be easier for an area to absorb if the housing stock can be increased at low cost. Therefore, we hypothesize that variables proxying for the cost of increasing the supply of housing should affect the time series properties of housing prices (Capozza et al. 2002). A construction cost index for the Netherlands from 1913 onwards is directly available from Statistics Netherlands. We used data from the Dutch Economic Historical Archives (in Dutch: 'Nederlandsch Economisch-Historisch Archief', abbreviated as Neha) as a basis to construct a measure for the construction costs index before 1913. The Neha reports the costs of all building materials in Amsterdam on a yearly basis from 1800 to 1913. Using the expert opinion of a Dutch architect specialized in 19$^{\text{th}}$ century buildings in Amsterdam we constructed a 'standard' home for this era. Next, the materials needed for this 'standard' home have been multiplied by the costs given by Neha. Based on the historic data from Statistics Netherlands, we assume that the material costs is constant at 70 percent of the total cost for new housing. For the remaining 30 percent, the costs are indexed by the national wage index (also obtained from Neha). Finally, the construction cost index is deflated by the CPI. The construction cost index quadrupled during our sample period (see Table 2.3). Also note the large increase in construction costs during World War I. This was mainly driven by the scarcity of (building) materials during this period.

Finally, we use Amsterdam specific housing supply to measure new housing construction. More specifically we use the number of housing units, both for the (social) rental and owner-

occupied market in Amsterdam, made available to us by Research, Information and Statistics, City of Amsterdam (OIS) after 1908.[12] Before 1900 the number of buildings are reported in the OIS data (multiple housing units can be in one building). We use an index of the number of buildings to proxy for the number of housing units before 1900. There is no data available on housing supply between 1900 and 1908 and for the first 10 years (1825 – 1835). In both instances we assume that during these periods there was no new construction.

During the 1930s the number of housing units sky-rocketed in Amsterdam. This reflects a change in policy view: Every labourer in Amsterdam should have a decent place to live. To this day, this is reflected in the substantial share of social housing in the Amsterdam (Van Ommeren and Koopman 2011). We expect that new housing supply has a negative effect on house prices. Differences in supply elasticity have been argued to explain differences across US metropolitan statistical areas (MSAs) in house price levels and volatility (Green, Malpezzi, and Mayo 2005; Glaeser, Gyourko, and Saiz 2008; Paciorek 2013; Wheaton, Chervachidze, and Nechayev 2014). In part, this may also reflect differences in regulation and space constraints (Hilber and Vermeulen 2012). To the extent that those changes also occur over time, the size of the housing investment effect can change over time.

Housing literature generally treats both population and housing supply to be endogenous to house prices. Population and house prices are endogenous due to omitted variables which affect both prices and population (Saiz 2007). House prices and supply are interlinked as they are jointly set in equilibrium (see Mayer and Somerville 2000; Paciorek 2013). In our case however, we use city center (Herengracht) house prices and Amsterdam level population and housing supply variables. The supply of houses on the Herengracht actually did not change *that much* over the analyzed period. As mentioned in Section 2.2, by 1680 most of the canal lots were already developed. The population of the city centre even decreased from almost $200,000$ before the 1850s to less than $80,000$ in 2012. Households moved to more modern and more spacious houses as new neighbourhoods were constructed. Thus, in our case population and supply can be considered (pre-)determined outside the model.[13]

2.4 Model

The effect of the macro-economic determinants on house prices reflects both short-run fluctuations and long-run trends. These price dynamics can be captured by an error correction model (ECM), in which the dynamics are captured by a combination of current and past shocks and a gradual adjustment towards equilibrium. This model is based on the idea that the included

[12] There are many other potential measures of housing construction, such as the number of building permits issued (Hilber and Vermeulen 2012; Paciorek 2013) or new housing starts (Mayer and Somerville 2000), however the actual housing supply is generally regarded as the most appropriate measure (Paciorek 2013).

[13] A Rolling Granger Causality test between the variables, revealed that house prices did not Granger-Cause both housing supply and population. In addition, our results indicate that housing supply and population are typically not in the same cointegrating equation, which is most likely due to multicolinearity.

time-series are, although non-stationary, cointegrated: Linear combinations of the variables are stationary. These linear combinations can be interpreted as equilibrium relationships. Therefore, it should be no surprise that error correction models are a popular tool in analysing long-run house prices. Again, Table 2.1 contains a few examples of error correction models in housing literature. The standard error correction model is given by:

$$p_t = \beta + x_t'\delta + \varepsilon_t, \tag{2.2}$$

$$\Delta p_t = \sum_{k=0}^{n} \lambda_k \Delta p_{t-k} + \sum_{k=0}^{n} \Delta x_{t-k}'\theta_k + \alpha\left(p_{t-1} - p_{t-1}^*\right) + \eta_t, \tag{2.3}$$

where Eq. (2.2) represents the long-run equilibrium relation and Eq. (2.3) represents the short-run relation. Variable p_t is the (log) house price index at time t, p^* are the fitted values of Eq. (2.2) and x is a vector of macro-economic covariates (i.e. population growth, housing supply, labor force, construction cost, unemployment, opportunity cost of capital, and GDP per capita). Parameter α, in the short-run relation (Eq. (2.3)), measures the degree of mean reversion and is estimated from the data. The series $\left(p_t - p_t^*\right)$ is also referred to as the error correction term. If the series $\left(p_t - p_t^*\right)$ is stationary, then $\left(p_t - p_t^*\right)$ is the co-integrating relation. In this study, we are especially interested in the parameters β and δ (the long-run cointegrating relationship) in Eq. (2.2). In the remainder of this Section we will discuss why the parameters β, δ, λ, θ and α are likely to be time-varying and how we model this.

The parameters are likely time-varying in the long-run because of (long) real estate cycles. The main reason for real estate cycles to occur is because developers tend to overbuilt if developers' future projection of demand (usually measured by macro-economic variables) is positive (Pyhrr, Roulac, and Born 1999). Especially delivery lags and illiquidity worsens the ability of developers to respond quickly to changes in demand. Too much supply suppresses prices (Mayer and Somerville 2000) for a considerable time, until aggregate demand and supply are in equilibrium again. Unfortunately, literature in the field of real estate cycles is not unambiguous on the average length of a typical cycle. The 'average' real estate cycle is somewhere between 18 years (Rabinowitz 1980) and 60 years (Kaiser 1997).

A second reason why the parameters are likely to be time-varying relates to regime shifts. The change of, or shift in, political and economic regimes usually occurs when a smooth change in an internal process (feedback) or a single disturbance (external shocks) triggers a completely different system behaviour. Common examples in the real estate literature are changes in legislation and innovations in the construction or mortgage market (Fernandez-Corugedo and Muellbauer 2006).

The challenge is to recognize when a cycle starts and ends, which variables are part of the cointegrating relationship, and when there has been a shift in regime. In practice this is very difficult to identify. A yearly rolling regression with changing combinations of covariates

is attractive in this regard, because it allows us to estimate a series of parameters without imposing any particular structure on the way in which conditional covariates change over time (Rossi 1996). To simplify the procedure we estimate the error correction model in a (rolling) 2-step Engle-Granger framework (Engle and Granger 1987). Since we estimate the long-run equation (first step, Eq. (2.2)) separate from the short-run equation (second step, Eq. (2.3)) and because no lags are included in the long-run equation, the total number of possible combinations of covariates reduces considerably.[14] To simplify the procedure even further, we use the same variables in the short-run equation as we use in the long-run equation.

Consequently, the specification of the rolling error correction model becomes (Eqs. (2.4) – (2.5)):

$$p_t = \beta_r + x_t'(r)\delta_r + \varepsilon_t, \tag{2.4}$$

$$\Delta p_t = \lambda_r \Delta p_{t-1} + \Delta x_t'(r)\theta_r + \alpha_r\left(p_{t-1} - p_{t-1}^*\right) + \eta_t, \tag{2.5}$$

for $t = r, \ldots, r+n-1$ and $r = 1, \ldots, T-n+1$. The dependent and independent variables are of fixed length for any regression and represents the n periods (denoted *the window length*) immediately preceding period t. The function r reflects different combinations of covariates (one such combinations could be: Population and construction costs) per window. Thus, we get estimates for δ in every window for every combination of covariates r. This estimation procedure provides consistent estimates of the β and δ values - provided that p and x are cointegrating (Lütkepohl and Krätzig 2004). In total the estimation and selection procedure consist of four steps.

Firstly, one important requirement is that the variables are integrated of order 1 (I(1)). If a variables is I(0) in a particular time window, the variable is excluded from the regression in that particular window (see Appendix A.1.4). Secondly, we regress all remaining combinations of covariates (r) in every window on house prices, using Eq. (2.4). We choose to fix the window length n at 30 years, as this is roughly the average length of a real estate cycle found in literate. For robustness, we also tried window lengths of 20, 25 and 40 years. However, the key results did not change. In addition, the number of cointegrating relationships was largest using 30 year windows.

In the third step we establish which combination of covariates (x_r) are cointegrated. The most important requirement is that the error correction term $\left(p_{t-1} - p_{t-1}^*\right)$ is stationary. If multiple combinations of x are cointegrated in one window, the combination of variables which are cointegrated at the 1% level are reported in favor of the combination of variables which

[14] Instead, estimating the R-ECM in a dynamic way, in an ADL framework or by the Johansen trace/eigenvalue test would acquire lags of the dependent and independent variables. The number of lags can be different for every variable. Different combinations of lag structures can result in different cointegrating relationships. This ammounts to an almost infinite number of possible relationships.

are cointegrated at the 5% level. If the degree of cointegration is similar for more than one combination of covariates in the same window, we look at the adjusted R^2. Another requirement is that the parameter estimates are at least significant at the 10% level. To account for the missing data for GDP per capita during the two war periods and, more in general, to estimate the effect of the wars on house prices a dummy for these periods is added to every regression in which one or both wars are within the window length.

In the fourth and final step, the model is re-estimated in first-differences, with the inclusion of the error correction term (lagged one period) estimated from the first step, see Eq. (2.5). Both (long- and short-run) models are estimated with OLS. In our application, we end up with 158 windows. Our 7 variables give a total of 127 possible combinations of covariates. Thus, we estimate more than $40,000$ different models (total long-run *and* short-run regressions). The next Section summerizes our findings.

2.5 Results

In this section, we discuss the most important findings. The results are summarized in Table 2.5 and Figure 2.3. Table 2.5 reports the number of times a variable was part of a cointegrating relationship during certain time periods. The final column of Table 2.5 also gives the average coefficient estimate over the entire period in parenthesis. The main drivers of house prices in the 19^{th} century were construction costs, housing supply and population. After 1900 the Gross Domestic Product per capita starts to play a role and after the 1970s interest rates as well. After World War II population and housing supply are key additional determinants of house prices.

In approximately 50% of all windows at least one cointegrating relationship was found. In most cases the number of variables in the cointegrating relationship is between 2 and 4 (including a constant), see Figure 2.3. The reason why we did not find a cointegrating relationship in in all periods could simply be explained by missing variables and measurement errors. However, it is important in this regard to realize that deviations from equilibrium do not adjust to the long-run equilibrium level as well when a housing market is in crisis. Indeed, both Hall, Psaradakis, and Sola (1997) and later Nneji, Brooks, and Ward (2013) found evidence for this using error correction Markov switching models for the UK and the US, respectively. The durable nature of housing and 'anchoring' of home-buyers are the main reasons explaining the absence of cointegration. More specifically, supply usually does not adjust negatively in considerable quantities (especially not in the short- or even long-run) in case demand for housing goes down (Glaeser and Gyourko 2005). In addition, in time of crisis households tend to have too high reservation prices due to negative (home) equity or because of loss aversion (Genesove and Mayer 1997; Genesove and Mayer 2001). Periods of consequent crises seem to coincide with windows with low number of cointegrating relationships. For example, the least number

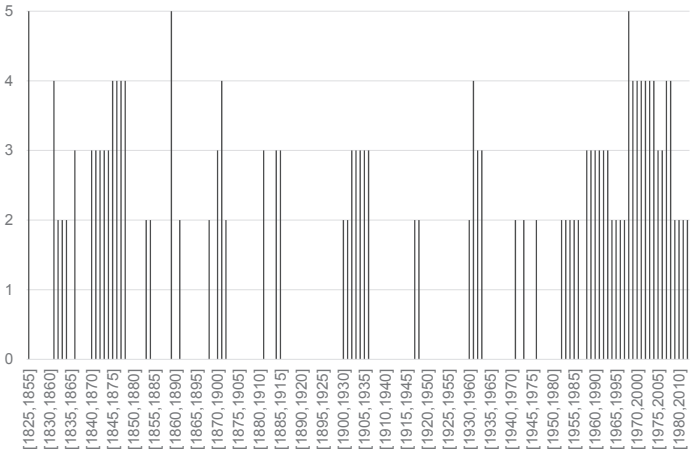
of cointegrating relationships are in the period 1900 – 1945. During this period, the First World War (1910s), the Great Depression (1930s) and the Second World War (1940s) all affected the Dutch economy severely.[15]

Table 2.5: Number of times a variable is part of a cointegrating relationship per subperiod.

Variable	**1825 – 1900**	**1900 – 1945**	**1945 – 1970**	**1970 – 2012**	**Total (Mean Coef.)**
Housing supply	12	5	1	11	29 (-1.48)
Construction costs	11	1	1	4	17 (1.07)
GDP per capita	3	5	3	16	27 (0.39)
Labor force	3	3	1	0	7 (4.57)
Opp. cost of capital	0	0	2	17	19 (-0.39)
Unemployment	7	5	1	2	15 (-0.49)
Population	8	3	2	9	22 (1.55)
Total	44	22	11	59	136
Number of regressions	21	12	7	32	72
Variables p. regression*	3.1	2.8	2.6	2.8	2.9

*A constant is included in this number. However, the war dummy is excluded from this number as it not used in the test for cointegration.

Figure 2.3: Number of variables within a cointegrating relationship.



In all cases a constant is included.

From Table 2.5 it is also evident that unemployment and labor force are not part of a cointegrating relationship in many windows. Even though these variables might not be as interesting from an economic perspective, we kept them included in the model as control variables.

[15]Other examples of crises in the 20th century are the Oil crisis in the 1970s and the dotcom and the Financial crisis in the beginning of the 21th century. In the 19th century the Belgian revolution (1830*s*) and two large crop failures (first one around 1850 and the second one at the end of the 19th century due to cheap imports from the US) resulted in an economic crisis.

In the remainder of this Section we are going to discuss the results in more detail. Section 2.5.1 contains the time-varying, long-run, estimates of the demand side factors, and Section 2.5.2 those of the supply side factors. In Section 2.5.3, the model diagnostics, the error correction term estimates (i.e. the adjustment parameter), and the impact of the war time period is discussed. For expositional reasons, the other short-run, second step, estimates are not reported.

2.5.1 Demand side Determinants of House Prices

Figure 2.4 shows the rolling window point-estimates of population on house prices and its effect on house prices. If an estimate is only statistically significant at the 10 percent significance level this is denoted by * (otherwise it is significant at the 5 percent level). The horizontal axis gives the time window for which the error correction model was estimated. The left vertical axis gives the value of the parameter estimate (marginal effect) and the right vertical axis gives the total (maximum) effect of population on house prices by multiplying the maximum population minus the minimum population in that window by the corresponding parameter coefficient.

The population variable is part of the cointegrating relationship in many of the rolling windows. Interestingly, population growth was mainly part of the cointegrating relationship in the 19$^{\text{th}}$ century and during the 1970s. The effect of a one percent population increase has an average positive effect of about one to two percent on house prices. The total maximum effect is between 5% and 60%. There is a spike in the population effect in the windows starting in the beginning of the 1950s, probably due to the high birth rates (baby boomers) after the Second World War.

Figure 2.5 contains the estimates and total effect of the labor force on house prices. The effect of changes in the labor force is only part of the cointegrating relationship in seven windows and it is only highly statistically significant in four cases. Six of the seven successful windows are in the 19$^{\text{th}}$ century. A one percent increase in the working age population as percentage of the total population has a positive 2 to 7 percent effect on house prices. However, the min-max range of labor force has been relatively low per window. During the 19$^{\text{th}}$ century the increase (decrease) therefore only resulted in roughly 14% higher (lower) house prices.

In Figure 2.6 the unemployment effects are depicted. Similarly to the effect of labor force, there are not many windows in which unemployment has a large effect on house prices. Especially before World War II, there seems to be some effect of unemployment. The total effect of a change in unemployment on house prices for this period is 28%.

The effect of GDP per capita and the opportunity cost of capital are presented in Figure 2.7 and Figure 2.8, respectively. There are two striking similarities between these figures. First, both variables are part of the same cointegrating relationship in many of the time windows. Second, the coefficient estimates increase in size especially from the 1970s onwards. Although house prices were affected by GDP per capita during most of the 20$^{\text{th}}$ century, the coefficient is relatively small, less than 0.2 percent after a one percent increase in GDP per

Figure 2.4: Effect of population growth.

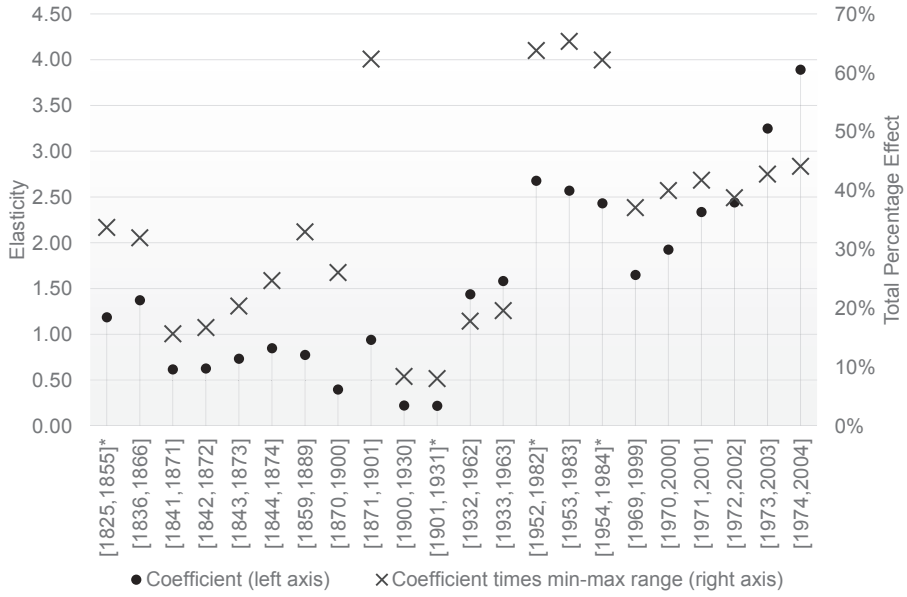


Figure 2.5: Effect of labor force.

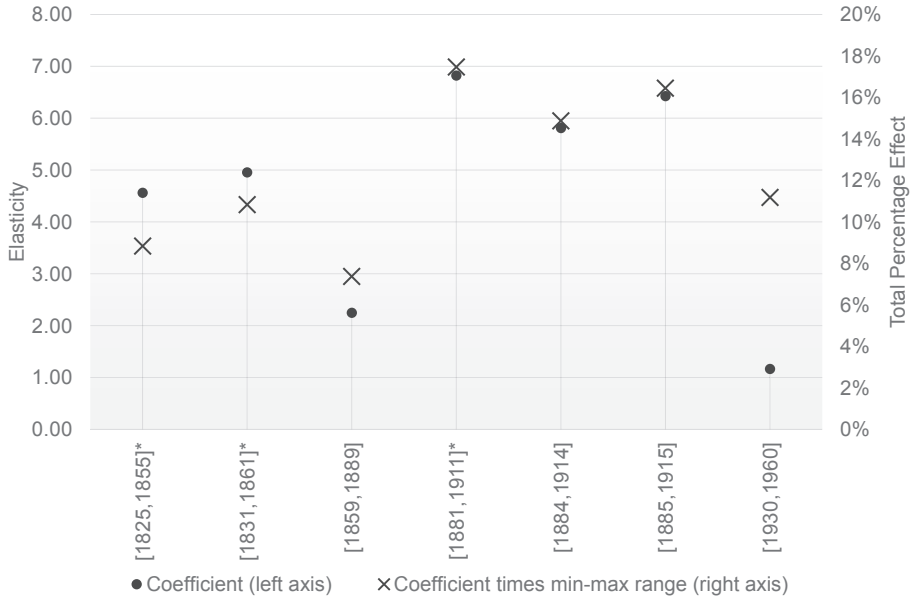
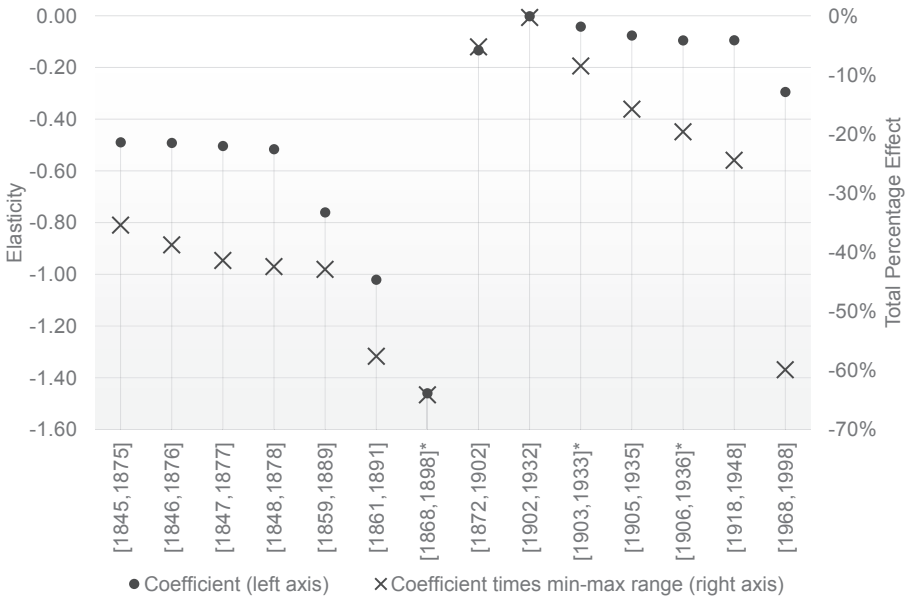


Figure 2.6: Effect of unemployment.



capita in most cases, before the 1960s. During this period most houses were financed by the own savings of households. Instead, during the 1970s financial innovation and liberalization, combined with tax benefits on mortgage debt, made the use of mortgage debt more popular (Fernandez-Corugedo and Muellbauer 2006) and, consequently, the impact of GDP on house prices increased. Interestingly, during the 1980s the Loan-to-Value cap increased to over 100%, a feature of the Dutch housing market which persists until this day (Andrews, Sánchez, and Johansson 2011).

The amount of mortgage debt a household can borrow is not only determined by income but also by interest rates. It is, therefore, not surprising that both variables have jointly determined house prices after 1970. A one percent increase in GDP per capita had an effect on house prices between 0.2 and 1 percent. A percent decrease in the opportunity cost of capital (again the variable is in logs) has had a positive effect of 0.2 to almost 1 percent on house prices. Although we argued that the opportunity cost of capital can also be viewed as a supply-side factor affecting housing construction, our empirical estimates suggest that the demand side impacts are dominating. The total maximum effect of the opportunity costs of capital after 1970 is 60% on average.

Figure 2.7: Effect of GDP per capita.

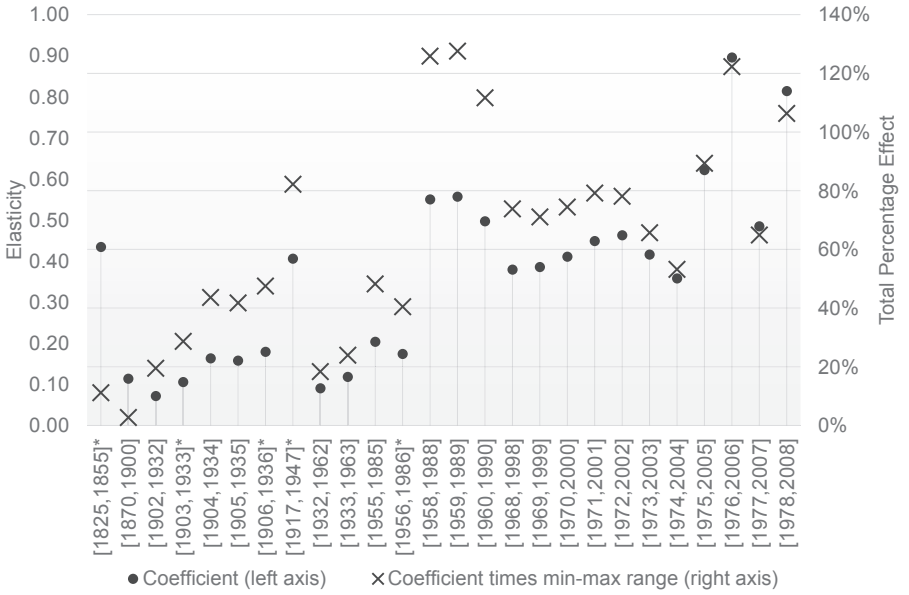
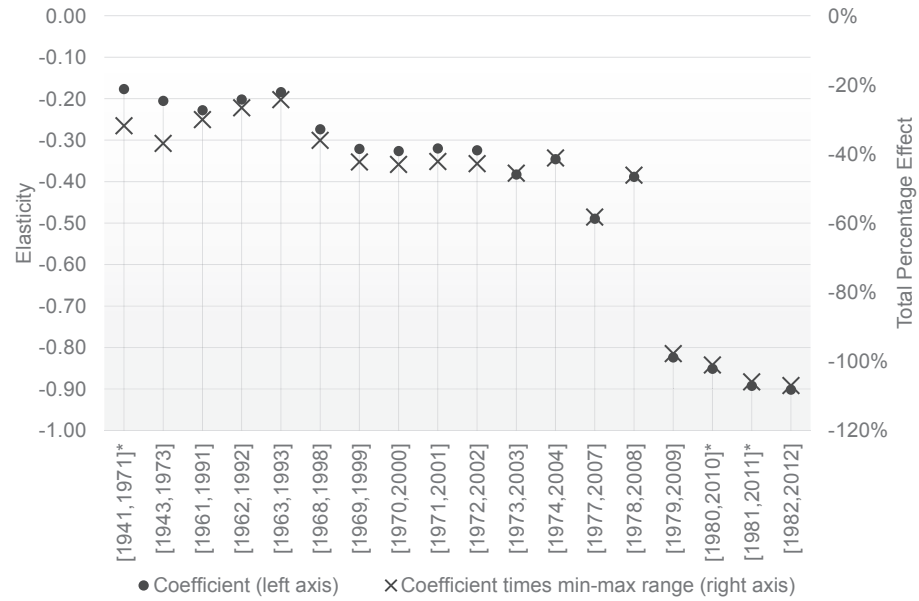


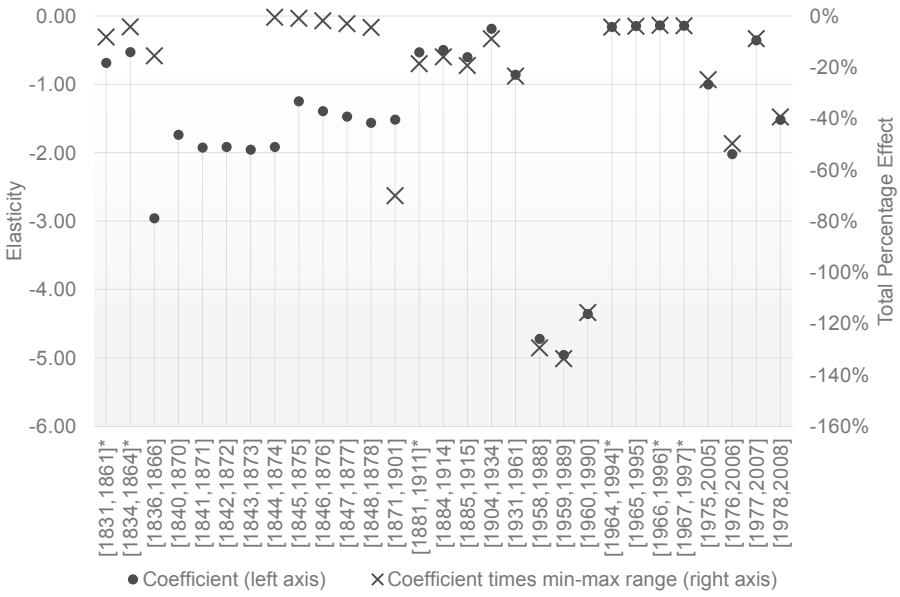
Figure 2.8: Effect of opportunity cost of capital.



2.5.2 Supply side Determinant of House Prices

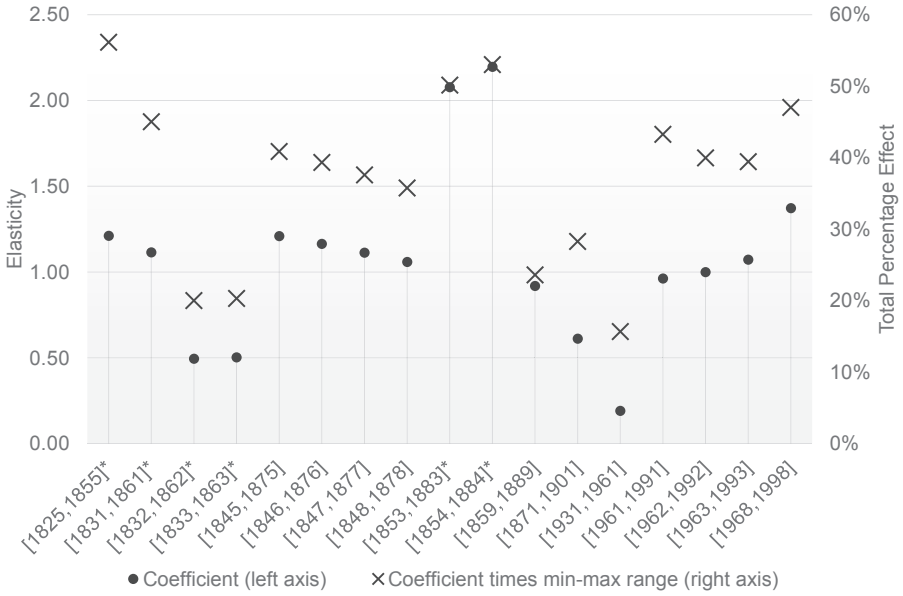
Housing supply and construction costs are considered supply side determinants of house prices. Figure 2.9 shows the long-run coefficient estimates for the housing supply variable. The effect of a one percent increase in housing supply results in a 1.5% house price drop on average. Between 1830 and 1860 the coefficient of housing investment on house prices is relatively large, compared to the other periods. However, the min-max range of investment in housing during this period is low, which attenuates the effect of investment in housing on house prices. Interestingly, between the periods 1958–1988 and 1960–1990 there is a relatively large effect of housing investment on house prices. This likely reflects the post-war reconstruction of the Netherlands.

Figure 2.9: Effect of housing supply.



The construction cost index is used to proxy for changes in structure values and for the rate at which constructors can add new housing supply to the market. Figure 2.10 shows the effect of construction costs on house prices. In most cases the elasticity is close to one. This suggest that house prices have mainly increased because the construction cost of houses increased. In a well-functioning market this is what one would expect. However, as mentioned earlier in Section 2.5.1, during most of this period population was also part of the cointegrating relationship. If housing markets would be efficient, however, supply should adjust immediately if prices increase and population should not have an effect on house prices. The maximum total effect of construction costs on house prices ranges between zero and 60 percent.

Figure 2.10: Effect of construction costs.



2.5.3 Model Diagnostics, Error Correction, and the War Time Period

This section discusses some remaining issues regarding model diagnostics, the adjustment parameter (α), and the effect of war on house prices. The upper left panel of Figure 2.11 presents the effect of the war time periods (World War I, World War II, we included a dummy in the rolling error correction model) on house prices. As mentioned, time series on GDP per capita are missing for this period. The Figure shows that the war time period had a negative effect on house prices of about zero to 54 percent. This is likely an underestimate since the price index is only based on those houses that have actually been sold.

The adjusted R-squared of the estimated regression models are depicted in the upper right panel in Figure 2.11. The average adjusted R-squared is quite high, about 0.6, which is not uncommon to see with this kind of macro-economic data. There is quite some variation around the average. During the mid (end) of the 19$^{\text{th}}$ century, and at the end of our sample period, the adjusted R-squared is above 0.80.

Finally, the lower panel of Figure 2.11 presents the rolling point-estimates of the coefficient of the error correction term in the short-term model, α_r in Eq. (2.5). The average effect of the error correction term is 0.28. This suggests that shocks out of equilibrium are absorbed within 3.5 years. However, there is large variation in this adjustment parameter. For example, during the beginning of the 19$^{\text{th}}$ century and 20$^{\text{th}}$ century there are several periods were shocks out

of equilibrium are corrected almost instantaneously. Instead, in some periods the parameter estimate is as low as 0.05. At that rate shocks out of equilibrium are only absorbed after 20 years.

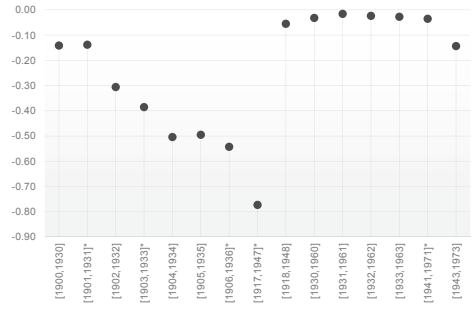
2.6 Concluding Remarks

This Chapter has examined the determinants of house prices using almost 200 years of data from the Amsterdam housing market, the Netherlands. The results show that at different points in time there are different key determinants of house prices (cointegrating relationships).

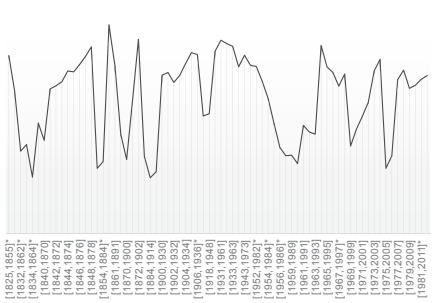
During the 19th century, population, housing supply, and construction costs are the main drivers of house price dynamics. At the start of the 20th century income starts to play a role. After World War II there are a few decades in which housing supply and population determine house prices. This reflects the post-war reconstruction efforts in the Netherlands and increases in housing demand as a result of the birth of the baby-boom generation and subsequent decrease in demand due to the adult baby-boomers leaving the city for greener and more spacious areas neighboring Amsterdam. Finally, from the 1970s onwards, income and interest rates start to have a large impact on house prices, most likely due to financial innovation and liberalization. Starting from the 1970s financing a house through mortgage debt became more popular. It also signals the beginning of a remarkable period in time in which house prices start to increase rapidly in many countries (i.e. the 1990s). Although the results in this research are, to some extent, not surprising, this paper is one of the first to document such long-term changes.

The results in this research can explain why in some instances the key determinant of house prices differ across studies, even if those studies focus on the same housing market, and it provides a more long-term perspective on the fundamentals of house prices. The rapid increase in house prices can, for example, easily be mistaken as a bubble if it is unclear what the impact of different determinants are and how such determinants have changed over time. This Chapter has provided an analysis from the perspective of the Amsterdam/Dutch housing market. It would be interesting to see a similar analysis for other countries to examine to what extent the broad trends discussed in this study are generalizable across housing markets.

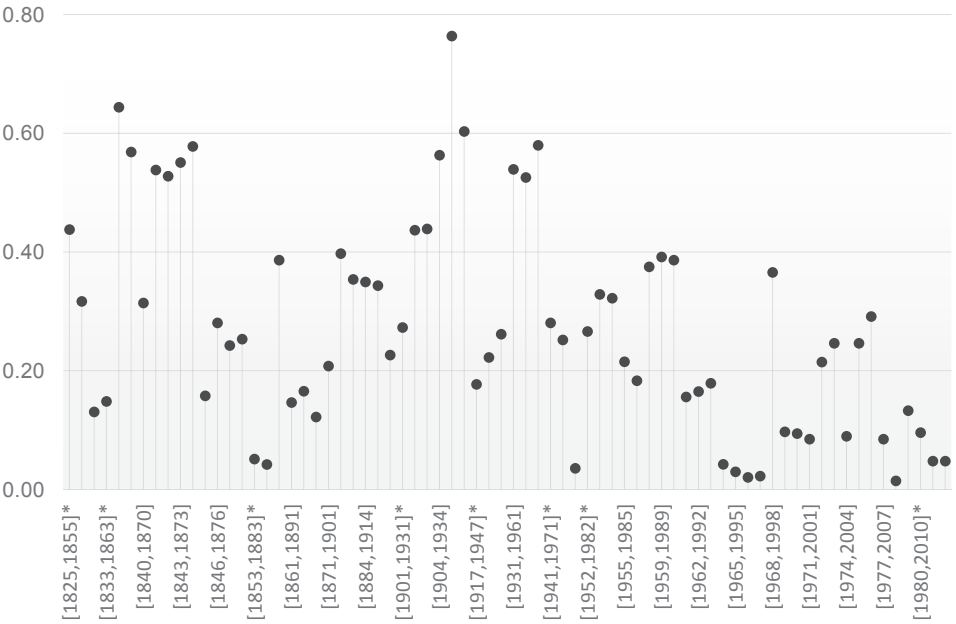
Figure 2.11: Model diagnostics and the War dummy.



(a) War dummy



(b) Rolling adjusted R^2



(c) Error Correction Term

Chapter 3

The Effect of Credit Conditions on House Prices

Abstract[1]

It is widely perceived that the supply of mortgages, especially since the extensive liberalization of the mortgage market of the 1980s, has had implications for the housing market in the Netherlands. In this Chapter we introduce a new method to estimate a credit condition index (CCI). The CCI has subsequently been used as an explanatory variable in an error correction model for house prices for the period 1995 – 2012. In real terms house prices declined about 25% from 2009 to 2012. The estimation results show that about half of this decline can be attributed to a decline in the CCI.

3.1 Introduction

Buying a house is the single most expensive acquisition of households in general. Few individuals have enough savings or liquid funds to enable them to purchase property outright. As a result, households will typically be dependent on a financial institution from which it can borrow a substantial portion of the needed funds. Other financial assets and liabilities are typically far less important than the house and its associated mortgage contract for household wealth (Cocco 2013). It should come as no surprise that theory predicts that house prices are affected by the availability of mortgage credit (Oikarinen 2009). Indeed, Gerlach and Peng (2005), Goodhart and Hofmann (2008) and Hofmann (2004) all find evidence that mortgage lending and house prices are inter-related.

Increasing levels of income and lower interest rates greatly facilitate the ability of financial institutions to advance higher levels of credit to households. However, developments within credit markets themselves also fuelled the availability of mortgage credit. Examples include: (1) the development of markets for financial futures, options, swaps, securitized loans and synthetic securities which allow for easy access to credit for financial intermediaries; (2) more sophisticated risk management, for example improved initial credit scoring; (3) changes in

[1]This chapter is based on Francke, Van de Minne, and Verbruggen (2014).

risk-perception by financial intermediaries due to changes in the macro-economic environment, like the unemployment rate[2]; (4) introduction of new mortgage products; (5) reduced transaction costs and asymmetric information as a result of innovations of information technology, telephony and data management (Bennett, Peach, and Peristiani 2001); and (6) financial liberation (FLIB), where FLIB is the relaxation or tightening of credit controls like liquidity ratios on banks, down-payment requirements, maximum repayment periods, allowed types of mortgages, etc.

These are a few examples which could affect the supply of mortgage credit in any given period, and are usually summarized as the *'credit conditions'*. The most widely used definitions for credit conditions are: '*the supply of credit on the mortgage market other than through the level of interest rates*' (Fernandez-Corugedo and Muellbauer 2006) and '*the strictness or easiness of bank lending standards*' (Hofmann 2004). Contrary to the level of income and interest rates, credit conditions are hard to measure.

The first aim of this Chapter is to derive an index representing the credit conditions in the Netherlands. The credit condition index (CCI) is specified as an unobserved component in an error correction model, where the dependent variable is either the average house price or the average mortgage debt, both for first time buyers (henceforward FTB), and the unobserved component is specified as a stochastic trend. The independent variables include the mortgage interest rates and household income. The model has been estimated on quarterly data in the Netherlands between 1995 and 2012. The second aim of this Section is to measure the impact of credit conditions on house prices. We include the CCI in an error correction model for house prices.

The contribution of this study is twofold. Firstly, to the best of our knowledge it is the first time that a CCI and its impact on house prices has been estimated for the Dutch housing market. The second contribution is that the CCI is specified as a stochastic trend in an error correction model. In previous papers the unobserved component was specified in a less flexible way like splines, trends, time step dummies, or even combinations of the aforementioned techniques. Finally, it should be noted that our measure for credit conditions is free of the well-known endogeneity criticism hampering research in the field of mortgage lending and house prices (see, Hofmann 2004; Gerlach and Peng 2005; Goodhart and Hofmann 2008, among others). Because mortgage lending and house prices in itself are endogenous it is usually difficult to measure the effect of one on the other.

The results show that the estimated CCI has a sharp decrease from 2010 onwards, which can be interpreted as a fall in the availability of credit on the mortgage market. In 2012 the availability of credit on the mortgage market is on the same level as it was in the period 2003 – 2004. Furthermore, the CCI has explanatory power in the error correction model for all house prices. In real terms house prices in the Netherlands declined about 25% from 2009 to 2012.

[2]This affects the probability of defaults (Vandell and Thibodeau 1985; Elul et al. 2010)

The estimation results show that 11%-points of this decline can be attributed to a decline in the CCI.

The setup of this Chapter is as follows. Section 3.2 gives a short description of the mortgage market in the Netherlands. Section 3.3 provides a literature review on credit conditions in mortgage markets. Section 3.4 provides a detailed description of the empirical model and the underlying assumptions. Section 3.5 describes the dataset and provides some statistics. Section 3.6 provides the estimation results and finally Section 3.7 concludes.

3.2 Dutch Mortgage Market

In 2012 housing accounts for 60% of Dutch household wealth (source: Statistics Netherlands). In total Dutch households have €1,154 billion in housing wealth and €675 billion in mortgage debt, divided over 4.3 million households in the owner-occupiers market. Around 1 million Dutch households are 'under water'. These households are mainly households who bought their first home after 2004. Still, the rate of default is relatively low (though the number is increasing) in the Netherlands with only 0.33% of Dutch owner-occupiers with a mortgage quarantee (see below) defaulting in 2012 (Francke and Schilder 2014).

As a result of high collective (second pillar) pension savings, Dutch households have relatively low banking deposits.[3] The average Loan-to-Deposits (LTD) of Dutch banks is almost 2.0, which is among the highest in Europe (together with Ireland and Spain). Because the Dutch mortgage market design is '*deposit funded*' in its core, banks are facing a structural funding gap of around €500 billion. Since the late 1990s Dutch banks have started to securitize mortgages in pools and selling these 'Special Purpose Vehicles' (SPV) to ultimate investors. However, after 2009 this market stalled completely. In the fourth quarter of 2012 the total assets of Dutch SPVs was worth around €276 billion (compared to €283 billion in the second quarter of 2009). More than half of these assets consisted of mortgages. The large funding gap also make banks vulnerable to maturity transformation between interest rates (Campbell 2013), since two-thirds of Dutch mortgage rates are fixed for a of period 10 years or more.

Since 1995 the National Guarantee Fund (government backed) has sold insurances and reimbursed losses, after a control process, to lenders by an organization called National Mortgage Guarantee (NHG). It is an insurance that only covers losses that are the result of unfortunate events like unemployment, divorce and disease. In the Netherlands, it is not the mortgage lenders that insure themselves against default, but the borrower. When borrowers wish to insure the mortgage by NHG, they pay a one-time fee upfront (1% of the loan as of 2014). In return borrowers can stipulate a lower mortgage interest rate. The NHG insurance is not aimed specifically at high-risk households (Francke and Schilder 2014). In the period preceding the global financial crisis banks used less stringent criteria for mortgages than the NHG. Since

[3] 70% of all Dutch savings is in either a retirement fund or in a life insurance.

the financial crisis the underwriting criteria of banks have changed and are currently in line with the criteria set by the NHG. There are three main criteria to qualify for the insurance program: a maximum loan-to-value (LTV), a maximum loan-to-income (LTI) and a maximum mortgage debt amount. These criteria have changed over time. The total number of insured mortgages in 2012 is just over 1 million. These mortgages represent an insured mortgage debt of over €154 billion.

The maximum allowed LTV in the Netherlands has always been among the highest worldwide (Andrews, Sánchez, and Johansson 2011) in modern history, with 112%. However, starting in 2010 the Dutch government has started gradually lowering the maximum allowed LTV on a yearly basis so that it will drop to 100% in 2018.

Financial institutions regulate themselves as well. In the 'Codes of Conduct Mortgage Loans' (GHF)[4] Dutch banks agree on, for example, how to calculate the borrowing limit of consumers. An example of financial liberation which strongly increased the availability of mortgage credit for households by GHF was the decision (around 1990) that households were allowed to use a share of the income of the partner as a basis for obtaining a mortgage. Other examples of financial liberation in the Netherlands are given in Appendix B.1. An international example of self-regulation by financial institutions are the Basel accords.

During the 1990s it became possible to fully deduct mortgage interest rates from your income in the Netherlands, giving a tax benefit. From 2013 onwards, however, interest rate deductibility is only applicable to linear and annuity type mortgages. In other countries where the interest payments are deductible from income (like the US), theory predicts that the demand for mortgage debt will increase considerably (Brueckner 1994; Ling and McGill 1998; Hendershott et al. 2002). If after-tax mortgage interest rates are lower or roughly on the same level as the interest rate on savings, households will not save money to invest in a home, but purchase the home outright using the highest mortgage debt possible.[5] Together with the high caps on LTV standards *and* the relatively low risk for lending on the Dutch mortgage market (due to NGH) the interest rate deductibility resulted in the highest Mortgage-debt-to-GDP ratio in the world (Campbell 2013). With a GDP of around €641 billion and a total mortgage debt of almost €675 billion (2012) the Mortgage-debt-to-GDP ratio is over 1 in the Netherlands.

3.3 Literature Review

Literature in the field of supply of credit on the mortgage market is in a somewhat nascent stage, especially in contrast to papers in the field of demand for credit. Multiple approaches

[4] 'Gedragscode Hypothecaire Financieringen' in Dutch.

[5] For example the 5-year annuity mortgage interest rate was 4% (3.7%) at the end of 2012 (2005), whereas the savings rate on deposits with 2 year maturity was 3.5% (3.1%). However, home equity interest payments are deductible from your income (lowest tax bracket in the Netherlands is around 30%), making the 'net' mortgage interest rate lower than the rate on savings.

to construct CCIs have been proposed. On the one hand authors extract an index out of survey data. In these surveys senior managers of banks are asked whether they think that lending policy either relaxed or tightened over the course of the last quarter, see for example Del Giovane, Eramo, and Nobili (2011) and Van der Veer and Hoeberichts (2013), who both use the Bank Lending Survey (BLS[6]) for their research on credit conditions.

On the other hand, recently authors have started to estimate the CCI by an unobserved component in a model with 'mortgage lending' as the dependant variable. The rationale is that mortgage lending is partly influenced by credit conditions. By controlling mortgage lending for different demographic and economic variables the unobserved component should capture the credit conditions. Mortgage lending itself is entered as total or average amount of secured debt, LTV, ITV, interest rate spreads, etc.

An influential example is Fernandez-Corugedo and Muellbauer (2006). Using a dataset for the UK economy from 1976 to 2001 they construct 10 different credit indicators on the basis of both micro and macro variables. Two indicators are the stocks of secured and unsecured debt held by households, while the remaining 8 indicators are based on LTV and LTI ratios for FTB. A measure for credit conditions is then extracted by formulating a system of equations for all 10 indicators, where the CCI enters as a common unobserved trend. The equations are also controlled for risk perception of banks (and households), demographics, interest rates and (macro) economic changes. The framework introduced by Fernandez-Corugedo and Muellbauer (2006) has been adapted to construct a CCI in Norway (Jansen and Krogh 2011), South Africa (Aron, Muellbauer, and Murphy 2006) and Australia (Williams 2009).

Using FTB only in the analysis has a few advantages for the analysis of CCI. The most important advantage is that FTB do not have any notable savings or liquid funds to free up and use to purchase houses, so we can disregard housing and non-housing wealth in the analysis.[7] This does not only make the group FTB more homogeneous (i.e. household wealth is the same within this group), but it also solves part of the reverse causality problem between house prices and mortgage lending. For example, if house prices decline households eventually end up with negative home equity, reducing the mortgage amount they can stipulate. This can not happen when only looking at FTB. Together with the interest rate deductibility the fact that FTB have no notable savings or liquid funds ensures that the demand for mortgage debt (leverage) is constant over time and is 'as high as possible'. Thus, there are less demand-side factors one needs to correct for if the supply of credit is of interest.

Addison-Smyth, McQuinn, and O'Reilly (2009) use a slightly different setup. Firstly the

[6] In Section 3.6 we use the Bank Lending Survey (BLS) to construct such a measure as well. We compare the outcome to our estimate CCI for robustness.

[7] The exact amount of non-housing wealth for first time buyers in the Netherlands (where our analysis will take place) is difficult to establish. According to the Housing Needs Survey 2012 (or WoON2012 in Dutch) less than 10% of all households under the age of 35 who moved from the rental sector into the owner-occupier sector had 'taxable non-housing wealth'. Non-housing wealth is taxable after €20,000. So even though we do not know the exact amount of non-housing wealth for this group of people, at least 90% has less than €20,000 of savings or other non-housing wealth to use to purchase the property.

authors assume an exogenous relationship between house prices, mortgage lending and (gross) borrowing capacity. In this case 'gross' means that the CCI is not yet taken into account. The relationship runs as follows:

$$\text{Borrowing Capacity}(BC_t) \Rightarrow \text{Mortgage Amount}(M_t) \Rightarrow \text{House Prices}(P_t),$$

The borrowing capacity is based on the present value of an annuity, where the annuity is a fixed fraction of 30% of current disposable income discounted at the current mortgage interest rate for a horizon equal to the term of the mortgage. In an error correction framework mortgage levels are (only) regressed on the borrowing capacity. Episodes where the actual mortgage level (M_t) is above the equilibrium mortgage levels based on the borrowing capacity (BC_t) are regarded as periods of excess credit and vice versa.

Addison-Smyth, McQuinn, and O'Reilly (2009) also simultaneously estimate a house price equation. In this equation house prices are regressed on the mortgage levels (the dependent variable in the mortgage equation) and house supply. Using the borrowing capacity of households to explain the mortgage levels and subsequent house prices - in contrary to directly regressing the mortgage amount on house prices - also circumvents an important omitted variable bias, because income and interest rates can affect both house prices and mortgage levels. Addison-Smyth, McQuinn, and O'Reilly (2009) estimate that house prices in Ireland were 24% overvalued at the end of their sample (2008) due to over-crediting.

Estimation results of Cameron, Muellbauer, and Murphy (2006) show that, over a 30 year period (1975 – 2005), credit conditions inflated house prices by almost 30% in Britain. The authors use the credit conditions model for from Fernandez-Corugedo and Muellbauer (2006). According to Williams (2009), the easing of credit supply conditions directly raised the long run level of real house prices by 51% between 1972 – 2006 in Australia.

3.4 Model

3.4.1 A Model for Mortgage Credit

The main empirical strategy of this paper is that we include an unobserved component in an error correction framework to 'capture' the credit conditions. We start with the following relationships:

$$M_t = f(BC_t, CCI_t, W_t), \tag{3.1a}$$

$$P_t = g(M_t, X_t), \tag{3.1b}$$

where M is the maximum real mortgage amount a household can stipulate for at period t, P is the average real transaction price, CCI is the *unobserved* credit conditions index, W is total (housing and non-housing) real wealth of households which can be freed up to purchase the home and X contains additional control variables. The control variables do not include variables that could influence the credit conditions such as unemployment rate and funding gap of banks. BC is the borrowing capacity. It is given by:

$$BC_t = \kappa_{ct} I_t \left(\frac{1 - (1 + R_t)^{-\tau}}{R_t} \right), \tag{3.1c}$$

where R is the real interest rate (5-year-annuity), I is the average household real income, κ is the fraction of I which can be spent on housing, τ is the length of the mortgage (which we will fix at 30 years).

The percentage of the household income (I) which can be spent on housing (κ) is based on the income of the main earner (subscript c) and not on the income of the entire household (I). Data on κ is given to us by Nibud.[8] This calculation method is also in accordance with the guidelines issued by the Nibud to financial intermediaries, the government and families. Every year the Nibud calculates κ for different income categories. The percentages are based on a residual method, where all non-housing costs of a representative family within the same income cohort are subtracted from the income. The non-housing costs are corrected for inflation and entail not only costs for food and beverages, but also costs for owning a car, costs for one holiday a year, etc. The 'basket' of non-housing costs is kept more or less constant over time, however the 'basket' of non-housing costs is different per income cohort c. The residual can be spent on housing and is expressed as a percentage of total household income (I).

Since the effect of wealth on mortgage lending is subject to various demand side factors and is endogenous to house prices (see Section 3.3) we only look at first time buyers in our analysis: for FTB we can assume that $W = 0$ and that the demand for mortgage debt is constant. We can also substitute Eq. (3.1a) in (3.1b). The mortgage and price equations (3.1a)–(3.1b) can be simplified as:

$$M_{FTB,t} = f(BC_{FTB,t}, CCI_t), \tag{3.2a}$$

$$P_{FTB,t} = g(BC_{FTB,t}, CCI_t, X_t), \tag{3.2b}$$

[8]Nibud (National Institute for Family Finance Information) is an independent foundation. Its goal is to promote a rational planning of family finances. The national government and the private financial sector finance around 30% of the projects. The rest is financed by the revenues of Nibud products.

where:

$$BC_{FTB,t} = \kappa_{ct} I_{FTB,t} \left(\frac{1-(1+R_t)^{-\tau}}{R_t} \right), \tag{3.2c}$$

In this paper we will use a specification of the error correction model (ECM) with an unobserved component to extract the credit conditions index. The specification is given by:

$$\Delta y_t = \sum_{j=1}^{r} \phi \Delta y_{t-j} + \sum_{j=0}^{s-1} \sum_{i=1}^{k} \beta_{ij} \Delta x_{i,t-j} + (1-\phi)\Big(y_{t-1} - \mu_t - \sum_{i=1}^{k} \delta_i x_{it-1} \Big) + \epsilon_t, \tag{3.3}$$

where y can be either house prices or average mortgage received, x_t are the explanatory variables, μ_t is the unobserved CCI component, and $\epsilon_t \sim NID(0, \sigma_\epsilon^2)$. We use three specifications for μ_t, resulting in three measures for credit conditions, a random walk (RW), a local linear trend model (LLT) and linear splines (LS), given by:

$$\text{RW: } \mu_{t+1} = \mu_t + \eta_t, \qquad \eta_t \sim NID(0, \sigma_\eta^2), \tag{3.4a}$$

$$\text{LLT: } \mu_{t+1} = \mu_t + \gamma_t + \eta_t, \qquad \eta_t \sim NID(0, \sigma_\eta^2),$$

$$\gamma_{t+1} = \gamma_t + \zeta_t, \qquad \zeta_t \sim NID(0, \sigma_\zeta^2), \tag{3.4b}$$

$$\text{LS: } \mu_t = \lambda_1 t + \sum_{w=2}^{W} \lambda_w (t - t_w^*)^+, \tag{3.4c}$$

where w is the placement of the knot in period t. The variable $(t - t_w^*)^+$ takes on a value of zero if $(t - t_w^*)^+ \leq 0$, and equals the actual value of $(t - t_w^*)^+$ otherwise.

The error correction models with the stochastic trends are formulated in state-space form and are estimated by the Kalman filter and smoother (Harvey 1989). Estimation results are generated using the Structural Time Series Analyzer, Modeler and Predictor (STAMP) software, see Koopman et al. (2007). Estimation results for the error correction model with linear splines are generated by PCGive (Doornik and Hendry 2007). The results of this stage of the research are presented in Section 3.6.1.

The interpretation of the RW model (Eq. (3.4a)) is that the expected level of credit conditions in the next period is the same as the level of the credit conditions in the current period. The difference between the credit conditions now and the period before is the error. With the LLT model (Eq. (3.4b)) the expected increase in credit conditions in the next period is the same as the increase in credit conditions in the previous period. There is also an error on the LLT model. Finally, with linear splines we assume that the credit conditions are following a trend with structural breaks in certain periods.

The estimated measures for credit conditions will subsequently be used to explain house prices. This analysis will be based on variables representing all households, not only first

time buyers, and will be performed in a more traditional 2-step Engle and Granger framework (Malpezzi 1999). The results of this stage of the research are presented in Section 3.6.2.

3.4.2 Limitations to the Model

It is important to stress that the CCI from Eq. (3.4) is derived from FTB data, but is subsequently used in an error correction framework to explain house prices for all Dutch households. Thus, one should be careful whether the FTB CCI is the same as the overall CCI. Also, we ignore LTV levels in this Chapter as the LTV caps did not change in the analysed period. If LTV levels *do* change (by either demand or supply for debt) over time, this could contaminate the unobserved component.. In Figure 3.1 we therefore present some stylized facts of the Dutch mortgage market for a selection of years.[9] If for example the market for FTB mortgages shows a different dynamic than the overall mortgage market, one should take these differences into account in Eq. (3.3).

Both (nominal) income development and unemployment development (which is measured as total number of unemployed people) of FTB are comparable to the overall development of the same metrics for all households.[10] The LTV (see Figure 3.1c) of newly issued mortgages to FTB has been remarkably stable. For the last 15 years the average LTV for FTB have been meandering between 101% and 104.5%. The decline in LTV observed at the end of the sample is explained by reduction of the transfer-tax and LTV-cap in 2011 (see Table B1 as well). The overall LTV ratio did rise for both yound households and the Dutch average. The main cause has been the disincentive of Dutch households to amortize mortgage debt (revisit Section 3.2) and declining house prices.

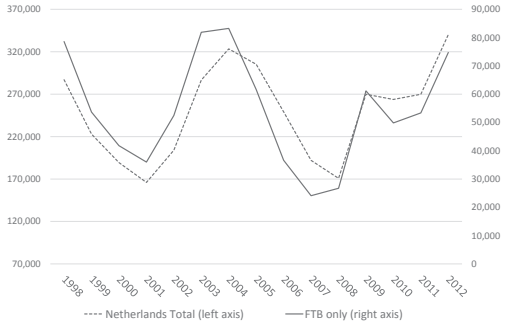
Home-ownership rates among FTB (Figure 3.1d) have been stable as well, ranging between 45% – 48% over a 14 year period. Note that we do not take into account the mortgage requests which were declined, because the data is not available to us. This could bias our estimates if banks start financing mortgages to different quality FTB over time.[11] However, the stable home-ownership rates among FTB suggest that inflow of FTB to the owner-occupier market is constant over time. Thus, the observed FTB *should* be more or less 'constant quality'. The number of mortgages to households of age 35 and younger to all mortgages did decline, however this is attributed to a relative decline of this age cohort, see Section 3.5 as well.

[9] All data is taken from the website of the Statistics Netherlands, except for the LTV for FTB, which is provided to us by NHG, see Section 3.5. Data in Figures 3.1a and 3.1b are on a yearly basis, the LTV of newly issued mortgages for FTB in Figure 3.1c is on quarterly basis. The average LTV levels of households younger than 35 years and the average Dutch LTV are both on yearly basis, although data is missing for 2001 – 2003 (both are interpolated in Figure 3.1c). Data used for Figure 3.1d is with a irregular interval.

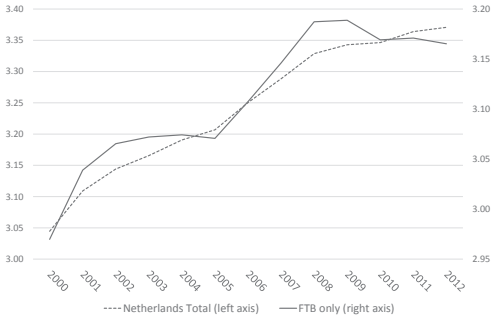
[10] In our application the inclusion of the difference of income and unemployment between FTB and all households resulted to be insignificant and not part of the cointegrated relationship.

[11] For example, if mortgage lenders start lending to relatively 'higher quality' FTB only (i.e. higher income, etc.), the average new mortgage level will rise, *ceteris paribus*. The subsequent results from our model would suggest that the availability of credit on the mortgage market would have gone up, whereas the opposite is true.

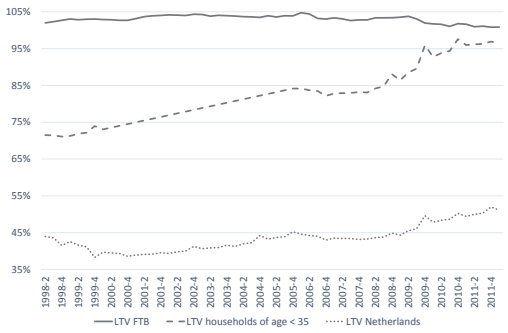
Figure 3.1: Stylized facts of FTB and all households in the Netherlands.



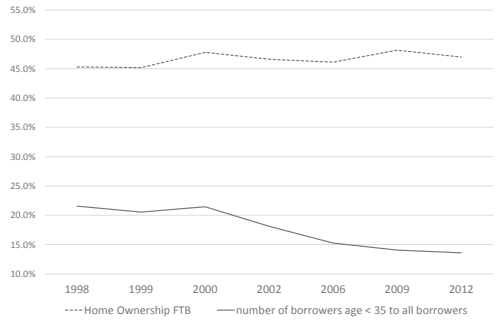
(a) Unemployment development.



(b) Income development.



(c) Loan-to-Value ratios.



(d) Home-ownership rates and number of mortgages of households of age ≤ 35 to total number of mortgages in the Netherlands.

Both the stable LTV ratios and the stable home-ownership rates of FTB gives us confidence that the unobserved component is uncontaminated and, thus, the constructed CCI should 'capture' the supply of debt.

3.5 Data and Descriptive Statistics

We obtained our data from six different sources: Statistics Netherlands (CBS), National Mortgage Guarantee (NHG), National Institute for Family Finance Information (Nibud), the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM), Bloomberg (BL) and Netherlands Bureau for Economic Policy Analysis (CPB). All variables are available for the period 1995 – 2012. Data is on a yearly (Y), quarterly (Q) and even monthly basis (Mth). If the frequency of the data is monthly the average of three months is taken. Yearly data is interpolated linearly, such that we end up with quarterly time series. This results in all time series being available on a quarterly basis. Only income is treated differently because income in the Netherlands is usually only adjusted once a year.[12] Income is therefore increased stepwise every year.

The financial time series in the data are in nominal terms, and are therefore deflated by the (harmonized) consumer price index (HICP) from Statistics Netherlands.[13] All variables and sources used in this paper are presented in Table 3.1. Some descriptives of the variables in (real) levels are given in Table 3.2 and in first differences ($\Delta \ln$) in Table 3.3. For comparability, all time series both in levels (ln) and in first differences ($\Delta \ln$), in Appendix B.4.

In Tables 3.1 – 3.3 subscripts t is for period and subscript FTB is for first time buyers. First time buyers are defined by households where the head of the household has an age of 35 years or younger and purchased a home, following Fernandez-Corugedo and Muellbauer (2006). Smaller case letters are log transformations of the corresponding upper case letters.

P are real house prices. The (constant quality) Sales-Price-Appraisal-Ratio (SPAR) index (Jansen et al. 2008; Bourassa, Hoesli, and Sun 2006) from the Statistics Netherlands is used as the measure for national house prices (P_t). House prices for first time buyers ($P_{FTB,t}$) is calculated as the *average* sales price per period observed by the NHG for households of age 35 or younger.[14] Total house price returns for both FTB specific and national average are more or less the same over the entire period. House prices for FTB increased 47% from 1995.Q1 to

[12] Salary for the next year per branch is determined by a collective labor agreement (in Dutch CAO).

[13] The financial time series are divided by the HICP. The yearly expected inflation (period % change of the HICP) is deducted from the mortgage interest rate to construct a real interest rate. We use the HICP instead of the more commonly used CPI, because imputed rent is an important component in the latter. The imputed rent is a percentage of the value of housing. Thus, house price appreciation (which we are deflating) is part of the CPI.

[14] Thus, the price index for First Time Buyers is not constant quality (as opposed to the SPAR index). Indeed, some evidence was found that First Time Buyers bought better quality houses in the 1990s and after the crisis, than they did during most of the 2000s. This mostly translated in First Time Buyers buying homes on better locations after the crisis.

Table 3.1: Description and sources of variables

Variable	Description	Period	Frequency	Source
$P_{FTB,t}$	Average sales prices FTB	1995 – 2012	Q	NHG
$M_{FTB,t}$	Mortgage level	1995 – 2012	Q	NHG
R_t	Mortgage interest rate (5-year annuity)	1995 – 2012	Mth	NVM
$BC_{FTB,t}$	Borrowing capacity	1995 – 2012	Q	
$I_{FTB,t}$	Average household income	1995 – 2012	Y	CBS
F_t	Total population of age ≤ 35	1995 – 2012	Y	CBS
P_t	Constant quality house price index (SPAR)	1995 – 2012	Q	CBS
EQR_t	Total equity returns index	1995 – 2012	Y	BL
W_t^n	Non-housing wealth index	1995 – 2012	Y	CPB
CC_t	Construction costs index	1995 – 2012	Q	CBS
κ_t	% of I which can be spent on housing	1995 – 2012	Q	Nibud
K_t/HH_t	Housing supply / Households	1995 – 2012	Y	CBS

Borrowing capacity (BC) is calculated using data from multiple sources, see text.
Y = yearly data, Q = quarterly data and Mth = monthly data.

Table 3.2: Summary statistics of the main variables in real levels

Variable	Mean	Max	Min	Std. Dev.	P-value
$P_{FTB,t}$	€127,319	€159,597	€83,417	€20,662	0.999
$M_{FTB,t}$	€118,733	€146,599	€75,776	€19,787	0.999
$BC_{FTB,t}$	€142,420	€169,869	€95,625	€18,248	0.319
$I_{FTB,t}$	€31,065	€33,315	€28,871	€841	0.960
F_t	3,914,457	4,389,670	3,621,835	250,757	0.964
P_t	174.98	216.67	99.86	35.48	0.997
EQR_t	218.29	339.39	100.00	58.84	0.402
W_t^n	103.14	117.36	92.99	6.87	0.523
CC_t	114.21	128.29	98.65	8.25	1.000
κ_t	28.88%	31.00%	25.50%	1.68%	0.567
K_t/HH_t	96.22%	96.95%	94.94%	0.42%	0.979

Note. The reported P-values are the significance levels at which you can reject the null hypothesis of a unit root (Augmented Dickey Fuller test). All ADF tests were done with a constant and a trend on the log values of the variables. Critical values are taken from (MacKinnon 2010).
The lag lengths differ per variable and are based on the Akaike Information Criterion.

Table 3.3: Summary statistics of the main variables in first differences ($\Delta \ln$)

Variable	Mean	Max	Min	Std. Dev.	P-value
$\Delta p_{FTB,t}$	0.007	0.059	-0.033	0.020	0.003
$\Delta m_{FTB,t}$	0.007	0.052	-0.032	0.019	0.006
$\Delta bc_{FTB,t}$	0.006	0.094	-0.130	0.044	0.000
$\Delta i_{FTB,t}$	-0.001	0.063	-0.030	0.020	0.232
Δf_t	-0.002	0.002	-0.005	0.002	0.350
Δp_t	0.007	0.062	-0.048	0.022	0.063
Δeqr_t	0.012	0.280	-0.298	0.103	0.000
Δw_t^n	0.001	0.095	-0.043	0.027	0.032
Δcc_t	0.000	0.055	-0.046	0.021	0.000
$\Delta \kappa_t$	0.000	0.096	-0.114	0.026	0.000
$\Delta(k - hh)_t$	0.000	0.002	-0.003	0.001	0.016

Note. The reported P-values are the significance levels at which you can reject the null hypothesis of a unit root (Augmented Dickey Fuller test). All ADF tests were done with a constant and a trend. Critical values are taken from (MacKinnon 2010).
The lag lengths differ per variable and is based on the Akaike Information Criterion.

2012.Q4, whereas average national house prices increased with 49% during the same period. However, three distinct periods in the development of house prices in the Netherlands can be distinguished.

First, there was a period of large national (FTB specific) house price appreciation in real terms of +86% (+40%) between 1995 – 2001, then from 2001 – 2008 house price increases more or less stalled with +14% (+16%) and finally for 2008 – 2012 house prices decreased with -22% (-5%).

M_t is the average new real mortgage amount received by FTB in period t. It is interesting to note that for first time buyers, the correlation between house prices ($P_{FTB,t}$) and the newly issued mortgage levels ($M_{FTB,t}$) is extremely high with 0.99. This was expected (from a mortgage demand perspective), since (1) the mortgage interest rate deductibility is an incentive to take up the highest possible leverage when purchasing a home and (2) FTB do not have any notable wealth or liquid funds which they can free up to invest in the home (revisit Section 3.3). Also interesting is that the Granger causality (see Appendix B.2) runs one-way from mortgage levels to house prices and not the other way for FTB in both levels and first differences. Both figures (correlation and causality) are in line with our economic theory that first time buyers are completely reliant on the mortgage market when entering the owner-occupier market. The results of Table B2 also further reduces the endogeneity criticism discussed in Section 3.3.

BC is the calculated borrowing capacity using Eq. (3.1c). The borrowing capacity was mainly fuelled by the real (5-year annuity) mortgage interest rates (R), which dropped sharply for the analysed period. The other variables to calculate borrowing capacity BC are income for first time buyers and κ.

F is the population of age > 20 and ≤ 35 years[15], I is the real gross average household income level, EQR are the real total equity returns of Dutch businesses (stock value + dividend), W^n is real total non-housing wealth in the Netherlands, and CC are the real construction costs. Figures B.4.1 and B.4.2 reveal that the average household income, the construction costs and non-housing wealth are decreasing, in real terms, from 2009 onwards. In Tables 3.1 – 3.3 the variable K_t/HH_t is a proxy variable for excess supply relative to demand, where K is the supply of housing units, HH are the total number of households in the Netherlands. Since housing is a durable object, it is expected that a decline in demand (measured as number of households) will result in house price decreases (Glaeser and Gyourko 2005).

All variables are I(1) except for F and I. However, they are still included in the long-term relation. Also note that income is used to compute BC, which is I(1) in itself.

3.6 Results

This Section contains the results for both the unobserved error correction models which gives us a measure for the credit conditions (Section 3.6.1) as well as the results for the error correction models which describes the effect of the credit conditions on house prices in the Netherlands (Section 3.6.2).

3.6.1 The Credit Conditions Index

In total three models[16] are presented in this paragraph. In model I (log) house prices (p) are explained by the (log) borrowing capacity (bc) and (log) population of age between 20 and 35 (f). Income (i) has a significant effect on house price in the short-run only. The unobserved component is specified as a Random Walk (RW, see Eq. (3.4a)). Model II has the same specification as Model I, only the unobserved component is specified as a Local Linear Trend model (LLT, see Eq. (3.4b)). In Model III (log) mortgage levels (m) are explained by the (log) borrowing capacity (bc) and income levels of FTB (i). The unobserved component is specified as a linear spline (LS). Insignificant splines were successively excluded until a parsimonious model was found.

The estimation results are presented in Table 3.4. The unobserved components (i.e. the CCI) are presented in Figure 3.2. Additional model diagnostics are found in Figure 3.3. Tests for co-integration are found in the Appendix B.3. For the unobserved ECM models (Models I and II) an alternative test for co-integration is used. Here we test whether the autoregressive parameter in a first-order autoregressive model is equal to 1.

[15]We also used population of age between 20 and 35 years as a fraction of total population in our analysis. However, the results did not change and the model diagnostics were actually a bit worse.

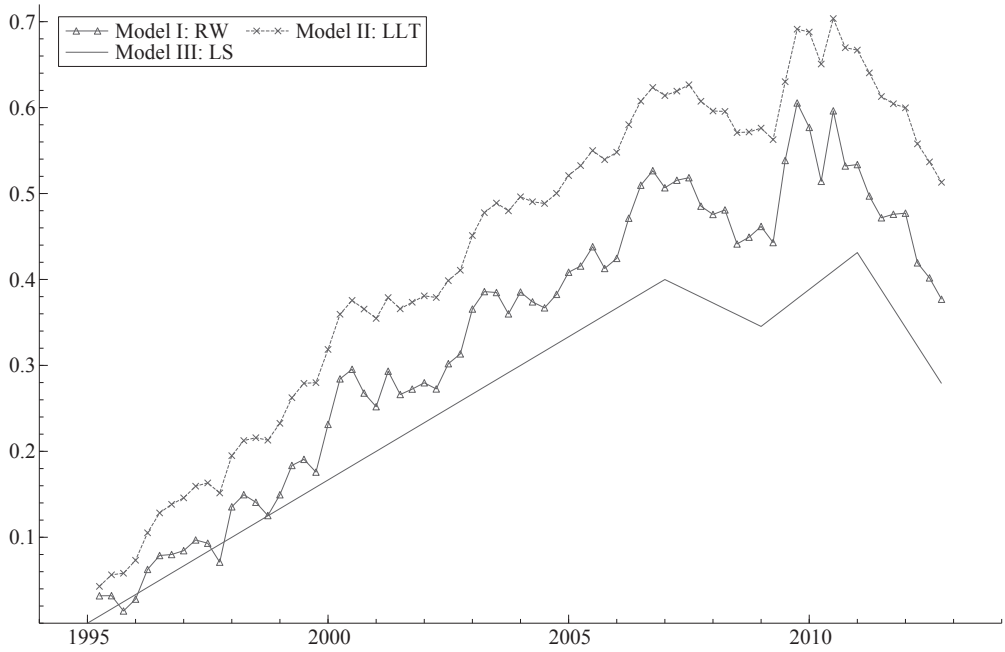
[16]For both, y is house prices and mortgages all three specification of μ were tried (so 6 models in total). The models presented here are the ones which had a co-integrated relationship.

Table 3.4: Main results unobserved ECM models, FTB only

	Model I	**Model II**	**Model III**
dep.var.	$\Delta p_{ftb,t}$	$\Delta p_{ftb,t}$	$\Delta m_{ftb,t}$
μ_t	RW	LLT	LS
	Short-run model estimates		
$\Delta i_{ftb,t}$	-0.287	-0.254	-0.233
	(-4.49)***	(-4.48)***	(-2.06)**
$\Delta bc_{ftb,t}$	-0.110		0.071
	(-2.37)***		(1.72)*
ECT_{t-1}	-0.490	-0.708	-0.433
	(-5.04)***	(-6.28)***	(-3.41)***
	Long-run model estimates		
$bc_{ftb,t}$	0.227	0.113	0.265
	(5.00)**	(10.07)***	(4.62)***
$i_{ftb,t}$			0.612
			(2.44)**
f_t	0.575	0.657	
	(12.21)***	(6.42)***	
Std. Error	0.015	0.015	0.013
R^2	0.425	0.638	0.584
LogLikelihood	269,457	269,005	254,515
p.e.v.	0.000	0.000	
DW	1.993	1.822	1.356

Note. Coefficient (t statistic),*** sig. within 99% prob. and ** sig. within 95% prob.
t-values are retrieved using the techniques proposed by (Bårdsen 1989) for models I through II. The long run coefficients and t-values for Model III are given by PCGive (Doornik and Hendry 2007).

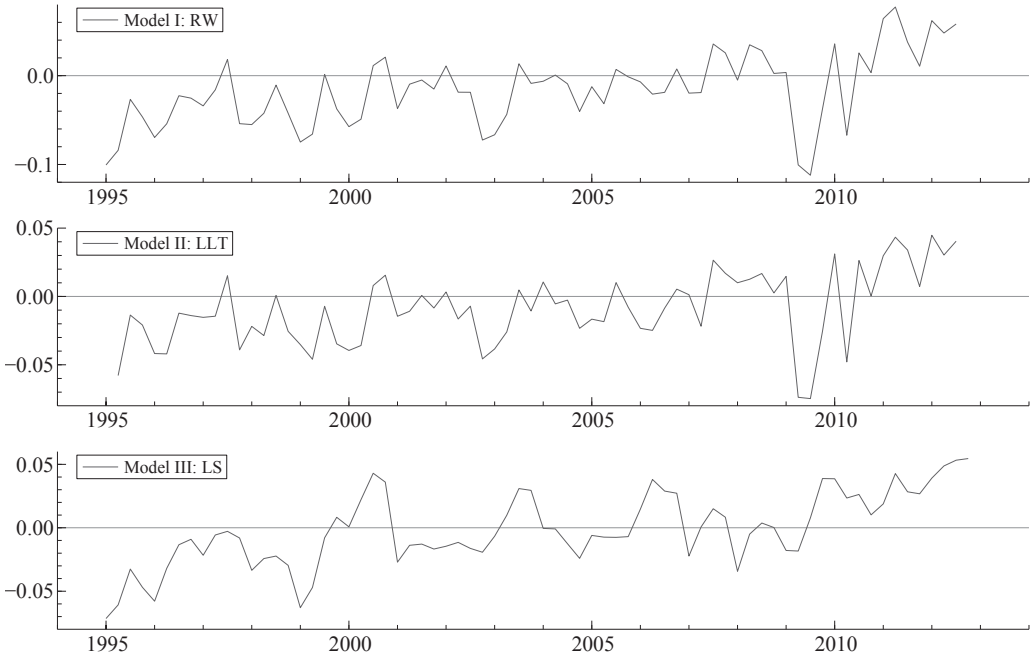
Figure 3.2: Unobserved components (CCI) for the different models



The estimation results in Table 3.4 show that all coefficients have the expected sign. On average, for every 1% increase in borrowing capacity, mortgage lending *or* house prices increase with 0.2%. Income has a separate effect on mortgage lending. For every 1% increase in real income, mortgage lending increases with an additional 0.6% in Model III. Assuming that supply is more or less fixed (especially in the short-run, Harter-Dreiman 2004) an increase in population results in an increase in demand for housing. Thus the positive sign for f was expected. In this case, a 1% in population aged between 20 and 35 results in 0.6% higher house prices for first time buyers on average.

In all models the credit conditions reveal a steady growth until 2009 with a small interruption in 2007, during the credit crunch (see Figure 3.2). The increasing levels of mortgage lending can be attributed to more households taking an interest only mortgage and the growing popularity of the NHG product which made mortgages less risky investments. After 2009 however, there was a steady decline, probably mostly fuelled by more stringent liquidity ratios on banks (Basel accords) and lower LTVs allowed by the Dutch government. In 2012.$Q4$ the supply of credit is on the same level as it was during the period 2003 – 2004. The short-lived increase in credit conditions around 2010 can be explained by realizing that the standards for getting a National Mortgage Guarantee (NHG) were temporarily relaxed. This meant that banks could lend credit with less risk involved to a wider audience decreasing the total mortgage portfolio risk.

Figure 3.3: error correction terms for all models



Next we compare our measures for credit conditions with the outcome of the Bank Lending Survey (BLS) for Dutch banks. The BLS is a quarterly survey among representatives of banks. A main question in the BLS is whether there was a tightening or relaxation of lending standards compared to the period before. This question is also specifically asked for mortgage lending, which we will also look at. If 100% of the respondents reported a relaxation of some sorts of mortgage criteria, the score for this period is 100. If 80% of the respondents say the mortgage lending criteria were relaxed and 20% says they were tightened a score of 80 is reported, etc. It should be noted that the scores of the respondents are weighted with the market share the financial institution they work for has in the market (source: De Nederlandsche Bank).

To make the BLS comparable to our measure for credit conditions, we first construct a variable for the level of a bank's lending standards by coding the qualitative answers given in the BLS in the same way as Van der Veer and Hoeberichts (2013) did. Thus we start with a zero level of bank lending standards at the beginning of our sample, and add a value of "+1" when lending standards are eased, "−1" (i.e. the reported score is higher than 0) if lending standards are tightened (i.e. the reported score is lower than 0), and "0" if a bank reports no change.[17] We do the same for our CCIs so the magnitude of the level index will be the same.

[17]Please note that in the BLS the signs are the other way around. So a relaxation of lending values actually gets "−1", etc. However, to make the BLS comparable to our study we inverted the signs first.

If Δcci_t is less than -4% (more than $+4\%$) we add a value of "-1" ("$+1$") to our normalized index. If $-4\% \leq \Delta cci_t \leq 4\%$ we add a value of "0" to the new index. We compare our results from the RW and LLT model to the BLS level index in Figure 3.4 from 2005 onwards.[18] Please note that we do not take the LS CCI into account, since the structure of this index in completely different. More specifically, it is impossible to set a "0" value.

The correlation between the two CCIs is quite high, with 0.86. More interestingly, the other correlations are quite high as well. The correlation between the RW CCI and the BLS level index is 0.84 and between the LLT CCI and the BLS level index is 0.48. In all indices we observe a severe drop in supply of credit from 2009 onwards. The big difference is that our measure reveals a short revival of credit conditions in 2010 (because of the temporary relaxation of NHG standards see above), whereas the BLS does not. This could partly be explained by semantics. Perhaps bank lending standards as such were tightened in this period, but financial institutions could still advance higher mortgage levels, because of relaxation of NHG standards (this reduces the risk for banks on the mortgage market). Still, taking into account the completely different ways of measurement, our measure for credit conditions is comparable to the BLS.

3.6.2 House Prices and the Supply of Credit

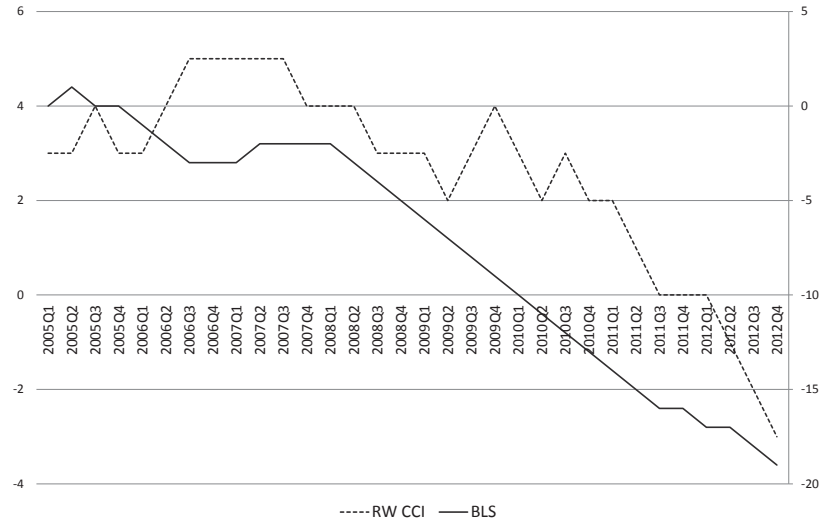
In this Section we regress our measures for the credit conditions found in Section 3.6.1 on the log real house prices in the Netherlands in a 2-step Engle and Granger (1987) framework. In the first model we include the RW CCI (resulting from Model I in Section 3.6.1), in the second model we include the LLT CCI (resulting from Model II in Section 3.6.1) and the third model includes the CCI based on the splines of Model III in Section 3.6.1. We also present two auxiliary models without a measure for credit conditions, so we can look for the importance of a measure for credit conditions in ECM models. The results for the static equations can be found in Table 3.5 and Figure 3.5 and for the short term model in Table 3.6. For completeness a Granger-Causality test for our measure for credit conditions and house prices can be found in Table B3. The Granger causality runs one-way from credit conditions to house prices and not the other way.

In Table 3.5 cci is the credit conditions, cc is the real construction costs (which is seen as a proxy for structure values, Bostic, Longhofer, and Redfearn 2007), i is the real household income, w^n is real non-housing wealth, eqr are the total real equity returns, bc is the real borrowing capacity (see Eq. (3.1c)) and $(k - hh)_t$ is a rough measure for vacancy. Subscript t denotes time and lower case letters denotes a variable in natural logarithm.

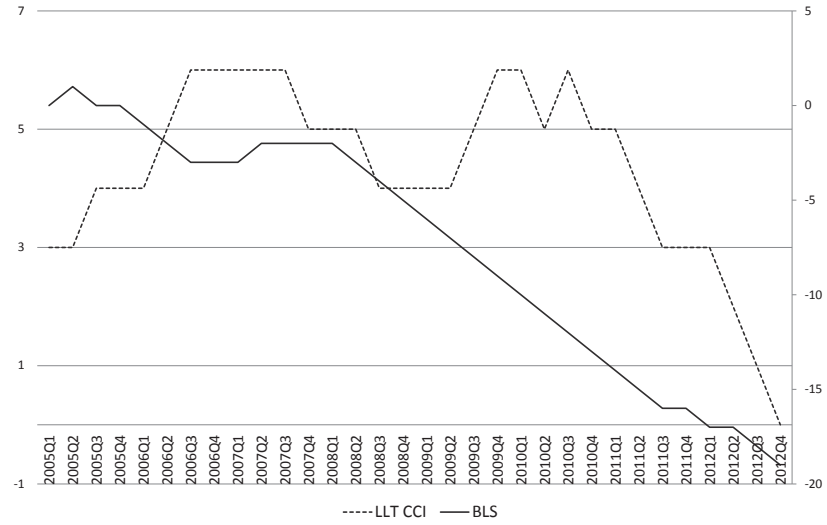
From the ADF tests shown in Table 3.5 it can be concluded that there is evidence for a

[18] The BLS actually starts in 2003, however in the first two years the outcome of the 'overall' BLS for mortgages specifically performs in a counter-intuitive way. More specifically, the BLS reports a relaxing in bank lending standards for both secured debt and unsecured debt alike, but for mortgages the BLS reports a severe tightening. According to sub-questions regarding the mortgage market there was also a relaxation of bank lending standards in 2003 and 2004.

Figure 3.4: Credit conditions (left axis) versus the BLS level index (right axis), between 2005.$Q1$ and 2012.$Q4$.



(a) Random Walk model.



(b) Local Linear Trend model.

Table 3.5: Static Equation house prices, all households.

	Model I	**Model II**	**Model III**	**Model IV**	**Model V**
Constant	-4.732	-4.274	-4.119	-10.302	-14.483
	(-8.10)***	(-7.80)***	(-7.48)***	(-12.40)***	(-19.50)***
$(k-hh)_t$	-8.023	-6.750	-7.199	-11.882	-7.213
	(-5.52)***	(-5.02)***	(-5.42)***	(-4.25)***	(-3.20)***
eqr_t	0.164	0.149	0.160	0.231	0.157
	(8.48)***	(8.30)***	(9.09)***	(6.28)***	(5.71)***
cc_t	1.777	1.706	1.651	2.905	1.914
	(15.40)***	(15.90)***	(15.10)***	(18.10)***	(10.70)***
cci_t	0.634	0.580	0.900		
	(13.80)***	(15.60)***	(15.70)***		
w_t^n					0.786
					(6.39)***
bc_t					0.411
					(4.58)***
CCI	RW	LLT	LS		
Sigma	0.042	0.038	0.038	0.082	0.056
R^2	0.967	0.972	0.973	0.870	0.941
Log-likelihood	127.139	133.448	133.984	78.781	106.846
DW	0.892	0.821	0.773	0.469	0.934
ADF T-statistic	-4.447	-4.170	-4.004	-2.830	-4.503
Critical Value 10%	-3.931	-3.931	-3.931	-3.542	-4.286
Critical Value 5%	-4.258	-4.258	-4.258	-3.865	-4.618

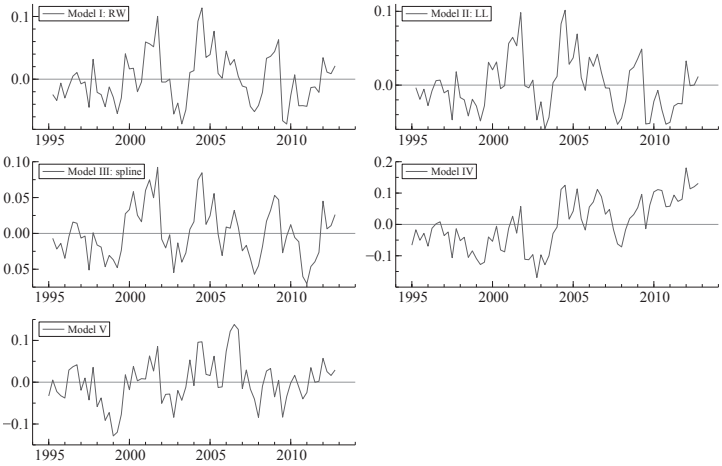
Note. Coefficient (t statistic),*** sig. within 99% prob.
Critical values for ADF test taken from (MacKinnon 2010), with T = 70 and a constant.

Table 3.6: ECM short term model, all households.

	Model I	**Model II**	**Model III**	**Model IV**	**Model V**
Constant	0.000	-0.001	-0.001	0.001	0.000
	(0.08)	(-0.48)	(-0.42)	(0.55)	(0.26)
Δp_{t-1}	0.748	0.730	0.734	0.744	0.800
	(11.30)***	(11.30)***	(10.40)***	(9.91)***	(11.40)***
Δcci_t	0.136	0.232	0.154		
	(3.27)***	(4.08)***	(2.69)***		
Δcc_t	0.240	0.237	0.212	0.193	0.202
	(3.44)***	(3.48)***	(3.01)***	(2.66)***	(2.67)***
ECT_{t-1}	-0.111	-0.108	-0.110	-0.042	-0.048
	(-3.39)***	(-3.14)***	(-3.03)***	(-2.31)**	(-1.86)*
Sigma	0.010	0.010	0.010	0.011	0.011
R^2	0.806	0.818	0.796	0.771	0.765
Log-likelihood	221.375	223.663	219.651	215.744	214.795
DW	1.47	1.54	1.67	1.56	1.59

Note. Coefficient (t statistic),*** sig. within 99% prob., ** sig. within 95% prob. and * sig. within 90% prob.

Figure 3.5: Error correction terms for all models.



cointegrating relationship for all models except for Model IV. However, it should be noted that the t-statistic of Model I is the only one to be below the 5% critical value. All coefficients have the expected sign. For every 1% increase in the credit conditions index house prices go up with 0.8% on average. The model diagnostics show that the models with credit conditions outperform the models without a measure for credit conditions. The R^2 and likelihood are higher, the standard error of regression is lower and the results of the aforementioned cointegration test (especially for Model I) are better. Shocks out of equilibrium are absorbed in approximately 9 quarters for the models with a measure for credit conditions and 21 quarters for models without a measure for credit conditions.

Nominal housing prices increased from 1995.$Q1$ to 2009.$Q4$ by more than 100% and subsequently decreased with 18% in the next three years at the end of our sample period. The contribution of the different measures of the credit conditions and the other explanatory variables of house price development is presented in Table 3.7. All three measures for the credit conditions render similar effects on house prices. The contribution of the relaxation or tightening of credit conditions to house prices was +37% for the period 1995.$Q1$ – 2009.$Q4$ on average and −11% for the period 2010.$Q1$ – 2012.$Q4$ on average.

Even though the effect of construction cost over the entire period is close to zero, the other large contributor to the house price decrease after 2010 has been the drop in construction costs. Construction costs are used as a proxy for structure values (Bourassa et al. 2011). Further, any given positive demand shock will be easier to absorb if the housing stock can be increased quickly and at low cost. Therefore the cost of adding to the supply of housing should affect the time series properties of housing prices as well (Capozza et al. 2002). Although this should (partly) be controlled for by our proxy for vacancy. Decreasing construction costs can be caused

Table 3.7: Contributions to real and nominal cumulated house price development (in $\Delta \ln$) in two subperiods.

	Model I: RW		Model II: LLT		Model III: Spline	
	1995 - 2009	**2010 - 2012**	**1995 - 2009**	**2010 - 2012**	**1995 - 2009**	**2010 - 2012**
Credit conditions	38.36%	-14.47%	40.07%	-10.33%	33.98%	-8.87%
Supply minus households	-9.34%	14.11%	-7.86%	11.87%	-8.38%	12.66%
Total equity returns	11.34%	2.37%	10.29%	2.15%	11.06%	2.31%
Construction costs	32.83%	-30.82%	31.51%	-29.58%	30.50%	-28.63%
Unexplained	2.02%	3.54%	1.20%	0.61%	8.05%	-2.74%
Total (real change)	75.21%	-25.27%	75.21%	-25.27%	75.21%	-25.27%
Inflation	31.34%	7.36%	31.34%	7.36%	31.34%	7.36%
Total (nominal change)	106.55%	-17.91%	106.55%	-17.91%	106.55%	-17.91%

by a decrease in labor and/or material costs (Davis and Heathcote 2007). If new investment in housing compared to demand (approximated by $k - hh$) would not have been as low as it was after 2009, house prices would have decreased with another 12% on average. The only other positive (albeit almost negligible) contributor to house prices in the post-2009 housing market has been total equity returns.

3.7 Concluding Remarks

In the 13 years prior to 2008, the Dutch housing market was synonymous with price growth and high levels of activity. The demand for housing was driven by a broad increase in borrowing capacity buoyed by economic growth and historically low interest rates. In parallel, mortgage lending and the supply of credit increased rapidly (Honohan 2008). However, the housing market and the supply of credit have contracted sharply in the period after 2008.

This Chapter proposes a intuitive-based model of the mortgage market. First, mortgage credit for first time buyers is modelled solely as a function of the borrowing capacity of first time buyers and a stochastic trend component, where the borrowing capacity is a combination of the income of first time buyers, mortgage interest rates and a percentage of the household income which should be reserved for other expenses. First time buyers do not have any notable savings or liquid funds to free up and use to invest in the home, while the deductibility of mortgage interest payments results in no incentive to down-pay the mortgage anyway, making them solely reliant on the mortgage market. The stochastic trend measures a structural increase or decrease in mortgage lending which cannot be explained by changes in borrowing capacity. This phenomenon is denoted credit conditions. We then model house prices as a function of the credit conditions. Our results show that the supply of credit increased during the period 1995 – 2009 continuously, with a small dip in 2007 during the credit crunch. This relaxation of credit conditions increased house prices with 37% during this period. However, since 2009 the supply of credit on the mortgage market decreased considerably. As of 2012 the supply of credit is on the same level as it was in the period 2004 – 2005. The subsequent decrease of credit on the mortgage market resulted in house price decreases of 11% on average.

Chapter 4

The Effects of Demographics and Supply Constraints on House Prices

Abstract[1]

Even though supply constraints are an important factor in explaining housing prices, it has not yet been implemented in research on demographics in urban economics. The aim of this Chapter is to analyse the effects of demographic changes on housing prices for local housing markets (municipalities) with different supply constraints in the Netherlands. We estimate that for every 1% decrease in population housing prices drop 1.8%, *ceteris paribus*. However, every 1% population increase will show a more ambiguous effect on housing prices depending on the size of local supply constraints.

4.1 Introduction

Glaeser and Gyourko (2005) found empirical evidence for the U.S. that urban growth is not a mirror image of urban decline. Whenever a city grows, delivery lags and imperfect foresight of agents will enable housing price increases on the short-run, until a new long-run equilibrium is reached (Harter-Dreiman 2004). Whenever urban decline sets in, measured as population decrease, durability of housing ensures that housing prices drop disproportionally large compared to the drop in population. This Chapter takes interest in the effects of population growth on house prices as well, however we introduce the influence of supply constraints on house prices.

Why are supply constraints an interesting part of urban dynamics? Intuitively, when supply is unable to keep pace with demand shocks quickly and cheaply, more of the demand shocks carry through into prices (Paciorek 2013). More specifically, a (positive) demand shock results in lower population growth, higher wages and higher house prices in locations were new construction is constraint (Saks 2008; Zabel 2012). Therefore, high house prices may mean that only more wealthy households can afford to move into a region with inelastic supply, while

[1]This Chapter is based on Francke and Van de Minne (2014).

poor households are forced to move out, leading to higher income inequality across regions (Saks 2008). Therefore, understanding the relationship between supply constraints and demand becomes imperative in understanding housing price volatility differences between regions (Sanchez and Johansson 2011).

In order to analyse the effects of demographics on housing prices in markets with supply constraints this study utilizes a data set on the Dutch owner-occupier housing market at *municipal level*. We look at municipalities firstly, because the most important instrument on spatial planning in the Netherlands is the zoning plan which is made on municipality level. Secondly, because 60% of Dutch households move within the same municipality. Thirdly, on a whole (or even on provincial level) the Netherlands did not see demographic decline in its modern history. However, there are many individual municipalities which are faced with demographic decline in recent years. In our database 15% of all municipalities has had a declining population for the last 15 years, see Table C2 in the Appendix.[2] One should also note that it is a relatively new phenomena in the Netherlands.

We assume *four* different types of relationships between supply and demand. Firstly, a housing market could be experiencing a demand *increase*, but supply is *fixed*, because of restrictive policy and/or physical constraints. It is expected that housing prices will increase. Secondly, a housing market could be experiencing a demand *increase*, and supply is *adjusting relatively well*. There is an elastic long-run supply function in these kinds of markets. However, supply still adjusts relatively slow to the long-run equilibrium due to the delivery lags and imperfect foresight of agents. Major demand shocks are therefore still expected to impact housing prices in the short-run. Thirdly, planning authorities can designate certain locations to be developed, irrespective whether or not there is actual demand for housing in said location. In this case the causality is actually the other way around. It is expected that *the increase in housing supply* will impact house prices negatively in both the short- and long-run. Finally, there are housing markets which are experiencing a demand *decrease*. Supply is *fixed*, certainly in the short-run. While the durability of supply may not be a crucial element of housing price dynamics for growing municipalities, it is a strong determinant of the nature of a municipality in decline. The durability of housing leads to amplification of falling housing prices. The percentage fall in prices will be larger than the percentage fall in population.

We find empirical evidence of these relationships. House price changes in the owner-occupied market are modelled by demand and supply (constraints) variables and additional control variables. The model is estimated on a panel data set consisting of 400 Dutch municipalities over the years 1995 to 2009. Population change is entered in a piecewise linear form to allow for differential effects in expanding versus declining municipalities and are subsequently interacted with a proxy for the severity of local supply constraints. A measure for local supply constraints

[2]The Dutch Association of Real Estate Brokers and Real Estate Experts (abbreviated to NVM in Dutch) and different banks (specifically the Rabobank and ING) already warned for the dangers demographic decline poses.

is estimated from a separate model. We estimate an almost 2% housing price drop for every 1% population decrease (independent of the local supply constraints), whereas the effect of 1% population growth on house prices depends on local supply constraints. In municipalities without supply constraints house prices actually decrease with 0.2% if the population increases with 1%. In this case we hypothesize that planning authorities decided (irrespective of local demand) to increase housing supply. Demand only reacts slowly (if at all), resulting in house price decreases. Population growth does not influence house prices in municipalities with 'medium' supply constraints. Here new construction reacts adequately to demand. Finally, in municipalities with high supply constraints a 1% population increase results in 0.4% increase in house prices. In this case it is expected that the new households require higher wages and/or amenities to compensate them for more expensive housing (Saiz 2010).

The most important contribution of this research is that - to the best of our knowledge - it is the first to take up population changes and supply constraints when explaining house prices simultaneously in one model: By controlling demographic growth and decline for local supply constraints, we show that the asymetries between growth and decline is even larger than previous literature indicated. Secondly, we find no evidence of an interaction effect between local supply constraints and population in regions experiencing urban decline.

The setup of this Chapter is as follows. First, Section 4.2 provides a literature review of mismatch between demographics and housing supply. Section 4.3 presents the model, and Section 4.4 describes the data. The main results are presented in Section 4.5. Section 4.6 concludes.

4.2 Literature Review

This Section reviews some of the relevant literature on the subject of the effect of demographic changes and supply constraints on housing prices. First we discuss the literature on urban decline versus urban growth, followed by literature on supply constraints.

A general theory on the impact of shifts in the demand for housing (based on demographic changes) and its effect on housing prices has been drawn up by Glaeser and Gyourko (2005). They suppose that dwellings are durable objects, because they usually last for decades, if not centuries (see also Green, Malpezzi, and Mayo 2005). And, because of this durable character, urban decline is not a mirror image of urban rise (Glaeser and Gyourko 2005). This asymmetry arises firstly, because a dwelling is built relatively quickly compared to dwellings being demolished. Thus, when demand for housing is high, new construction ensures that this demand is translated in more supply. In contrast when a region is expierencing a decrease in demand, supply remains fixed. The durability of housing means that it can take decades for negative urban shocks to be fully reflected in housing supply levels, making decline a lot more persistent then growth. The other consequence of durability is that housing prices will not grow indefi-

nitely when there is a positive shock. However, because of the slow adaptation of existing stock during decreasing demand, housing prices will fall disproportionally large. A city will start to decline when housing prices are below construction costs, because investments in housing will stop being feasible. When urban productivity falls, the most active members of the labor force will naturally flee; but durable housing ensures that their homes will then be occupied by those that are less connected to the labor market (decline in *human capital*[3]).

Glaeser and Gyourko (2005) based their research on 321 metropolitan areas (MSA[4]) in the United States of America. The authors include MSAs with at least 30,000 people in 1970 and with consistent data over the 1970s, 1980s and 1990s. By regressing housing prices with separate variables for population growth and loss, they estimated that housing prices would go up with 0.23% if there would be a demographic growth of 1% and housing prices would go down 1.8% if there would be a decline of 1%, proving prior statements.

However, increase in demand has a more ambiguous effect on house prices than a decrease in demand. Communities use an array of policy tools for protecting open space. One important consequence is that the market cannot absorb increases in demand via supply if the supply constraints are too heavy (Green, Malpezzi, and Mayo 2005), at least in the short-run. In this case the increase in demand will be absorbed via house prices instead of via additional supply.

Multiple papers support this mechanism. Hilber and Vermeulen (2012) find that differences in housing supply constraints across Local Planning authorities[5] (LPA) in the UK result in differences in affordability. The authors define two different types of supply constraints in their research; (1) physical space constraints and (2) regulatory constraints. Physical space constraints refers to the scarcity of land (amount of developable land) and uneven topography (steep slopes etc.). Regulatory constraints are measured by the percentage of residential projects consisting of ten or more dwellings that were refused by an LPA. Their findings suggest that especially regulatory constraints pose a considerable threat to affordability in the Greater London area. The effect of physical constraints is significant, but not as large as regulatory constraints. In constrast, Saiz (2010) finds evidence that most areas in the U.S. in which housing supply is regarded as inelastic are severely land-constrained as well and that land-constraints are actually an important determinant of the supply elasticity.

A study by Hilber and Robert-Nicoud (2012) reveals similar results concerning regulatory

[3]Human capital refers to the stock of competences, knowledge and personality attributes embodied in the ability to perform labor (mainly education level and income) so as to produce economic value.

[4]Metropolitan statistical area (MSA) refers to a geographical region with a relatively high population density at its core and close economic ties throughout the area. Such regions are not legally incorporated as a city or town would be, nor are they legal administrative divisions like counties or sovereign entities like states. As such the precise definition of any given metropolitan area can vary with the source. A typical metropolitan area is centred around a single large city that wields substantial influence over the region. However, some metropolitan areas contain more than one large city with no single municipality holding a dominant position. MSAs are defined by the U.S. Office of Management and Budget only, and used by the U.S. Census Bureau and other U.S. government agencies for statistical purposes only.

[5]A Local Planning Authority (LPA) is the local authority or council that is empowered by law to exercise planning functions for a particular area of the United Kingdom.

constraints. Using the Wharton regulatory index the authors found that locations with more desirable amenities are more developed *and* more regulated. They show that regulations slow down new development and that locations with more home-owners favour regulations because it raises their property value. By various lobbies the planning board gets influenced. The 'home-voter hypothesis' of Fischel (2001) also implies that there is a reverse causal relationship from initially high land values to increased regulations. Finally, Glaeser, Gyourko, and Saiz (2008) find that housing price volatility during a boom-bust cycle is more severe in a region with heavy supply constraints than in a region with less supply constraints.

There are more theories on how demographics influence housing prices. Börsch-Supan (1986) and later Börsch-Supan and Pitkin (1988) specify and estimate a logit model of housing demand that explicitly includes the decision of individuals to form independent households. These studies find proof that, if the income of households grows relative to out-of-pocket costs for living, households will dissolve more easily into multiple households in multiple smaller housing units; decreasing the average human capital per dwelling and decreasing the average household size per dwelling. If an area becomes more expensive multiple households will merge and move into fewer more expensive dwellings, increasing the average human capital per dwelling and the average household size.

4.3 Model

4.3.1 Theoretical Framework

In this Section we present a theoretical model in order to more fully understand the impact of demographic changes on housing prices in a housing market with (generally) heavy supply constraints. Building on Section 4.2 the supply and demand curve can be found in Figure 4.1. Figure 4.2 shows the theoretical framework visually.

The horizontal axis in Figure 4.1 represents the number of dwellings (Q) en the vertical axis represents the housing prices (P). The supply curve (S) is displayed as the kinked and split line and the demand (demographic) curve is displayed as three curved lines (D). Whenever demand decreases (from D to $D-$) housing prices (P) will fall dramatically, but supply (Q) will not change. Whenever demand increases (from D to $D+$) two scenarios are possible. Either housing prices increase a lot, but supply will not increase ($S =$) or prices remain virtually the same, but supply increases a lot ($S+$). This would suggest that whenever supply increases in a relative inelastic housing market the general housing price level in that housing market would decrease (from $S =$ to $S+$). This will prove to be important in understanding later results.

The leftmost node (1) in Figure 4.2 implies that because the out-of-pocket costs are high ($P+$) in a given market due to increases in demand ($D+$) and constraint supply ($S =$), the average household size will increase and/or the household income will increase (Saiz 2010). Whenever a housing market is experiencing a housing demand increase and (contrary to housing

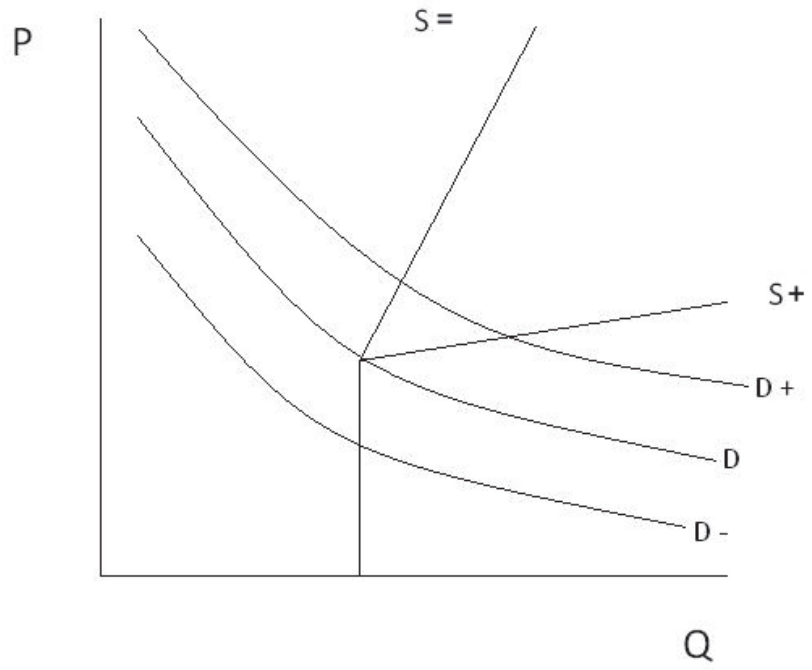


Figure 4.1: Demand- supply curve.

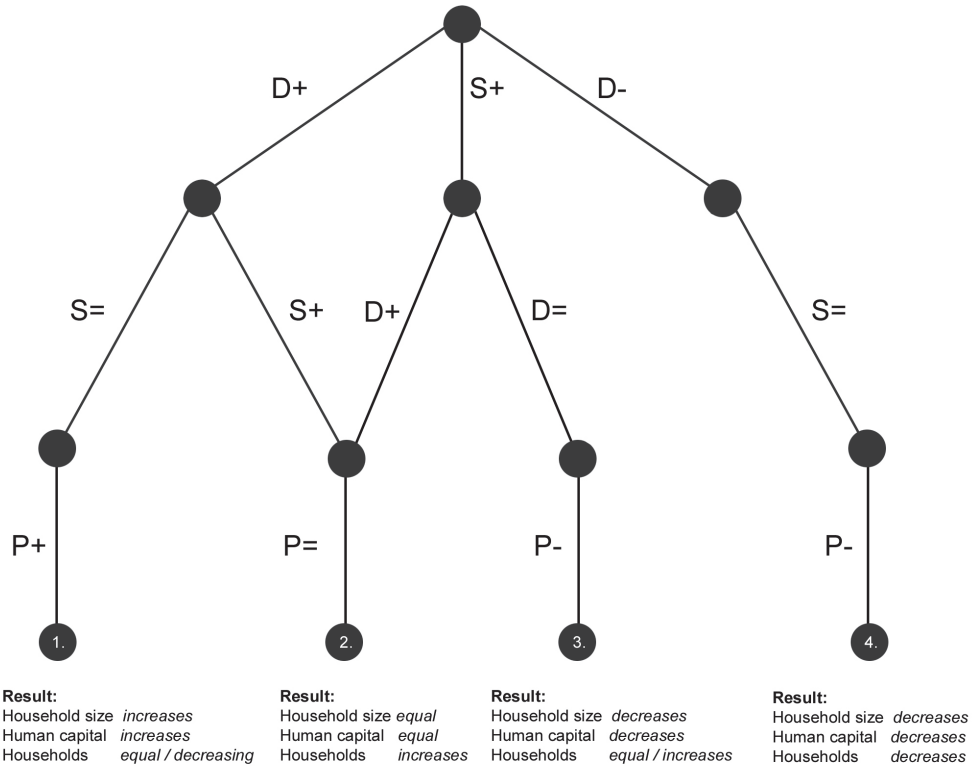


Figure 4.2: The game tree.

D is housing demand, S is housing supply and P are house prices. Please note that the game tree gives the equilibrium outcome.

markets with inelastic supply) housing supply is adjusting well ($S+$) with the increase in demand (elastic supply), nothing out of the ordinary will happen with both housing prices, average household size and income levels. This is represented by node 2 in Figure 4.2. Although it should be mentioned that intervention in the housing market by planning authorities (first an increase in supply) could also increase demand for housing. However, the result is the same (i.e. also node 2). In contrast, if demand for housing is unaltered after an increases in supply, house prices will decrease, see node 3. The durability of housing leads to housing prices being affected disproportionally large by declines in demand (node 4), showing that house price responsiveness of housing supply is not absent in case of housing price decreases. This will give opportunities for households to dissolve. Average income and educational level (human capital) should be relatively low in these areas.

So if all statements above are valid it implies that during an increase in housing demand, housing prices should increase more in housing markets with heavy supply constraints than in housing markets with low supply constraints, because local supply constraints ensure demand being translated more in housing prices. This process is visualised in Figures 4.1 – 4.2.

Of course, it is important to define *housing markets* in this context. First, and most importantly, the most important planning authority in the Netherlands are the so called zoning plans (*bestemmingsplan* in Dutch), which are made by municipalities. Also, according to Statistics Netherlands 60% of Dutch households move within the municipality. Therefore, this Section will treat the Dutch housing markets on municipality level.

4.3.2 Empirical Model

Growth is defined as a prolonged increase of population and decline is defined as a prolonged[6] decrease in population per municipality. By looking at declining municipalities we also prove the statement that decline in demand is reflected more in prices than in population.

In order to correct for time-dependent effects like interest rates, inflation and construction costs on housing prices we look at housing prices as a deviation from national average:

$$\Delta\tilde{p}_{jt} = \Delta p_{jt} - \Delta p_{nl,t}, \tag{4.1}$$

where p is the log housing price and p_{nl} is the average log housing price for the Netherlands[7]. The subscripts t and j indicate year and municipality, respectively. Please note that Glaeser and Gyourko (2005) use a comparable method to correct for a common price trend.[8] In total

[6] In later analysis 15 years proves to be a sufficient time period. See Section 4.4 as well.
[7] All lowercases represent log transformation of the corresponding variable in capitals.
[8] They used time-dummies instead of looking at price deviations.

the panel data model can be expressed as:

$$\Delta_l \tilde{p}_{jt} = \Delta_l b^+_{jt}\beta_1 + (\Delta_l b^+_{jt}\psi^+_j)\beta_2 + \Delta_l b^-_{jt}\beta_3 + (\Delta_l b^-_{jt}\psi^-_j)\beta_4 + \Delta_l x'_{jt}\delta + \epsilon_{jt}, \tag{4.2}$$

where b denotes log population and x for other (control) variables. Population change is entered in piecewise linear form to allow for differential effects in expanding b^+ versus declining b^- municipalities. Specifically, the variable b^+ (b^-) takes on a value of zero if municipality i had a population decline (growth) at time t, and equals the municipalities' actual population change otherwise. The error term is denounced ϵ. Because, urban growth and decline can only be analysed over an extended period (Glaeser and Gyourko 2005; Saiz 2010), we difference the variables over an extended period l: $\Delta_l q_{jt} = q_{jt} - q_{j,t-l}$ where q is every (both dependent and independent) variable used in the model.

In Eq. (4.2) the population change variables $\Delta_l b^+$ ($\Delta_l b^-$) are interacted with a measure for local supply constraints ψ^+_j (ψ^-_j). In our case ψ will be entered as dummy variables, indicating whether or not there are heavy supply constraints in municipality j. As the population growth and decline is interacted with a measure for supply constraints, the corresponding coefficient reflects the effect of population change, conditional on local supply constraints, in equilibrium. In contrast to the U.S. (with the Wharton Residential Land Use Regulatory Index), there is no 'standard' to measure supply constraints in the Netherlands. Therefore, we propose three different ways to measure the local supply constraints, denoted; simple, myopic and forward looking. We will use all three measures of supply constraints in this research for robustness. In the subsequent subsections we will discuss the three different measures for ψ_j.

4.3.3 A Simple measure for Local Supply Constraints (ψ^1_j)

The first simple - albeit rough - way to measure local supply constraints is to look at the discrepancies between general country-wide growth in demand (measured by average household development) and local supply development, assuming that increase in demand is uniform over locations.[9] Subsequently we group municipalities in categories based on the local supply growth. If the increases in supply was lower than a certain predefined threshold value, the municipality is categorized as a municipality with low supply elasticity, etc. These groups are expressed as dummy variables and entered in Eq. (4.2) as interaction with population growth and demand.

As long as total household growth and corresponding supply growth in the Netherlands is unrelated to other municipalitywide economic shocks, the proposed methododology is a valid instrument (Saiz 2010). The obvious problem is that total growth in households and supply is not likely to predict local demand shocks very well, reducing the usability. In this case, it

[9]Because housing stock and population are heavily correlated over space and time we would expect that an increase in supply is also indicative of a concurrent population increase.

might be possible that low demand, high elasticity municipalities will look exactly like a high demand, low elasticity municipality by this measure.

4.3.4 A Myopic Model to Measure Local Supply Constraints (ψ_j^2)

One problem with the method proposed in Section 4.3.3 is that increase in demand differs per location. Measuring supply constraints is usually done by considering the price elasticity of supply of housing. Regressing changes in housing stock on (lagged) house prices per region without additional controls (Green, Malpezzi, and Mayo 2005) or with additional controls (Mayer and Somerville 2000) is the most popular way of achieving this. The parameter estimate for change in house prices can be seen as the price elasticity of supply in this case. We start with the with the following equation (Paciorek 2013):

$$I_{jt}^{*} = \gamma_1 \Delta \ln\left(\frac{P_{jt} - RC_{jt}}{P_{jt}}\right) + \gamma_2 \frac{K_{jt-1}}{A_{jt-1}} + \alpha_t + \alpha_j + \epsilon_{jt}, \tag{4.3}$$

where I^* is the investment in housing, γ_1 represents the national-wide price elasticity of supply , γ_2 captures the fixed costs that change with increasing density, α_j are municipality fixed effects, α_t are time fixed effects and ϵ_{jt} is the normally distributed error-term.

Usually this regression - without the municipality level fixed effects (α_j) - is done per location, so different values for γ_1 per location are retrieved. A higher value for γ_1 represents higher price elasticity of supply (Mayer and Somerville 2000). However, in our case (see Section 4.4) we only have 15 years of data on 402 municipalities. This is too little information to identify separate parameters for every municipality. We take advantage of the panel structure of the data and include municipality-level fixed effects α_j. In this case the local supply constraints are identified using the municipality fixed effects, in the same fashion as Sims and Schuetz (2009) did. The rationale is fairly straightforward. If for example, land prices increase (decrease) for several years in municipality j, but investment in housing is relatively low (high) - relative to what we would expect based on the model outcomes - the municipality fixed effect will be negative (positive). Other heterogeneous differences between regions are differenced out. The obvious caveat of this system is that the *actual* price elasticity is lost.

Investment in housing I^* is defined as $I_{jt}/(A_{jt-1} - K_{jt-1})$. Subsequently, I is defined as number of new units, K is the total number of (existing) housing units, A is the total number of units possible in municipality j. A is calculated by multiplying the maximum amount of units possible square kilometre by the size, in square kilometres, of the municipality.[10] The dependent variable can now be seen as new units added to housing as percentage of what maximum number of units that *could* have been added. One intuitive way of looking at the

[10]The maximum number of units possible per square kilometre is around $12,000$. This density is realized in the neighbourhood called Kinkerbuurt in Amsterdam. The total number of square kilometres which can be built on is the square kilometres of the municipality minus rivers, sea, dunes and forests.

construct I^* compared to simply using I as dependent variable, is that if less 'slots' are available, the marginal cost of investment will increase.

P_j] is the average house price and RC_j is the average reconstruction value in municipality j. Subtracting the reconstruction value from house prices gives a measure for land prices. By dividing the land prices by total house prices the dependent variable becomes the average land fraction per municipality per year. As long as this fraction is increasing, building entrepreneurs will try to use this opportunity to buy land and build new homes, which could be sold at attractive prices (Francke, Vujić, and Vos 2009).[11] The share of unavailable land for development $(\frac{K_{jt-1}}{A_{jt-1}})$ is considered predetermined and exogenous to supply side shocks (Saiz 2010). The time fixed effects (α_t) 'capture' nationwide changes which affects investment in housing, like changes in interest rates, construction costs or nationwide legislation.

Eq. (4.3) is a reduced form regression, whereas in reality supply and demand for housing is determined in equilibrium (Mayer and Somerville 2000; Green, Malpezzi, and Mayo 2005; Sims and Schuetz 2009; Paciorek 2013). We therefore use typical demand-side shocks to identify the (reduced form) supply-side equation. Therefore Z_{jt-1} is used as an instrument[12], with Z_{jt} being:

$$Z_{jt} = \Big(\text{Industry}_{jt}, \text{Population Age Cohorts}_{jt}\Big), \tag{4.4}$$

The first instrument (Industry_{jt}) imputes shifts in local labor demand by interacting national-level shifts in industry-specific employment with the average shares (across time) of employment that those industries have in particular municipalities. We allow for four different types of industries: (1) Agricultural, forestry and fishery, (2) industrial workers and energy, (3) financial services and (4) non-financial services. This is also referred to as the Bartik (1991) measure and has been used in recent literature by Saks (2008), Saiz (2010), Zabel (2012) and Paciorek (2013).

In Section 4.2 we established that household dissolution and formation is an important house price determinant. However household size itself is endogenous (see Börsch-Supan 1986, Börsch-Supan and Pitkin 1988 and Green and Hendershott 1996). We argue that the age distribution ($\text{Population Age Cohorts}_{jt}$) in municipalities forms a good predictor of the formation and dissolution of households and so provides an exogenous instrument for housing demand, especially given the relatively immobility of European households compared to households in the U.S.[13] We distinguish four different age distributions: (1) Percentage of people of age 25

[11] Other dependent variables are used in literature as well, without changing the interpretation of the results. In some case house prices themselves are used (see for example Mayer and Somerville 2000) or the land prices themselves (for example Paciorek 2013). We tried all of these variables, however land prices as fraction of total house prices performed best.

[12] Under the rational expectations assumption anything in the information set of the agents must ne orthogonal to the future forecast errors (Paciorek 2013). We therefore prefer to use the lag of the instruments, instead of the instrument themselves.

[13] Although admittedly, in the U.S. still almost 50% of children spend their adulthood in the city where they grew up (Bartik 2009).

or younger, (2) percentage of people aged between 26 and 45, (3) percentage of people aged between 46 and 65 and finally (4) the percentage of people older than 65 for each individual municipality. It may be possible that the construction industry anticipates on these demand 'shocks', reducing the usefulness of this instrument. However, DellaVigna and Pollet (2007) show that investors are inattentive to changes in cohort sizes that can lead to excess profits stemming from increases in demand for goods in age-sensitive sectors. Recently, age cohorts has been used as an instrument for housing demand by Zabel (2012).

Since we identify the supply-side equation, it is expected that the parameter γ_1 is larger than 0 (i.e. higher prices should result in more supply). Finally, note that having multiple sources of identifying variation enhances the value of the traditional over-identification tests, which demonstrates stability of the estimated parameters over the different sources of identifying variation (Davidson and MacKinnon 1993, pp. 232 – 237).

4.3.5 The Forward Looking Model to Measure Local Supply Constraints (ψ_j^3)

We also estimate the structural parameters of a dynamic model based on Eq. (4.3) by the General Method of Moments (GMM). The issue is that Eq. (4.3) ignores forward looking behaviour on the part of landowners. We expect that the true elasticities - the response of supply to a one-time increase in price - to be substantially higher, since price changes are positively autocorrelated (Paciorek 2013). In other words, developers postpone new construction as a rational response to future expected (further) land price increases. Also in the context of '*large N, small T*'[14], first differencing the data possibly creates a correlation between regressor and error in Eq. (4.3), resulting in inconsistent estimates (Nickell 1981; Arellano and Bond 1991). The dynamic model circumvents these issues and is given by:

$$E\Big[\Big(\frac{(p_{jt}-\lambda p_{jt+1})-(rc_{jt}-\lambda rc_{jt+1})}{p_{jt}-\lambda p_{jt+1}}\Big)-\gamma_1\Big(\log\Big(\frac{I^*_{jt}}{1-I^*_{jt+1}}\Big)-\lambda\log\Big(I^*_{jt+1}\Big)\Big)- \\ \gamma_2\Big(\frac{K_{jt-1}}{A_{jt-1}}-\lambda\frac{K_{jt}}{A_{jt}}\Big)+\alpha_j+\alpha_t|Z_{jt}\Big]=0, \tag{4.5}$$

where λ is the discount rate. Following Paciorek (2013), we fix it at 0.95. Changing the discount rate to 0.90 or 0.99 did not change the estimates erratically. The reciprocal of the γ_1 parameter can be seen as the national-wide supply elasticity. Similar to Eq. (4.3), the municipality fixed effect (α_j) 'capture' the severity of the local supply constraints. All lowercase variables represent log transformation of the corresponding variable in capitals. The same set of underlying instruments - which are denoted Z_{jt} - are used as in Eq. (4.3). For a full description and derivation of the model, see Paciorek (2013).

[14]In our application 402 municipalities times 15 time periods, see Section 4.4

4.3.6 Further Discussion and Limitations

In both the myopic and forward looking model the local supply constraints are measured using municipality fixed effects. However, as we established in Section 4.2, supply constraints are endogenous to house prices (Fischel 2001; Hilber and Robert-Nicoud 2012). We therefore rank the municipalities from most constraint to least constraint. So the most constraint municipality gets a value of 1 and the least constraint municipality gets a value of N^+, with N^+ being the maximum number of municipalities with growing populations. We do the same for declining municipalities. In this case:

$$\psi^+ = \alpha_{(1)}, \alpha_{(2)}, \ldots, \alpha_{(N^+)}, \tag{4.6}$$

$$\psi^- = \alpha_{(1)}, \alpha_{(2)}, \ldots, \alpha_{(N^-)}. \tag{4.7}$$

Next, we arrange $\alpha_{(n)}$ into q groups. The groups are expressed as dummy variables and interacted with population growth/decline in Eq. (4.2). Thus, the municipalities are subdivided into categories, depending on the local supply constraints in the same fashion as we did in the 'simple' model in Section 4.3.3.

If the ranking is relatively unaffected by the errors the rank should be a good instrumental variable in itself (Durbin 1954; Bourassa et al. 2011). However, it is *still* expected that ψ will be endogenous, since the measure is based on the residuals (through the munipality fixed effects) and is influenced by both demand and supply factors. For example, unattractive municipalities will have low prices and lower than expected new construction suggesting high price responsiveness. This could bias the parameter estimate of ψ downward, suggesting that the parameter estimates are conservative. However, note that the grouping of the municipalities based on their rank (instead of taking up the rank itself in the regression) reduces this caveat considerably (Durbin 1954).

4.4 Data and Descriptive Statistics

The main database used in this study is freely available from the website of Statistics Netherlands. For each municipality we observe the population size, number of households, average household size (Börsch-Supan 1986; Haurin, Hendershott, and Kim 1993), total housing stock, construction cost index, the number of permits issued for new units in the owner-occupier market and the maximum number of housing units possible. We use number of permits instead of change in housing stock ($\Delta \log K$) or new-builds, because the first also includes homes which were demolished and the second can be prone to lagging issues. We specifically look at the owner-occupier market, because the rental market is heavily regulated in the Netherlands (Schilder 2012). The development of income is mainly determined on country level in the

Netherlands.[15] As a result, the variability of (changes) in income is very low in the Netherlands between municipalities. Therefore we rather use (changes in) unemployment as a proxy for the economic activity of a municipality (De Wit, Englund, and Francke 2013). Data on (constant quality) changes in housing prices were made available to us by Ortec Finance. It is a repeat sales price index based on micro data from the Land Registry office (Kadaster). Data on square meter construction costs per province are retrieved from Bouwkosten Kompas and the average house size per municipality between 1995 – 2009 is made available to us by the NVM. For the complete list, see Table 4.1. More extensive details are given in Appendix C.3. Using the

Table 4.1: List of variables on municipality level

Variable	Definition	Source	Period
B	inhabitants	CBS	1995-2009
HH	households	CBS	1995-2009
HS	average household-size	CBS	1995-2009
I	given permits for new units in the owner-occupied market	CBS	1995-2009
U	number of people with requested unemployment benefits	CBS	1995-2009
P	housing prices	OF	1995-2009
RC.sq	sq. meter reconstruction value	BK	2011
Sq	Average house size	NVM	1995-2009
CC	construction cost index	CBS	1995-2011
K	total supply housing stock	CBS	1995-2009
A	maximum possible units	CBS	1995-2009

Note BK: Bouwkosten Kompas, CBS: Statistics Netherlands & OF: Ortec Finance.

average square meter reconstruction value in 2011, the average house size per municipality and the (national wide) construction cost index it is possible to measure the average reconstruction value (designated RC) per municipality per year.

All the municipality data obtained by the Statistics Netherlands (CBS) had to be rearranged, because multiple municipalities split up, merged or changed names in the sampled period. There are a total of 441 (January 2009) municipalities in the Netherlands. The reduced sample used contains a total of 402 cases. This is due to the fact that some municipalities have been split up and allocated to multiple neighbouring municipalities. Data on these 39 municipalities are unusable because it is unknown what the population groups did before they were split up. Examples are the municipality of Breda and The Hague (see Table C1 in the Appendix for a full list of absent municipalities).

Table 4.2 provides the descriptive statistics of the (first) differenced variables per year and per municipality.[16] All lowercase variables represent corresponding capital variables in natural logarithms. Housing prices increased (on average in nominal terms) with 7.5% per year between 1995 and 2009. The average increase in land values was lower, but the standard deviation is larger. We see that both housing stock, investment in housing, land use and households had

[15]Salary for the next year per branch is determined by a collective labor agreement (in Dutch CAO).

[16]First the descriptive statistics are found per municipality. The numbers found in Table 4.2 are the averages of these descriptives per municipality.

Table 4.2: Descriptive statistics key variables, 1995 – 2009

	$\Delta\overline{p}_{.j}$	$\Delta\overline{k}_{.j}$	$\Delta\overline{b}_{.j}$	$\Delta\overline{hs}_{.j}$	$\frac{K_{jt-1}}{A_{jt}}$	$\Delta\overline{(p-rc)}_{.j}$	$\overline{I}^{*}_{jt}$	$\Delta\overline{u}_{.j}$
Mean	0.0751	0.0100	0.0041	-0.0052	0.0369	0.0360	0.0004	-0.0386
Median	0.0751	0.0090	0.0031	-0.0054	0.0166	0.0366	0.0003	-0.0848
Minimum	0.0414	-0.0060	-0.0099	-0.0102	0.0020	-0.0358	0.0001	-0.7282
Maximum	0.1018	0.0556	0.0538	0.0032	0.2995	0.1041	0.0010	0.9555
Std. Dev.	0.0078	0.0058	0.0064	0.0020	0.0488	0.0442	0.0003	0.2431
Skewness	-0.2454	2.8265	2.8133	0.6281	2.4475	-0.0740	0.9287	0.7527
Kurtosis	4.6846	17.7216	17.6226	3.6107	9.5035	1.9766	3.4395	3.1846

a small increase on year-to-year basis. Over the entire 15-year period only 1% extra of the entire possible space was used up for housing. However, we do find large differences over municipalities. The difference between the municipality with the smallest yearly investment in housing and the one with the largest yearly investment in housing is a factor 10. On average only 4% of the possible space for housing is actually used for housing. Next we will explore the basic correlations between the key variables visually.

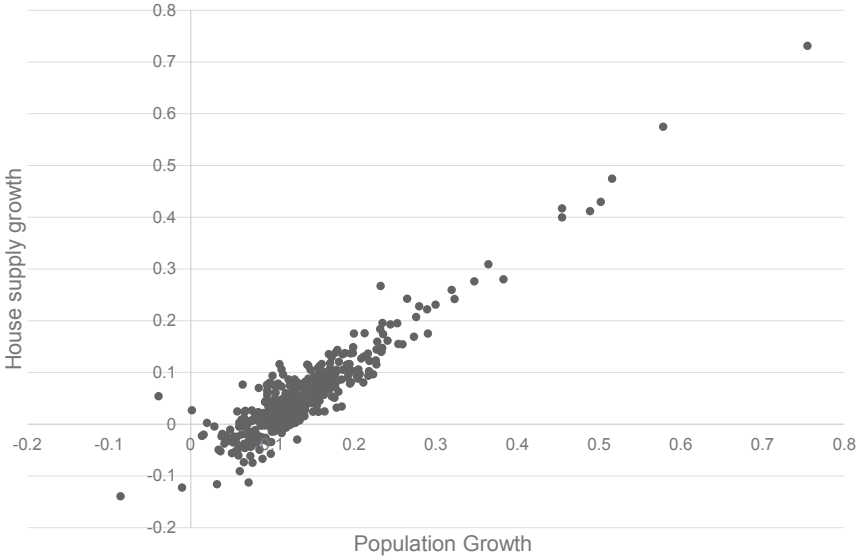
In Figure 4.3 we see two scatterplots. In both panels the horizontal axis represents the average annual change in population (in %) during the sample period. In the top panel of Figure 4.3 the vertical axis represents the average annual change in housing stock (in %) and in the bottom panel the vertical axis represents the average annual price deviation from Dutch average (in %) during the sample period. The top panel of Figure 4.3 shows the strong correlation of 0.7 between supply and population per municipality. The bottom panel of Figure 4.3 shows the difference of expanding versus declining municipalities visually. All municipalities who had a high price increase had a relative low population development. All municipalities who had a high population increase, had a lower than average housing price change. Municipalities who had even the slightest decrease in population had a high decrease in housing prices compared to the Dutch average. This is in accordance with the theoretical framework (see Section 4.3.1).

Finally, there are two general remarks to be made. The Dutch islands are over represented in the outliers. The islands are mainly used recreational and not many people live there permanently. Therefore, small changes can have a big impact. Secondly, if we look at the municipalities with a prolonged decline in population we see strong geographic trends. Almost all municipalities are in peripheral regions close to the border with Belgium or Germany.

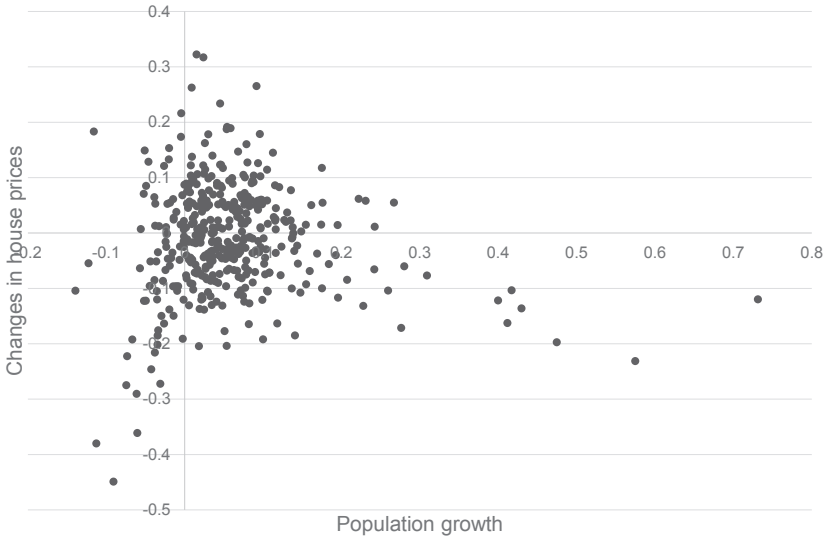
4.5 Results

The following Section presents the effects of demographic growth and decline on house prices. Only persistent shifts in demand affect house prices (Glaeser and Gyourko 2005; Saiz 2010), we therefore difference the variables over the longest possible period ($l = 15$ years, revisit Eqs.

Figure 4.3: Scatterplots of key variables



(a) Population growth versus house supply growth.



(b) Population growth versus changes in house prices.

(4.1) – (4.2))[17].

The estimation results can be found in Table 4.3. Column (I) presents the effect of demographic growth and decline while disregarding local supply constraints. Unemployment is entered as a control variables in all specifications. Household size is also included in column (I), even though it is endogenous.

Even though we are primarily interested in equilibrium outcomes, we instrument for population growth and decline in column (II). Population changes itself is endogenous to house prices, mainly due to omitted variable bias (Saiz 2010). The results give us a better understanding of the causal effect of population on house prices. We use the age distribution instrument as introduced in Section 4.3.4. A second - *immigration* based instrument - is used as well. We take the fraction of total number of immigrants living in municipality j in a certain year (1994 in our case) and multiply these fractions with national-wide increases in immigrants for every year. Here we use the fact that immigrants tend to move to areas where other immigrants settled before (see Saiz 2007 for a more detailed description of this instrument).[18] The model is estimated using Two Staged Least Squares (TSLS). We also omit household size from column (II) onwards.

Column (III) introduces the effect of local supply constraints measured by the 'simple' model described in Section 4.3.3. In column (IV) local supply constraints are measured by the 'myopic' model described in Section 4.3.4 and finally column (V) measures supply constraints by using the 'forward looking' model described in Section 4.3.5. The results and some diagnostics of the 'myopic' and 'forward looking' models can be found in Appendix C.2. Since we are interested in the conditional relationship in equilibrium, we do not instrument for b^+ and b^- in columns (III) through (V).

For the simple, myopic and forward looking models, the municipalities are grouped into *three* (*two*) categories in case of population growth (decline), depending on the local supply constraints according to said three different measures. The subdivision of municipalities based on local supply constraints for the simple model is explained in more detail in Appendix C.2. In columns (IV) and (V), if a municipality, which experienced population growth, is ranked in the top 50 of municipalities with the most supply constraints, the municipality is grouped in the (dummy) category 'heavy constraint' (ψ^+_{heavy}). If a municipality, which experienced population growth, is ranked between 150 and 50 of municipalities which are most supply constraint, the municipality is grouped in the (dummy) category 'medium constraints' (ψ^+_{medium}) in columns (IV) and (V). We only have two categories for municipalities with demographic decline in columns (IV) and (V), due to the fact that there are lower numbers of observations for this

[17] One-, three- and five-year cycles were modelled as well. The results - however - showed autocorrelation. One other remark is that in total over 90% of the municipalities has seen demographic decline in one year or the other between 1995 and 2009, including many of the municipalities which have inelastic supply according to our measurements. Differencing the variables over a larger period make them less sensitive to 'accidental' changes in 'demand'.

[18] In this case the Bartik-measure did not contribute to the overall model performance.

group. In this case we group the municipalities ranked into the top 35 with the most supply constraints in the (dummy) category 'heavy constraint' (ψ^{-}_{heavy}).

Table 4.3: Main results

Variable		**(I)**	**(II)**	**(III)**	**(IV)**	**(V)**
Population decline	$\Delta_{15}b^{-}$	1.74	1.32	3.25	1.95	1.86
		(6.85)***	(1.70)*	(5.60)***	(6.17)***	(5.45)***
Supply constraints^{-}	$(\Delta_{15}b^{-} \times \psi^{-}_{\text{heavy}})$			-1.80	-0.13	0.09
				(2.97)***	(-0.27)	(0.18)
Population growth	$\Delta_{15}b^{+}$	-0.26	-0.05	-0.17	-0.20	-0.21
		(-4.17)***	(-0.32)	(-2.82)***	(-3.13)***	(-3.24)***
Supply constraints^{+}	$(\Delta_{15}b^{+} \times \psi^{+}_{\text{medium}})$			0.20	0.25	0.19
				(1.49)	(1.79)*	(-1.75)*
	$(\Delta_{15}b^{+} \times \psi^{+}_{\text{heavy}})$			0.82	0.30	0.47
				(3.00)***	(1.88)*	(2.01)**
Household size	$\Delta_{15}hs$	0.97				
		(5.75)***				
Unemployment	$\Delta_{15}u$	-0.08	-0.10	-0.08	-0.09	-0.08
		(-4.17)***	(-3.84)***	(-4.03)***	(-4.35)***	(-4.13)***
Constant	λ_0	0.04	-0.05	-0.04	-0.05	-0.04
		(2.21)**	(-3.84)***	(-2.95)***	(-2.89)***	(-2.77)***
Method		OLS	TSLS	OLS	OLS	OLS
Adj. R^2		0.22	0.15	0.21	0.20	0.21
S.E. of regression		0.09	0.09	0.09	0.09	0.09
N		395	395	395	395	395
ψ				Simple	Myopic	Forward

Note. The full specification is given by:
$\Delta_{15}\tilde{p}_{jt} = \Delta_{15}b^{-}_{jt}\beta_1 + (\Delta_{15}b^{-}_{jt}\psi^{-}_{\text{heavy},j})\beta_2 + \Delta_{15}b^{+}_{jt}\beta_3 + (\Delta_{15}b^{+}_{jt}\psi^{+}_{\text{medium},j})\beta_4 + (\Delta_{15}b^{+}_{jt}\psi^{+}_{\text{heavy},j})\beta_5 + \Delta_{15}u_{jt}\beta_6 + \lambda_0 + \epsilon_{jt}$
Standard errors in parenthesis. *** Significance within 99% probability, ** Significance within 95% and * Significance within 90% probability.

In all cases we find evidence that demographic decline has a disproportional large effect on house prices, which is consistent with previous literature. The effect is smallest for the Two-Staged-Least-Squared model in column (II). This makes sense, since the hatted values for population decline (estimated in the first step) are almost always larger than the original values (and vice versa). It was expected that supply barely reacts to negative demand shocks. Thus, it should come as no surprise that the interaction between our measure for supply constraints and demographic decline are not-significant for both the myopic and forward looking model. The 'simple' model (column III), estimates that population decline has a larger (negative) effect on house prices in municipalities with elastic supply. This large effect is probably a supply side

effect instead of a demand effect. In other words: Adding supply in a region with demographic decline results in more house prices decreases.

The effect of population growth is negative in column (I). This is a supply side effect as well, as municipalities with low supply constraints increased capital stock considerably in case of an increase in demand and vice versa. When instrumenting populating growth (column II), the effect of population growth is insignificant, which is indicative of an efficient housing market (Malpezzi, Ozanne, and Thibodeau 1987). The results in columns (III) trough (V) all indicate that the effect of population growth in municipalities with little supply constraints is negative. This is very likely due to planing decisions made on the municipality and/or central government level. In the Netherlands many municipalities were 'chosen' to add supply by the central government, through the so called *national spatial planning key decisions* (PKB in Dutch).[19] The PKB prescribes where and how much new construction should be initiated. Municipalities must take up this new construction in their local zoning plans. In this case the causality is actually reversed. Supply is added due to policy, resulting in (municipality level) house prices decreases.

Population growth barely affects house prices in municipalities with 'medium' supply constraints in columns (III) through (V). In this case supply (in equilibrium) reacts to demand in a sufficient manner. The small positive sign in columns (IV) and (V) can be caused by a number of reasons. First of all, as indicated earlier, it could caused by omitted variables affecting both population and house prices (hence explaining why we do not find a positive effect of population growth on house prices in column II). Secondly, it could 'simply' be caused by the grouping procedure.[20]

Population growth *does* result in higher house prices in municipalities with high supply constraints. A 1% increase in population results (in equilibrium) in 0.82%, 0.30% and 0.47% higher house prices according to the simple, myopic and forward looking models respectively. In this case demand is translated more in prices than in population. Population can only grow by household formation, or by increasing (existing) supply conjoined with a relative large marginal cost of investment due to high land prices. Therefore, high house prices may mean that only more wealthy households can afford to move into a municipality with inelastic supply, while poor households are forced to move out, leading to higher income inequality across municipalities (Saks 2008).

Unemployment has a negative effect on house prices in all specifications and is quit stable over all specifications. A 1% increase in unemployment results in a 0.1% decrease in house prices. The negative sign was expected and is in line with literature.

[19]The system of PKB was abolished starting in 2009. This is the moment our data ends, see Section 4.4.
[20] However, we did try different groups as robustness. The results did not alter erratically.

4.6 Concluding Remarks

The focus of this Chapter is the asymmetry between the effect of population growth and decline on housing prices taking into account local supply constraints. A theoretical framework is introduced which shows us that population growth has an ambiguous effect on housing prices depending on the supply constraints. In house markets with little supply constraints, constructors can 'overreact' to shocks in demand, resulting in falling house prices. In countries with heavy supply constraints, such as the UK and the Netherlands, population growth will result in higher house prices. Local supply constraints ensure demand being translated more in housing prices than in population. Empirical evidence was found to support this mechanism.

A decrease in demand for housing almost automatically results in a disproportionally large decrease in housing prices. Theory tells us that this is due to the physical nature of cities. If we look at municipalities that had a prolonged decline in population, we see a clear pattern. We estimate that a population decline of 1%, results in a 1.8% drop in housing prices on average. In contrast to municipalities experiencing population growth, we find no empirical evidence that local supply constraints affect house prices in case of population decline.

Chapter 5

The Effect of Depreciation on House Prices

Abstract[1]

In this Chapter we introduce a hedonic price model which enables us to disentangle the value of a property into the value of land and the value of structure. For given reconstruction costs our model gives a good approximation of the impact of physical deterioration, functional obsolescence and vintage effects on the structure and the impact of time on sale (external obsolescence) on the land value simultaneously. Our findings show that maintenance has a substantial impact on the rate of physical deterioration. After 50 years of not or barely maintaining a home a typical structure has lost around 43% of its value. In contrast, maintaining a home very well results in virtually no physical deterioration in the long run.

5.1 Introduction

As of 2011 housing capital accounts for 35% of the total capital stock in the US and almost 60% of household wealth in the Netherlands (US Bureau of Economic Analysis and Statistics Netherlands respectively). However, as all tangible assets do, housing loses its value as it ages. Also, widely publicized measures for house price appreciation overstate the capital gain from homeownership, because they do not take into account the cost of maintaining a home (Harding, Rosenthal, and Sirmans 2007). Therefore, knowing the pattern of depreciation and the effect of maintenance becomes important for tax policies and for national income and wealth accounting alike (Leigh 1980; Smith 2004).

Depreciation is defined as *"to be the decline in asset values (or shadow price) due to ageing"* (Malpezzi, Ozanne, and Thibodeau 1987; Shilling, Sirmans, and Dombrow 1991), suggesting that if depreciation is sufficiently large houses will actually decrease in value. However, this definition leaves room for three types of categories within depreciation: Physical deterioration, functional and external obsolescence.

[1]This chapter is based on Francke and Van de Minne (2015).

Physical deterioration is the simple wear and tear on the structure and all its components. Evolution in technologies (building quality) and tastes also affect preferences for residential living. This can make a home *functionally obsolete* (Lusht 2001) or at least less valuable.[2] An example could be an unappealing floor plan or a kitchen without sufficient space to add modern day appliances. The main difference between physical deterioration and functional obsolescence is that physical deterioration affects the actual structure, whereas functional obsolescence affects the amount of housing services provided by the structure. As a result functional obsolescence does *not need* to occur (Conijn 1995), whereas (as with all physical assets) deterioration will always be present (Wilhelmsson 2008). Also, *maintenance* activities benefit the owner by slowing the rate of physical deterioration. Some maintenance decisions may even allow the value of property to go up (Knight and Sirmans 1996; Arnott and Braid 1997). However, maintenance is never sufficient to cure the effects of functional obsolescence.[3] The final component of depreciation is *external obsolescence* (Knight and Sirmans 1996; Lusht 2001). This encompasses changes, not to the property itself, but to the area surrounding the property (such as changes in traffic volume). Apart from depreciation it is important to distinguish the *vintage effect*: a preference for specific structure characteristics. These characteristics often correlate with the construction period. The vintage effect may even offset the negative effect of physical deterioration on the structure value (Wilhelmsson 2008).[4]

The main contribution of this study is that we introduce a model which gives a good approximation of the effect of all age effects (physical deterioration 'net' of maintenance, functional and external obsolescence and vintage effects) on house prices simultaneously. This benefits us in many ways. Most importantly, we show that the rate at which a home deteriorates is heavily dependent on the level of maintenance. Before describing the model we first list the most common problems in traditional hedonic models with respect to measuring depreciation.

Firstly, key variables in the field of depreciation are *perfectly collinear*: time of sale, construction year and age (McKenzie 2006; Coulson and McMillen 2008).[5] Time of sale represents the general market conditions which is reflected in land value (Bourassa et al. 2011). Time of sale also impacts structure values due to changes in reconstruction costs, such as labor and material costs. Age is a measure of the physical deterioration of the structure (Malpezzi, Ozanne, and Thibodeau 1987). Construction year measures the separate impact of functional obsoles-

[2] In some cases functional obsolescence is also referred to as ageing, for example Conijn (1995) and Bostic, Longhofer, and Redfearn (2007).

[3] Although in reality, some maintenance decisions actually will cure at least some function obsolescence. When households decide to maintain a home, they will likely take this opportunity to alter their home to better suit their current tastes (think of wall papers).

[4] Vintage effects have impact on property prices, because replacing and changing structure characteristics is time consuming and even in some cases impossible. Structures with all the desirable characteristics in place will therefore be perceived by buyers as having higher appreciation potential, since the buyers demand a premium for the risk and time involved in changing the characteristics (if even possible).

[5] Time of sale = age + construction year.

cence[6] as well as vintage effects (Wilhelmsson 2008). Even worse, since changes in tastes for residential living changes over time, both functional obsolescence and vintage effects are time varying. A common strategy to circumvent the multicollinearity issue in traditional hedonic models is by omitting one of the variables. However, this strategy has the caveat that it biases (upward or downward) the age estimate for physical deterioration. For example, if older homes are appreciated more for its distinct architecture one would get a positive age estimate if the vintage effect is not taken into account. Another option is to impose some structure on the functional form for the variables age, construction year and time of sale. However, the choice of the functional form is arbitrary and the results for all age effects (physical deterioration 'net' of maintenance, functional and external obsolescence and vintage effects) heavily depend on the chosen functional form.

Secondly, assuming the property is a composite of land and structure value and the land value is positive, regressing age – again as proxy for physical deterioration – on the property value will *always* bias the estimate downward. The size of the bias depends on the fraction of structure value to total property value. The precision of the estimated age parameters also suffers if the study is carried out over multiple regions and over a large time-span, as the structure value as fraction of total property value can vary substantially over space and time (Bostic, Longhofer, and Redfearn 2007; Davis and Heathcote 2007; Davis and Palumbo 2008; Bourassa et al. 2011; Sirmans and Slade 2011).

Both problems can be circumvented by realizing that age and construction year only impact structure value, and time of sale only land value, the last conditional on known reconstruction costs over time.[7] This approach enables us to simultaneously estimate the impact of physical deterioration (age), the joint impact of functional obsolescence and vintage effects (construction year) on structure value, and the effect of time of sale on land value.

In this Chapter we disentangle house prices into land and structure values in a nonlinear hedonic price model from transactions of houses including land. The structure value is equal to the *given* reconstruction costs minus the *estimated* depreciation, corrected for the effects of maintenance. Using reconstruction costs as basis for structure values is quite common in literature (see for example Bourassa et al. 2011, Davis and Heathcote 2007, Davis and Palumbo 2008 and Diewert, De Haan, and Hendriks 2015). Due to severe zoning restrictions (which are quite common in most industrialized countries), there is no option value in structures (i.e.

[6] As Stahl (1985) noted, the supply of housing services a structure provides barely changes after construction.

[7] The theory behind this framework is that land and structure components are unique goods and therefore their prices respond differently to demand and supply side variables (see, Bostic, Longhofer, and Redfearn 2007; Davis and Heathcote 2007; Davis and Palumbo 2008; Bourassa et al. 2011, among others). On the demand side structures can be seen as capital input for housing production, whereas land capitalizes the market value of local amenities such as infrastructure and accessibility to employment and facilities. Although there will always be delivery lags and, to some extend, imperfect foresight of agents (Harter-Dreiman 2004), structures are relatively easily reproducible on the supply side. On the other hand, (desirable) land is by definition *not* reproducible. The direct consequence is that, contrary to the value of the structure, the value of the land is subject to demand factors, such as income, interest rates and demographics (Bourassa et al. 2011).

the current structure is the optimal structure). The law of one price now dictates that in order to reproduce the cash flow generated by the property (imputed rent in the case of the owner-occupied market) one must purchase the land and *reproduce the structure* minus any accumulated depreciation. The land value is further disentangled into the value of the footprint of the structure and the value of the yard, because of their completely different uses. The value of the footprint is expressed as a function of its size, house type, time of sale and location. The yard value is expressed as a function of its size, time of sale and location. In case reconstruction costs are known – an assumption that is not unrealistic in practice – we are able to estimate the impact of depreciation on the structure value and the impact of time of sale on the total land value. We estimate our model on an extensive and reliable micro dataset, made available to us by the Dutch Association of Real Estate Brokers and Real Estate Experts (NVM), covering the period of 2000 up to 2012 for the region 's-Hertogenbosch in the Netherlands.

There are two major assumption we need to make for the model to work. The *first* assumption is that in case of small sample periods the functional obsolescence and vintage effect (construction year) on house prices is time-invariant. When looking at small sample periods only, the change in preferences for living could not have changed *that* much over the analysed period. Still, we need to acknowledge that the effect of functional obsolescence and vintage are in fact time-varying. As a result, part of the function obsolescence and vintage effects are likely to be 'caught' by the time of sale dummies.

The *second* assumption is that there is no (redevelopment) option value on land ownership (or conversely there is no economic obsolescence). This is in contrast with the more recent perspective of the interaction between structure and land values. From this perspective, the value of land ownership (distinct from ownership of a built structure) derives purely from the development or redevelopment option value that such ownership entails (Geltner et al. 2014).[8] As the current structure moves away from its highest and best use (HBU) over time, the redevelopment option on land ownership will grow. Thus, it becomes near impossible to disentangle the value of the structure with the value of the land, since demolition is the exercise of a *call option* on the new building, with the strike price being the construction cost plus demolition cost plus the opportunity cost of the preexisting building and it is the *location* which affects the value of the call option. In case of the Netherlands (where our analysis will take place) we are comfortable making the assumption that there is no (substantial) redevelopment option, since it is mainly legislation that depicts what structures should look like due to severe zoning restrictions (Andrews, Sánchez, and Johansson 2011; Sanchez and Johansson 2011), so the 'optimal structure' is equal to the current structure at all times. This is buttressed by the extreme low number of demolished structures in the Netherlands.[9]

[8] Note that this is consistent with the 'real options' model of land value as a development option (see, Yamazaki 2001, Titman 1985, Clapp, Lindenthal, and Eichholtz 2010 and Clapp, Bardos, and Wong 2012, for example) .

[9] Other assumptions concerning the real option theory do not hold in real estate markets as well, such as the assumptions on liquidity, arbitrage opportunity and zero transaction costs (Chang and Chen 2011).

Our findings show that the total effect of physical deterioration of structures over time differ significantly between a well maintained and a poorly maintained structure. The flexible specification of the age function also empirically verifies that year-to-year physical deterioration decreases with the age of the structure, in line with the findings of Cannaday and Sunderman (1986) and Goodman and Thibodeau (1995). Barely maintaining a home results in a 1.6% annual physical deterioration for the first 15 years, 0.9% annually for the first 30 years and 0.9% annually for the first 50 years. Maintaining a home very well results in almost no physical deterioration.

By comparing the footprint, yard and structure price indices we find that the average rate of return is lowest for the structure and highest for the footprint. The volatility is highest for the yard index, followed by the footprint and structure index. Worthy of note, the structure, footprint and yard price indices are barely correlated.

The setup of this paper is as follows: Chapter 5.2 provides a literature review on depreciation and disentangling land and structure values. Chapter 5.3 provides a detailed description of the empirical model. Chapter 5.4 describes the dataset used and provides descriptive statistics. Chapter 5.5 discusses the estimation results and, finally, Chapter 5.6 concludes.

5.2 Literature Review

Using the age and construction year of a property as a proxy for its depreciation in a hedonic framework is quite common in housing, as well as non-housing models (Wilhelmsson 2008). It is also quite common to use the construction year of the structure as a measure for the combined effect of functional obsolescence and vintage, by claiming that structure characteristics are usually highly correlated with the year they were built in (Coulson and McMillen 2008; Wilhelmsson 2008). The way households appreciate properties from a certain vintage, changes over time. Papers in which maintenance data is available usually analyse the level of maintenance in combination with the age of the property to find the physical deterioration 'net' of maintenance (Harding, Rosenthal, and Sirmans 2007). In the remainder of this Chapter we will describe the results of previous papers in the field of depreciation and try to answer the question why different papers find various depreciation rates.

Malpezzi, Ozanne, and Thibodeau (1987) conducted a survey on depreciation models based on literature prior to 1987. From the 12 selected studies only one study (Leigh 1980) did not use a hedonic model with age as proxy for physical deterioration on the right-hand side and transaction prices on the left-hand side. The estimated annual depreciation rates in these studies varied significantly between 0.38% and 2.40%. Malpezzi, Ozanne, and Thibodeau (1987) concluded that the variations in the reported results were due to differences in the definition of depreciation, differences in the models and data used and the conditions of the (local) real estate market at the time of the study. By using the same hedonic model and data for 59

metropolitan areas in the US Malpezzi, Ozanne, and Thibodeau (1987) showed that physical deterioration – which was modeled by age, age^2 and age^3 in a hedonic framework – varies spatially. Table 5.1 shows the average age effect for several studies.

Building quality and climate differ over space. Therefore, the rate at which homes deteriorate can differ spatially as well. However, if we look in more detail at the different age coefficients Malpezzi, Ozanne, and Thibodeau (1987) estimate per metropolitan area, we see that in some regions age has a positive effect on house prices. Similarly, Rubin (1993) and Chang and Chen (2011) estimate a positive age coefficient in one or more regions in a hedonic framework. In general we can say that these studies (together with Shilling, Sirmans, and Dombrow 1991; Smith 2004; Sirmans et al. 2006) find a very small effect of age on property value.

The difference between the studies mentioned above and the other studies in Table 5.1 is that they incorporate neither construction year nor maintenance as control variables, or use low quality maintenance data alone in the regression. The most obvious reason to omit the construction year is to circumvent the multicollinearity problem between transaction year, construction year and age. The most plausible reason to omit the maintenance effect is a lack of available maintenance data.

Omitting maintenance from the regression biases the age effect downward for obvious reasons. Omitting the level of maintenance will also induce age-related heteroskedasticity (Goodman and Thibodeau 1995). The reason is that the variance of the price will increase with the age of the property, as the condition of the house (renovated, maintained or completely run down) is likely to vary more.

Shilling, Sirmans, and Dombrow (1991), Knight and Sirmans (1996), and Bourassa et al. (2011) claim that vintage and maintenance *can* be omitted if only relatively newly constructed homes (Age $\leq$ 20 years) are considered. Even though this solves the aforementioned identification issue, the question is to what extent these assumptions hold and what the (short-run) age estimate says about long-run physical deterioration. Wilhelmsson (2008) argues the construction year can be omitted, again to circumvent the multicollinearity problem, as long as age is entered in a nonlinear (in this case quadratic) form. In this setup age measures the combined effect of physical deterioration, vintage effects and functional obsolescence. However, this strategy has two drawbacks. Firstly, this makes it impossible to disentangle the effects of physical deterioration, functional obsolescence and vintage. Secondly, previous studies have shown that the vintage effect should be entered in a more flexible (less rigid) way (Goodman and Thibodeau 1995).

Two papers (Harding, Rosenthal, and Sirmans 2007; Coulson and McMillen 2008) do actually include the variables age, construction year and time of sale, using two completely different strategies. Firstly, Harding, Rosenthal, and Sirmans (2007) modify the standard Case and Shiller (1987) repeat sales index by taking the time-varying variables age and maintenance into account. Assuming that the characteristics (and subsequent shadow prices) of a structure do

Table 5.1: Summary of the depreciation literature.

Author(s)	Age	NLAge	CY	Time	Maint.	L & S	Comments
Malpezzi, Ozanne, and Thibodeau (1987)	−1.00%	✓	X	✓/X	X	X	Time variable is entered as trend. Meta analysis. Some regressions have positive age estimate. Also Age^3. Micro data (AHS).
Shilling, Sirmans, and Dombrow (1991)	−1.18%	✓	X*	✓/X	X	X	Only new builds.* Time variable is entered as trend. Age is entered piecewise constant. (Small) micro data.
Rubin (1993)	−0.25%	X	X	X	✓/X	X	Some regressions have positive age estimate. Meta analysis. Characteristics are as assessed by the owner-occupiers themselves. 1 regression has a positive age estimate. Micro data (AHS).
Goodman and Thibodeau (1995)	−1.46%	✓	X	✓	X	X	Only transactions from 2 years. Also Age^2, Age^3 and Age^4 in separate regression. Micro data on single-family homes in Dallas, US.
Knight and Sirmans (1996)	−1.89%	✓	X*	✓	✓	X	Only new builds.* Unreliable database. (Small) micro data.

NLAge is Non-Linear Age specification, CY is construction year (vintage), Maint. is level of maintenance, L & S stands for whether or not the authors separate land and structure values, AHS stands for Annual Household Survey and N/A is not available. In case of a meta analysis the age effect is the average beta coefficient, in case of multiple regressions or piecewise constant age specification (Shilling, Sirmans, and Dombrow 1991) the most representative beta coefficient is presented.

* Because these authors only look at new builds they assume there is no vintage effect and that no maintenance has been done as of yet. On average the oldest structures in these papers are 20 years.

Author(s)	Age	NLAge	CY	Time	Maint.	L & S	Comments
Smith (2004)	−1.11%	✓	X*	✓	✓/X	✓/X	The assessed land values are assumed to be constant over time. Assessed land values for one year only. Author interacts time of sale and location with age. Only (linear) vintage effect for properties built before 1930.* Maintenance level for one year only and assessed area-wide. Land specific variables regressed on structure value.
Sirmans et al. (2006)	−0.89%	X	X	✓/X	X	X	Time variable is entered as trend. Meta analysis. Multiple data sources.
Harding, Rosenthal, and Sirmans (2007)	−2.50%	✓	✓/X**	✓	✓	X	Repeat Sales Model.** Age is entered on a logarithmic scale. Micro data (AHS).
Wilhelmsson (2008)	−1.18%	✓	X	X	✓	X	The derivative of the age function is 0 at 23 years. Separate indoor and outdoor maintenance. Micro data on Stockholm, Sweden.
Coulson and McMillen (2008)	−1.65%	✓	✓	✓	X	X	Also Age^3 and Age^4. Also a semi-parametric approach as (McKenzie 2006) proposed. Micro data on the city of Chicago.
Chang and Chen (2011)	−0.46%	X	X	✓	✓/X	✓	Characteristics are as assessed by the owner-occupiers themselves. 2 of the 6 regressions have positive age estimate. Meta analysis. Micro data (AHS).

NLAge is nonlinear Age specification, CY is construction year (vintage), Maint. is level of maintenance, L & S stands for whether or not the authors separate land and structure values, AHS stands for Annual Household Survey and N/A is not available. In case of a meta analysis the age effect is the average beta coefficient, in case of multiple regressions the most representative beta coefficient is presented.

not change over time, the construction year should be omitted from the regression. The unfortunate outcome is that in this framework one cannot measure the joint effect of functional obsolescence and vintage. Subsequently, Harding, Rosenthal, and Sirmans (2007) *force* an arbitrary nonlinear (log) transformation on age to avoid perfect collinearity with the annual house price index. The estimate of ln(Age) is -0.14, which results in an annual physical deterioration of about 2% for the first 20 years (of total property value).

In contrast to the heavily restricted specification of the age effect in the model of Harding, Rosenthal, and Sirmans (2007), Coulson and McMillen (2008) employ a more flexible approach, as proposed by McKenzie (2006) to estimate the age, construction year and time of sale effect simultaneously.[10] The multicollinearity is solved by assuming that some neighbouring parameters in the age, construction year and time of sale effect ($\beta_j - \beta_{j-1}$) are equal to a known constant (which in practice is set to 0). The big caveat with this approach is that the final estimates are sensitive to the parameters that are assumed to be equal and that many alternative restrictions on neighboring parameters may be considered (corresponding to the age, construction year and time of sale variables).

Coulson and McMillen (2008) estimate that the effect of age on property values is actually positive after the structure hit the age of 43 years. This is very likely to be a maintenance effect (the authors do not include level of maintenance in their model, see Table 5.1), since they include construction years to counteract the vintage (and functional obsolescence) effect.

Finally, the separability of land and structure values should be taken into account when estimating the depreciation effects (Chinloy 1980; Smith 2004). Physical deterioration and functional obsolescence (as well as vintage) only affect the structure value of the property and not the land value. As stated in Chapter 5.1 ignoring this will bias the age effect downward. As shown in Table 5.1 only two studies (Smith 2004; Chang and Chen 2011) considered this in their analysis.

In the case of Smith (2004) assessed land prices are subtracted from property prices to end up with structure values. However, these assessed values are only available to the author for one year (1996). The author makes the unrealistic assumption (see Bostic, Longhofer, and Redfearn 2007; Davis and Heathcote 2007; Davis and Palumbo 2008; Bourassa et al. 2011) that land values are constant over time in real terms in order to determine land values of properties in other years than 1996. This influences some key results. For example, Smith (2004) interacts time of sale with age and concludes that the age effect decreased between 1993 and 2000. This could, however, be explained be realizing that land values increased at a higher rate than structure values over this period.

In summary, one could say that in order to find the net physical deterioration of structures (with age as its proxy) in a hedonic framework one should control for maintenance, construc-

[10] By comparison, the authors also employ a more standard hedonic model where they force a nonlinear structure on age as Harding, Rosenthal, and Sirmans (2007) did. However, here we only discuss their nonparametric approach (McKenzie 2006).

tion year (as proxy for vintage and functional obsolescence) and time of sale. It has also been argued that physical deterioration and construction year should be attributed specifically to the structure value of the property. Omitting maintenance and not separating the property value into land and structure components will bias the age coefficient downward, and omitting the construction years will bias the age coefficient either upward or downward. A summary of the key variables is given in Table 5.2.

Table 5.2: Summary of proxy variables for construction costs, depreciation and vintage effects.

Proxy variable	Structure	Land
Time of sale	- Changes in construction costs	- Changes in land prices. (External obsolescence (D))
Age & Maintenance	- Physical deterioration (D)	
Construction period	- Functional obsolescence (D) - Vintage effects	

D = part of depreciation.

5.3 Model

In this Chapter we provide econometric model specifications. We start with a 'base-line' model in Chapter 5.3.1. This is a traditional hedonic model in which we do not make the distinction between land and structure components. In Chapter 5.3.2 we provide the model in which we *do* decompose the transaction price into structure and land value. Chapter 5.3.3 discusses assumptions and some limitations to this model. The findings of both models will be compared in Chapter 5.5.

5.3.1 Base-line Specification

In this Chapter we provide the base-line specification. It is a traditional hedonic model with log house prices ($\ln P$) on the left hand side and house characteristics on the right hand side. This basic specification is in line with most of the models presented in Table 5.1, and is given by:

$$\begin{aligned}\ln P_{it} =&(d_{it}^{M} \times A_{it})\beta_1^{Age} + (d_{it}^{M} \times A_{it}^2)\beta_2^{Age} + \\ & d_{it}^{Time}\beta^{Time} + d_{it}^{CY}\beta^{CY} + x_{it}'\phi + \varepsilon_{it}.\end{aligned} \tag{5.1}$$

The subscripts $i = 1, \ldots, N$ and $t = 1, \ldots, T$ denote an individual property and time, where N is the number of observations and T is the number of time periods. The variable P is transaction price and A is age. The row vectors d_{it}^{M}, d_{it}^{CY}, and d_{it}^{Time} contain dummy variables

for the accumulative level of maintenance up to time of sale, construction years and time of sale[11] and have the corresponding coefficient vectors β^{Age}, β^{CY} and β^{Time}.

Age (A) is used to measure the rate of physical deterioration. In case the renovation year is available in the data, it is better to define age as the difference between time of sale and year of renovation (Lusht 2001). This means that we will likely get a conservative estimate of the rate of physical deterioration. However this is a data issue and not so much a model issue. We argued that (only) physical deterioration can be retarded by maintenance (M) activity, thus age is interacted with maintenance. Even though this assumption is made by several papers (Wilhelmsson 2008), there are real life examples which indicate that some maintenance activities also affects functional obsolescence. If households for example need to replace the 'old' heating system, they will probably not replicate the system as it was, but upgrade to a system which better reflects current tastes and preferences. In this regard there is also a semantic discussion on what the difference is between 'regular' maintenance and renovations. As with the age parameter, not having renovation data is unfortunate when estimating functional obsolescence. Thus, the construction estimates will probably be an underestimation as well, especially when considering older properties. Both vintage effects and functional obsolescence are dependent on construction year (or renovation year in case of functional obsolescence), although the concepts are different. By using construction year as only explanatory variable it is not possible to distinguish between vintage effects and functional obsolescence. Time of sale ($Time$) represents the general market conditions.

Because time of sale, construction year and age are perfectly collinear we either have to omit one of these variables, or force a structure on the functional form on at least one of these variables. We choose to force both a linear and a quadratic function on age, because this is commonly practised in literature (Goodman and Thibodeau 1995).[12]

The vector x_{it} contains all other (control) variables of interest, such as location dummies, floor size and land size, with corresponding coefficient vector ϕ. These variables will be discussed in more detail in Chapter 5.3.2.

The error term ε is assumed to be normally and independently distributed with fixed variance σ^2. In contrast to Diewert, De Haan, and Hendriks (2015), we use the natural logarithm of the transaction price, instead of the transaction price itself, for two reasons. First, the resulting residuals are closer to normality. Second, it makes more sense to minimize the relative difference between model value and transaction price, as opposed to the difference itself. The first can be done approximately by using the natural logarithm of the transaction price as the dependent variable. The model is estimated by ordinary least squares.

[11] Obviously one category for the row vectors of dummy variables should be omitted to avoid the dummy trap.
[12] In case of the linear specification the age square term must be omitted from Eq. (5.1).

5.3.2 Model for Structure and Land Values

In this Chapter we provide the model in which we decompose the transaction price in structure and land value. The age and construction year effects are attributed specifically to the structure value. In its simplest form the model is provided by:

$$\ln(P_{it}) = \ln(S_{it} + L_{it}) + \varepsilon_{it} \tag{5.2}$$

$$S_{it} = C_{it} \times \exp(D_{it}), \tag{5.3}$$

$$L_{it} = IL_{it} + G_{it}, \tag{5.4}$$

where S is the value of the structure, L is the value of the land, C is the (re)construction value, and $\exp(D) - 1 \approx D$ is the percentage impact of physical deterioration, functional obsolescence and vintage effects on the value of the structure. By taking the exponent of D we assume that the value of the structure cannot be lower than 0.[13] It is assumed that the value of the yard (G) and the value of the footprint (IL) add up to the value of the (total) land (L).

The individual components of Eqs. (5.2) – (5.4) are specified as follows:

$$C_{it} = \mathrm{FS}_{it}^{\gamma} \times c_{ref,t} \times d_{it}^{Dem}, \tag{5.5}$$

$$D_{it} = \underbrace{(d_{it}^{M} \times d_{it}^{A})\beta^{Age}}_{\text{physical deterioration}} + \underbrace{d_{it}^{CY}\beta^{CY}}_{\text{vintage}}, \tag{5.6}$$

$$\begin{aligned} IL_{it} = {} & \mu_{t_0}^{IL} \times (\mathrm{ILS}_{it}^{s} + \mathrm{ILS}_{it}^{l}\alpha_l) \times (1 + d_{it}^{\mathrm{Time}}\beta^{\mathrm{Time}}) \\ & \times (1 + d_{it}^{\mathrm{LOC}}\beta^{\mathrm{LOC}}) \times (1 + d_{it}^{\mathrm{PT}}\beta^{\mathrm{PT}}), \end{aligned} \tag{5.7}$$

$$\begin{aligned} G_{it} = {} & \mu_{t_0}^{G} \times (\mathrm{GS}_{it}^{s} + \mathrm{GS}_{it}^{l}\delta_l) \times (1 + d_{it}^{\mathrm{Time}}\lambda^{\mathrm{Time}}) \\ & \times (1 + d_{it}^{\mathrm{LOC}}\lambda^{\mathrm{LOC}}). \end{aligned} \tag{5.8}$$

Eq. (5.5) represents the (re-)construction cost (C). The (re-)construction value per square meter is based on a reference property. It depends on structure type (for example, single family homes, apartments, etc.), time (t) and region, and is denoted by c_{ref}. FS is the floor size. For $\gamma = 1$ the construction costs are proportional to the floor size, for $\gamma < (>)1$, the construction costs are less (more) than proportional to the floor size. The parameter γ will be estimated from the data. Dummy variable d_{it}^{Dem} is 0 in case the property is bought to be demolished and 1 otherwise. This effectively corrects for the right censoring of the age data. However, in our case we do not observe which properties are bought to be demolished. In addition, homes are barely demolished in the Netherlands. According to *Statistics Netherlands* less than 100 homes were 'extracted' after 1988. This number also includes homes that were burned down or

[13] One can think of real world situations in which the structure value is actually lower than 0. The most straightforward example is the case in which the cost of demolishing the structure is more than the actual value of the structure itself. However, in reality this rarely happens since structures are usually demolished a considerable time before the structure value hits 0, see Bokhari and Geltner (2014).

multiple homes that were converted to (for example) one home. Thus, for this application, we fix d_{it}^{Dem} at 1.

Eq. (5.6) represents the impact of physical deterioration and vintage effects on the construction value (D). In the base-line model we had to force a structure on the functional form of age to circumvent perfect collinearity with time of sale and construction year. However, disentangling house prices into structure values and land values solves the identification problem in itself. The rate of physical deterioration should be estimated with as little structure on the age parameter as possible (Cannaday and Sunderman 1986; Goodman and Thibodeau 1995). Therefore, age is entered in Eq. (5.6) by dummy variables (d_{it}^{Age}). As in the base-line model age is interacted with maintenance. The joint effect of functional obsolescence and vintage is captured by construction year dummy variables (d_{it}^{CY}).

To avoid the dummy trap the most recent construction year, age = 0 and 'good' maintenance level should be omitted, since these omitted categories represent the reconstruction value best.[14] It is also preferred that the construction year cohort reference group overlaps the time of sale period. Otherwise, you could find a vintage effect on newly constructed homes. Furthermore, note that including time of sale in Eg. (5.6) – in case changes in reconstruction cost over time are unknown and need to be estimated – would lead to unidentifiable coefficients. [15]

The value of footprint IL in Eq. (5.7) depends on the size of the footprint (ILS), time of sale (d_{it}^{Time}), location (d_{it}^{LOC}) and property type (d_{it}^{PT}). The value of the yard G in Eq. (5.8) depends on the size of the yard, time of sale and location.

We expect that the marginal price per square meter of land decreases when the size of the land increases (Lusht 2001), irrespective of the use of the land. We model this by entering the land size as a linear spline. We first split both land sizes in small and large. In case of the footprint this would look like: $ILS = ILS^s + ILS^l$. In our case the difference between small and large is 75m^2. For example, in case the footprint size is 200m^2, then ILS^s is 75m^2 and ILS^l is 125m^2. The same knot is used for the split in yard size: $GS = GS^s + GS^l$.

Location (LOC) captures all kinds of location-specific amenities, which influence demand. It also – together with time of sale – controls for external obsolescence. We model location as dummy variables for four digit ZIP codes. Time of sale captures general market conditions and external obsolescence, and is modelled by dummy variables for the year of sale.

Zoning restrictions also restrict the property type (PT) allowed on the footprint. This will likely result in differences in value for the footprint (because of local availability or affordability of each property type, for example). We model property type as dummy variables as well.

The coefficient $\mu_{t_0}^{IL}$ ($\mu_{t_0}^{G}$) gives the price per square meter for the footprint IL (yard G) for

[14] Theory predicts that the housing services provided by a newly constructed structure is proportional to the value of the structure (Conijn 1995).

[15] In case the reconstruction values are not a good approximation of the structure value, due to option value and economic obsolescence, one could replace $c_{ref,t}$ with a coefficient χ_t and subsequently estimate it from the data (on a disaggregate level as possible). The big issue here is that χ also depends on time of sale and is thus not identifiable. In this case a structure needs to forced on χ_t. However, this is out of the scope of this research.

the reference home in period t_0. The coefficient β^{Time} (λ^{Time}) gives the percentage of land price changes over time for the footprint (yard). The coefficient β^{LOC} (λ^{LOC}) gives the percentage premium or discount of the prices per square meter relative to the reference location for the footprint (yard). The coefficient α_l (δ_l) provides the relative prices of large land sizes compared to small land sizes for the footprint (yard). Finally, the coefficient β^{PT} gives the percentage premium or discount of the price for a certain property type relative to the reference property type for the footprint.

The model is nonlinear in its parameters and is estimated by nonlinear least squares.

5.3.3 Further Model Assumptions and Limitations

In Section 5.1 we introduced two major assumptions: (1) Functional obsolescence is time-invariant in short sample periods and (2) there is no redevelopment option value on land in case of the Netherlands. This Section reviews some smaller assumptions we make.

The first is that physical deterioration is uniform across structures. Obviously, a home built with low quality materials (or by a low quality contractor) will have a different rate of physical deterioration than a home built with high quality materials (or by a high quality contractor). However, we do not have data on the quality of the structure. Moreover, there is a possibility that building quality is correlated with the construction year. In this case, the vintage / functional obsolescence effect we find could actually be a physical deterioration effect. Even though we cannot completely rule out this possibility we should mention that one of the oldest still existing laws in the Netherlands is the Housing Act (in Dutch: *Woningwet*), which was introduced in 1902. The main purpose of this law is to guarantee a relatively high quality of newly constructed dwellings.[16]

Depreciation and vintage can vary with location (Malpezzi, Ozanne, and Thibodeau 1987; Smith 2004). For example, homes built near the ocean will deteriorate relativity quickly and 1930s homes will be valued differently (i.e. vintage) between New York and Miami. Since, in our application we will only look at a single region with relative a small number of dwellings the second assumption is that the parameters for physical deterioration and vintage are fixed within this region.

Furthermore, older structures tend to filter down to families of lower economic status (Rosenthal 2008), thus lowering land prices (Glaeser and Gyourko 2005). This last argument introduces the notion of endogeneity between structure value and level of maintenance, because the lower income households have fewer means to maintain their homes (Harding, Rosenthal, and Sirmans 2007)[17]. However, the endogeneity of house prices and maintenance is a smaller issue

[16] The quality of the structure can also be correlated with location. More specifically, we expect higher structural quality at better locations. In Chapter 5.5 we introduce a robustness check which allows for higher structure values at more expensive locations.

[17] This self-reinforcing decline is punctuated by increases in demand as obsolete and dilapidated structures are demolished and replaced by new structures attractive to higher income families (Rosenthal 2008).

in the Netherlands since the way the mortgage market is designed in the Netherlands excludes households with low incomes or low wealth from the owner-occupier market (Schilder 2012). Thus, the third assumption is the level of maintenance is exogenous to house prices.

Still, as mentioned before, one major issue with our data is that we do not observe the year of renovation. Even though dwellings are hardly demolished, and the main characteristics of dwellings remain fixed (due to legislation) in the Netherlands, many (smaller scale) characteristics still alter during major renovations. This will bias the age estimates downwards. However, note that this is a data issue and not a issue of the model. In case the date of renovation is observed, one should take the renovation year to measure functional obsolescence and take the age of a property from year of renovation to measure physical deterioration.

Given the caveats (and mitigating circumstances) separating property values in land and structure values is still assumed to be a good working assumption. It should also be noted that none of the existing models are successful in circumventing all of the critiques described above.

5.4 Data and Descriptive Statistics

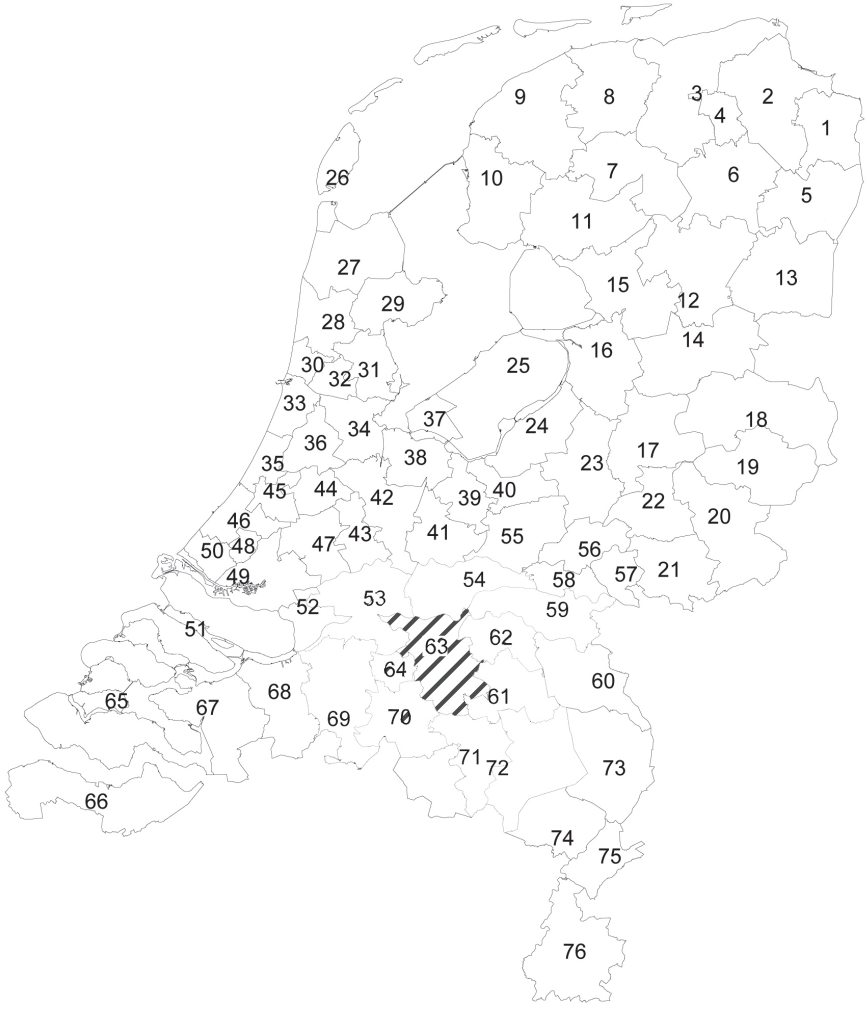
We estimate our model on the region of 's-Hertogenbosch in the Netherlands. Figure 5.1 provides a map of the distribution of the different regions within the Netherlands. Note that the largest city in the region of 's-Hertogenbosch (with a population of 150, 000) is the city with the same name. Except for the relatively large city of 's-Hertogenbosch, the region also entails smaller cities (like Zaltbommel, population 28, 000) and rural areas, making it a diverse area. The sales dataset is provided by the NVM, the largest brokers organization in the Netherlands; about 70% of all real estate brokers in the Netherlands is affiliated to the NVM. A total of 171 brokerage firms were active in the region of 's-Hertogenbosch in our sample period from 2000 up to 2012. On average they sold 55 houses during this period. In total, 56 brokerage firms were responsible for only 1 transaction. The most successful brokerage firm in terms of sales was responsible for 11.90% of the sales.[18]

For each house we observe the transaction price and the date of sale, that is the date of signing the preliminary sales contract. We also observe the house type (12 types), the construction year of the house, the number of floors, the total land size in square meters, the size of the yard in square meters, the maintenance level (9 categories varying from very poorly maintained to perfectly, separate numbers for inside and outside maintenance), the roof type (4 in total), parking facilities (4 types), and address.

The calculation of the construction costs is based on data from Bouwkostenkompas. It contains construction costs for 58 reference homes and eight types of extensions (including parking facilities) for the 12 different provinces in the Netherlands. By comparing the characteristics of the houses in the NVM database to the 58 reference homes we are able to calculate construc-

[18] These numbers were taken after the filters were applied, see below.

Figure 5.1: Distribution of the NVM districts in the Netherlands.



The 's-Hertogenbosch region is 63. For your reference, 34 is Amsterdam.

tion costs of individual houses. However, the data obtained from Bouwkostenkompas are only available for 2011. In order to calculate the construction costs in preceding years we backtrack to the year of sale, using the (non-constant quality) construction costs index provided by the national statistical agency, Statistics Netherlands.[19] The different data sources are summarized in Table 5.3.

Table 5.3: Overview of the data and sources.

Source	Data	Years
NVM	Sale and house characteristics	1985 – 2012
Calcsoft	Construction costs per m^2 for 60 reference homes in 2011	2011
Statistics Netherlands	Construction cost index	1906 - 2013

Since we do not observe land sizes (let alone yard sizes) for apartments in the data, we are forced to omit apartments from the analysis. The remaining house types are terraced, semi-detached and detached homes. Due to data limitations we can match the NVM transactions to the construction cost database for transactions in 2000 and upward; for transactions prior to 2000 essential data on, for example, type of roof is missing. Other filters have been applied as well. For example, houses with extreme transaction prices or lot sizes and newly constructed homes are omitted. [20] After applying the data filters $9,331$ observations are available.

Subsequently, a few data transformations are made. Age is calculated by subtracting the construction year from the year of sale. The size of the footprint is calculated by subtracting the size of the yard from the total land size.

For maintenance 18 categories are available, 9 for both inside and outside maintenance, potentially resulting in 81 different combinations. However, the interior and exterior maintenance figures are highly correlated, and some categories have a very low incidence. Therefore, we reduce the number of maintenance categories to 3, based on the total of interior and exterior maintenance, varying from 'poorly to mediocre maintained' (denoted category -1) to 'well maintained' (denoted category $+1$). Reducing the number of maintenance categories also reduces potential bias in the brokers' reported view of maintenance. More details on definitions and coverage can be found in Table 5.4.

The level of maintenance in our analysis is as assessed by the individual sales brokers. Even though there are no specific guidelines for assessing the level of maintenance, the individual

[19]Obviously an index on the most disaggregate level is advised. However, in the case of the Netherlands, national level data will suffice, because distances in the Netherlands are small. With roughly $12,000$ square miles the Netherlands is comparable in size to a relatively small state in the US like Massachusetts ($10,555$ sq mi).

[20]We omit newly constructed homes, since land prices in the Netherlands for new construction are usually pre-determined by municipalities and are thus not market prices in itself. Also, since construction can take a year or more, the prices of the properties when finished, might not be representative of the same properties when the contracts were signed.

Table 5.4: Summary of the maintenance variable.

Level	Description	Criteria	N. observation	%
-1	Bad to mediocre	$M < 13$	740	7.9%
0	Normal	$13 \leq M < 16$	7,264	77.8%
1	Very good	$M \geq 16$	1,327	14.2%
Total			9,331	100.0%

M denotes the total of interior and exterior maintenance.

brokers affiliated to the NVM are supposed to take courses in engineering, which are provided by the NVM itself. The brokers have to redo these courses on a yearly basis in order to keep their NVM license. Thus, we assume that the building quality/maintenance is assessed uniformly by the different (171) brokerage firms active in 's-Hertogenbosch.

There is the question whether or not the age of the structure influences the way brokers assess the level of maintenance. If maintenance is measured in an absolute way, one expects that on average the older the property the lower the average maintenance. If it is measured relative to the age of the structure, one would expect that the average maintenance does not depend on age. Figure 5.2 shows the average maintenance level per construction year. If Figure 5.2 would be a flat line, it would be evident that brokers assess the level of maintenance relative to the age of the structure. In this case there would be an interaction effect between maintenance and age. However, Figure 5.2 reveals that, on average, older structures *are* assessed to be maintained less than newer structures. Still, we do now what the 'true' slope of Figure 5.2 would be if brokers truly assessed the level of maintenance in an absolute way. Thus, whether or not brokers asses the level of maintenance relative or absolute to age is more of an empirical question and we will keep the interaction between maintenance and age in the model.

Some details on terraced and (semi-) detached homes in the region 's-Hertogenbosch, from 2000 onwards, are given in Table 5.5. The frequencies of construction periods, house types, years of sale and zip codes can be found in Table 5.6.

Table 5.5 shows that the average floor size, footprint, yard size and transaction price per m^2 floor size are highest for detached houses, and lowest for terraced houses. Table 5.6 shows that terraced houses constitute 55% of the transactions and detached houses only 6%.

Since the age of the houses is the most important variable in this paper, we will look into it in more detail. First of all, neighborhoods tend to be developed in roughly the same time period (Clapp and Giaccotto 1998). This suggests that there should be more variation in the age of the housing stock throughout 's-Hertogenbosch than within the individual 4 digit zipcodes (Rosenthal 2008). To confirm that premise, we first measure the standard deviation of the age of the housing stock as of 2012, within each 4 digit zipcode (LOC). Secondly, we order the standard deviations per 4 digit zip code from lowest to highest. The percentiles presented in Table 5.8 are based on this ordering. As a comparison, the difference between the standard deviations of the individual 4 digit zip code and the entire region of 's-Hertogenbosch ($HERTOG$)

Table 5.5: Some descriptive statistics for 's-Hertogenbosch, 2000 - 2012.

		Total	Terraced	Semi-detached	Detached
Number of observations		9,331	5,095	3,659	577
Transaction price	mean	€261,672	€215,654	€297,614	€440,095
	std. dev	€88,684	€51,062	€68,570	€125,084
	min	€90,000	€99,832	€90,000	€142,500
	max	€1,200,000	€680,000	€837,500	€1,200,000
Transaction price per m^2 floor size	mean	€1,961	€1,782	€2,127	€2,497
	std. dev	€571	€433	€391	€1,378
	min	€876	€876	€1,144	€1,332
	max	€4,492	€4,492	€4,442	€3,933
Reconstruction costs	mean	€180,257	€139,221	€216,615	€312,056
	std. dev	€65,951	€31,142	€45,941	€88,200
	min	€13,252	€13,252	€63,182	€33,763
	max	€691,514	€438,332	€530,402	€691,514
Reconstruction costs per m^2 floor size	mean	€1,328	€1,136	€1,533	€1,722
	std. dev	€268	€138	€148	€330
	min	€850	€850	€1,028	€939
	max	€3,376	€2,465	€2,032	€3,376
Floor size in m^2	mean	134	122	142	183
	std. dev	31	20	29	50
	min	10	12	45	10
	max	450	265	350	450
Footprint in m^2	mean	127	88	158	278
	std. dev	69	26	50	112
	min	10	10	24	10
	max	590	511	564	590
Yard in m^2	mean	98	61	126	241
	std. dev	92	34	95	179
	min	1	1	1	16
	max	1,500	1,400	1,400	1,500
Maintenance	mean	1.063	1.027	1.092	1.196
	std. dev	0.466	0.454	0.464	0.548
	min	0.000	0.000	0.000	0.000
	max	2.000	2.000	2.000	2.000
Age in years	mean	29	31	27	25
	std. dev	19	19	19	20
	min	1	1	1	1
	max	106	106	105	98
Number of rooms	mean	4.895	4.740	5.022	5.458
	std. dev	0.975	0.860	0.999	1.380
	min	1.000	1.000	1.000	2.000
	max	14.000	14.000	12.000	14.000

Table 5.6: Frequencies on construction period, house type, and year of sale.

	N. obs	Frequency
Construction Period		
1906-1930	237	2.5%
1931-1944	521	5.6%
1945-1959	554	5.9%
1960-1970	1,768	18.9%
1971-1980	2,019	21.6%
1981-1990	1,919	20.6%
1991-2000	1,991	21.3%
After 2000 (R)	322	3.5%
House type		
Terraced (R)	5095	54.6%
Semi-detached	3659	39.2%
Detached	577	6.2%
Year of sale		
2000 (R)	643	6.9%
2001	682	7.3%
2002	761	8.2%
2003	796	8.5%
2004	868	9.3%
2005	926	9.9%
2006	907	9.7%
2007	929	10.0%
2008	709	7.6%
2009	522	5.6%
2010	539	5.8%
2011	495	5.3%
2012	554	5.9%

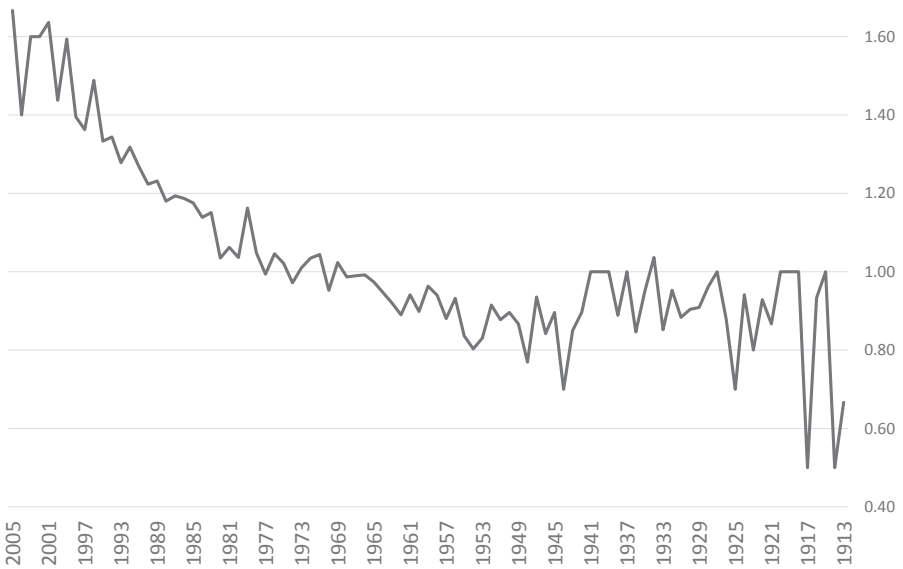
R = reference group.

Table 5.7: Frequencies for zip codes in 's-Hertogenbosch.

ZIP-code	N. obs	Frequency	ZIP-code	N. obs	Frequency
5076	49	0.5%	5268	49	0.5%
5211	75	0.8%	5271	384	4.1%
5212	259	2.8%	5272	92	1.0%
5213	188	2.0%	5275	85	0.9%
5215	179	1.9%	5281	161	1.7%
5216	114	1.2%	5282	166	1.8%
5221	158	1.7%	5283	561	6.0%
5223	122	1.3%	5291	33	0.4%
5224	316	3.4%	5293	10	0.1%
5231	246	2.6%	5296	34	0.4%
5232	26	0.3%	5298	90	1.0%
5233	240	2.6%	5301	477	5.1%
5235	310	3.3%	5302	108	1.2%
5236	338	3.6%	5305	17	0.2%
5237 (R)	768	8.2%	5306	27	0.3%
5241	196	2.1%	5308	32	0.3%
5242	135	1.4%	5311	28	0.3%
5243	87	0.9%	5313	10	0.1%
5244	91	1.0%	5314	34	0.4%
5246	243	2.6%	5321	125	1.3%
5247	162	1.7%	5324	53	0.6%
5248	53	0.6%	5325	8	0.1%
5251	316	3.4%	5327	18	0.2%
5252	102	1.1%	5328	53	0.6%
5253	34	0.4%	5331	76	0.8%
5254	26	0.3%	5334	12	0.1%
5256	137	1.5%	5335	11	0.1%
5258	293	3.1%	5481	267	2.9%
5261	136	1.5%	5482	297	3.2%
5262	481	5.2%	6624	20	0.2%
5263	113	1.2%			

R = reference group.

Figure 5.2: Average maintenance level per construction year.



is reported as well. Rosenthal (2008) argues that maintenance is also correlated with 4 digit zip codes. Therefore, we carry out the exact same analysis for level of maintenance as well. Finally, Figure 5.3 shows the construction year distribution within the different maintenance categories.

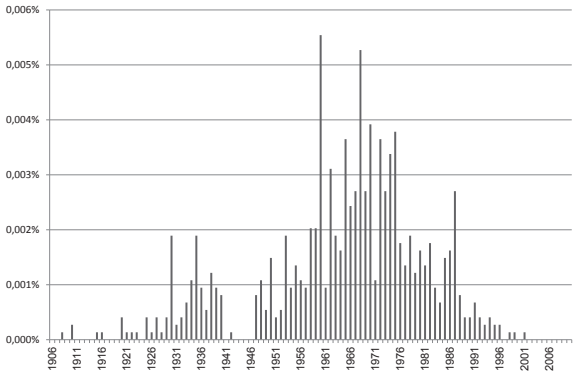
Table 5.8: Standard deviation of age and maintenance of the housing stock in 2012.

	σ^{Age}		σ^{M}	
Percentiles	Within 4 digit zipcode	Difference between 4 digit zipcode and 's-Hertogenbosch	Within 4 digit zipcode	Difference between 4 digit zipcode and 's-Hertogenbosch
10	4.77	-14.38	0.346	-0.122
25	10.94	-8.20	0.405	-0.063
50	14.91	-4.23	0.464	-0.005
75	19.41	0.27	0.502	0.034
90	23.57	4.43	0.564	0.096

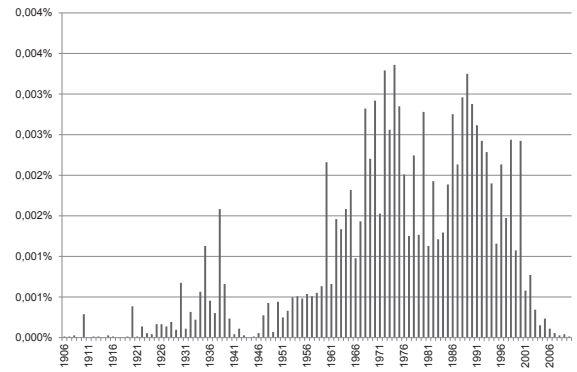
The average age of the housing stock in 2012 was 33 years.

Table 5.8 confirms that homes within a given 4 digit zip code tend to have more similar construction years compared to the total region. Only at the 7th decile is $\sigma^{Age}_{LOC} \geq \sigma^{Age}_{HERTOG}$. On the other hand, the level of maintenance does seem to be more equally distributed over the 4 digit zip codes. Already around the median it holds that $\sigma^{M}_{LOC} \geq \sigma^{M}_{HERTOG}$. In Figure 5.3 we see that the number of homes built before the 1960s is relatively sparse. Still, there

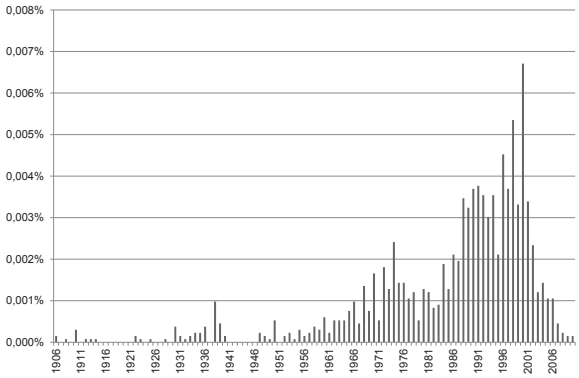
Figure 5.3: Distribution of construction years per maintenance category.



(a) M(-1)



(b) M(0)



(c) M(+1)

The average age of the housing stock in M(−1) is 42 years, in M(0) 30 years and in M(+1) 19 years.

is more than enough age variation within the maintenance groups, despite the fact that the construction year distribution is skewed to the right for well maintained homes and skewed to the left for poorly maintained homes.

5.5 Results

In this Chapter we present the estimation results. Because some of the frequencies of the joint distribution of age and level of maintenance are low (see Figure 5.3), we group the age into 5-year cohorts for the first 50 years (ending up with 10 groups of 5-year age cohorts) and 1 dummy for properties of age 50 and older. We also group the construction year cohorts in groups of 10 years on average to 'capture' the functional obsolescence and vintage effect. Note that this is a limitation of the data and that this grouping is not necessary if the data would allow for it.

The main results are presented in Table 5.9. The first column of Table 5.9 presents the results of the base-line model with the linear specification for age (denoted *Base A*). The base-line model with the quadratic specification of age is given in the second column of Table 5.9 (denoted *Base B*). The third column of Table 5.9 presents the results of the full model (which we will refer to as the *main model*), as given by Eq. (5.2). The fourth column of Table 5.9 displays the estimation results from the main model, in which location dummies have been omitted in order to check for possible correlation between construction year and location. This correlation could change the coefficient estimates (for construction year and age in particular) erratically. Finally, we expect higher unobserved structural quality at better locations, so the measurement error in replacement costs is possibly correlated with land price.[21] This could affect the coefficient estimates as well. The fifth column of Table 5.9, therefore, presents the estimation results of the main model with higher structural quality at better locations, using a 2-step approach.

In the first step we estimate the location values using the main model (third column of Table 5.9). We subsequently rank the location values from cheapest to most expensive and use the low (high) construction costs given in the Bouwkostenkompas data (in the main model we use average construction costs) to compute the 'new' reconstruction value of structures on the cheapest (most expensive) location. A straight-line between the low and high construction costs is used to determine the reconstruction value for structures on the other locations, based on their ranking.[22] In the second step we re-estimate the model, using the new reconstruction values for structures. Please note that if we would observe the quality of the structure in the

[21] Although it should be stressed - once more - that demolishing dwellings is highly unusual in the Netherlands. Thus, this correlation does not exist because highly valued locations are redeveloped with higher standards.

[22] We actually use a kinked line, because the average construction costs are not exactly in the middle of the high and low construction costs figures. Low construction costs are about 8% lower than average, whereas high construction costs are 12% higher than the average construction costs.

data directly, this robustness check would not be necessary.

The age effect of the base-line models and the main model can be found in Figure 5.4. A price index for both land uses (estimated from the main model) and construction costs (from Statistics Netherlands) can be found in Figure 5.5.[23] The contribution of the individual components to total value is given in Figure 5.6 which is based on the main model as well. Total house price appreciation according to the main and base-line models is given in Figure 5.7. Finally mean returns, volatility of the returns and the correlations between the returns can be found in Table 5.10.[24]

We will discuss the results extensively in the remainder of this Chapter. Chapter 5.5.1 discusses the results for the structure variables and Chapter 5.5.2 discusses the results for the land variables.

5.5.1 Structure variables

The negative coefficients on age for all models (see Figure 5.4) indicate that structures tend to deteriorate with age, reducing the appreciation of the structure. All non-linear specifications of age result in homes deteriorating at a faster rate for the first 20 years. Analogously, maintaining a home decreases the effective age of a home considerably. However, it is evident that the rate of deterioration differs substantially between the base-line models and the main model. Part of this difference can easily be explained by realizing that the main model estimates the effect of age on the structure, whereas the base-line models estimate the effect of age on total property value. The average structure value is only 50% – 60% of the total value of the property (Figure 5.6). Indeed, the quadratic base-line model (Base B) 'underestimates' the physical deterioration and joint functional obsolescence and vintage effect by approximately 50% *on average*. However, the base-line model with the linear specification of age provides vastly different estimates.

In general, the linear base-line model (Base A) overestimates the joint effect of functional obsolescence and vintage and underestimates the effect of physical deterioration. This emphasizes that the results for all age effects (physical deterioration 'net' of maintenance, functional obsolescence and vintage) heavily depend on the chosen functional form. Other functional forms of age (like a log transformation of age, not presented) resulted in vastly different estimates for the construction year dummies as well.

The loss of value for a not or barely maintained structure, aged between 11 and 15 years, is almost three times as large for the main model compared (28%) to the quadratic base-line model (10%), and four times as large compared to the linear base-line model (7%). On the other hand, the loss of value for the same structure, aged between 46 and 50 years, is 'only' 1.5 times as large for the main model compared (43%) to the quadratic base-line model (28%), and

[23] For a full report on the age parameters see Table D2 in the Appendix. The coefficient estimates and t-values for time of sale can be found in the Appendix (Table D1) for all specifications.

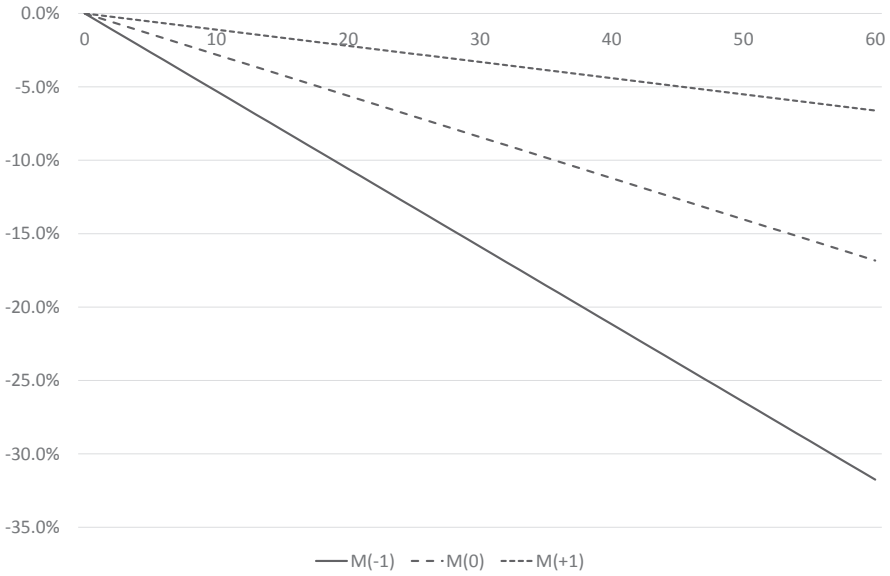
[24] The estimates for the 4 digit zipcodes for both the yard and footprint are not presented here to conserve space, but are available upon request.

Table 5.9: Estimation results.

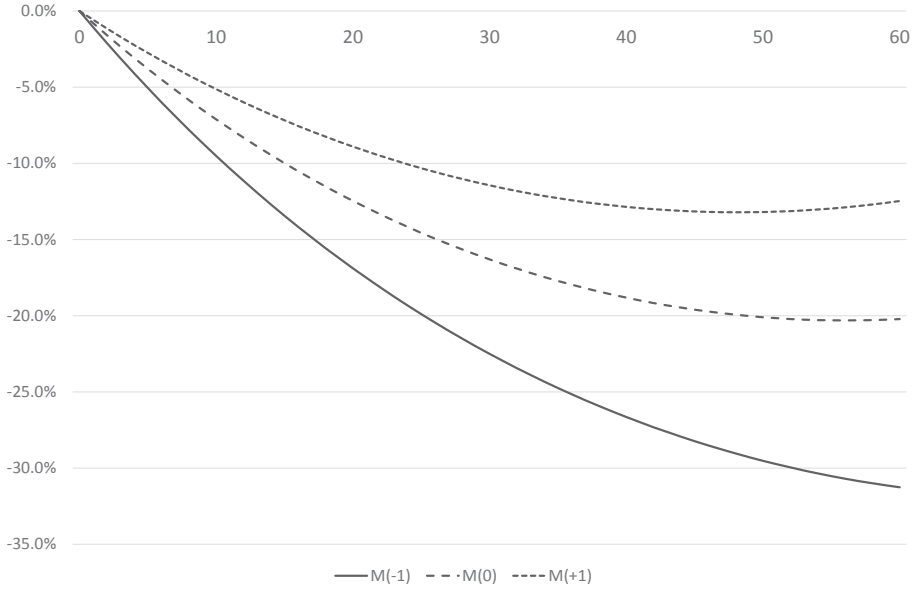
	(I)	(II)	(III)	(IV)	(V)
Variable	Base A	Base B	Main model	Robustness	
FS(γ)	0.373	0.370	0.982	1.005	0.979
	(50.22)***	(50.17)***	(334.15)***	(347.11)***	(333.17)***
CY[1906,1930]	0.076	-0.014	0.069	0.072	0.064
	(2.54)**	(-0.51)	(1.67)*	(1.87)*	(1.56)
CY[1931,1944]	0.092	0.085	0.209	0.177	0.200
	(4.16)***	(3.86)***	(5.36)***	(4.75)***	(5.13)***
CY[1945,1959]	-0.071	-0.020	-0.035	-0.017	-0.036
	(-4.19)***	(-1.16)	(-1.00)	(-0.52)	(-1.04)
CY[1960,1970]	-0.142	-0.073	-0.147	-0.168	-0.151
	(-10.59)***	(-5.08)***	(-5.42)***	(-6.17)***	(-5.50)***
CY[1971,1980]	-0.114	-0.047	-0.116	-0.147	-0.119
	(-10.40)***	(-3.88)***	(-5.13)***	(-6.40)***	(-5.22)***
CY[1981,1990]	-0.103	-0.056	-0.101	-0.100	-0.104
	(-11.79)***	(-5.92)***	(-5.66)***	(-5.58)***	(-5.79)***
CY[1991,2000]	-0.062	-0.041	-0.073	-0.071	-0.074
	(-8.49)***	(-5.50)***	(-5.19)***	(-5.02)***	(-5.23)***
m^2 land ILS^s	0.245	0.247	€808	€698	€819
	(24.94)***	(21.59)***	(25.33)***	(18.90)***	(21.71)***
m^2 land GS^s	-0.011	-0.011	€328	€316	€334
	(-2.13)***	(-2.19)**	(7.52)***	(8.28)***	(7.63)***
ILS^l	-0.001	-0.001	0.152	0.152	0.150
	(-0.99)	(-0.86)	(17.09)***	(11.85)***	(16.95)***
GS^l	0.000	0.000	0.431	0.376	0.440
	(0.28)	(0.23)	(14.03)***	(10.76)***	(14.10)***
Semi-detached	0.113	0.111	-0.035	-0.125	-0.032
	(26.67)***	(26.35)***	(-3.23)***	(-8.35)***	(-2.97)***
Detached	0.270	0.266	0.193	0.126	0.196
	(36.31)***	(36.04)***	(7.65)***	(3.62)***	(7.71)***
N. of Rooms	0.083	0.087			
	(12.64)***	(13.32)***			
Parking-spot	0.010	0.010			
	(1.35)	(1.38)			
Carport	0.003	0.003			
	(0.59)	(0.58)			
Garage	0.029	0.030			
	(9.09)***	(9.34)***			
Separate L & S	No	No	Yes	Yes	Yes
Location dummies	Yes	Yes	Yes	No	Yes
Age specification	Linear	Quadratic	Dummies	Dummies	Dummies
2-step correction	No	No	No	No	Yes
R^2	0.860	0.867	0.866	0.810	0.865
RMSE	0.110	0.110	0.110	0.130	0.110
N	9,331	9,331	9,331	9,331	9,331

Note Coefficient (t statistic),*** sig. within 99% prob.,** sig. within 95% prob. and * sig. within 90% prob. The reference categories are: *After* 2000 for CY periods, *terraced* for house type, 5237 for location, 2000 for year of sale and *no parking place* for the parking variables.

Figure 5.4: Physical deterioration.

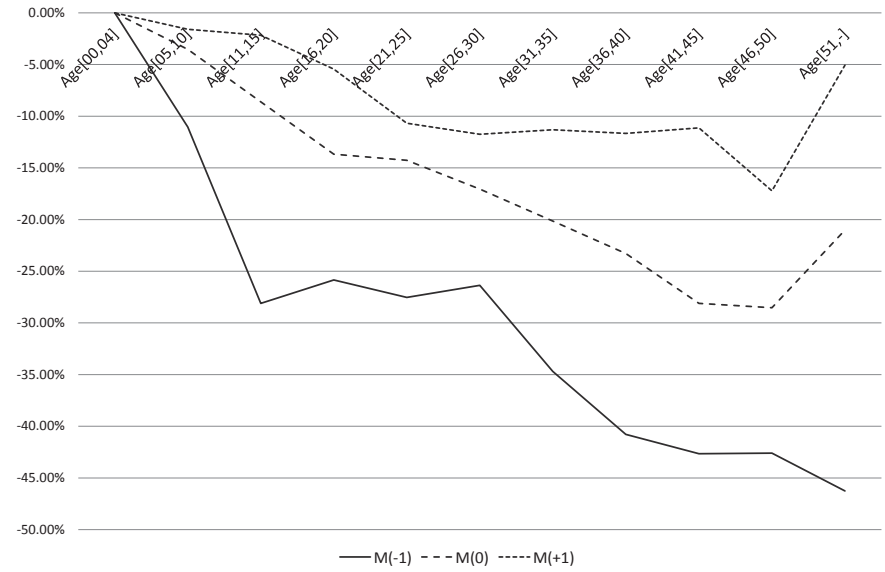


(a) Linear base-line model (Base A). Total property loss in value (in%) due physical deterioration.



(b) Quadratic base-line model (Base B). Total property loss in value (in%) due physical deterioration.

Figure 5.4: Age depreciation effect. *Continued*



(c) Main Model. Structure loss in value (in%) due physical deterioration.

Figure 5.5: Footprint, yard and structure price indices from 2000 (= 100) up to 2012 based on the main model.

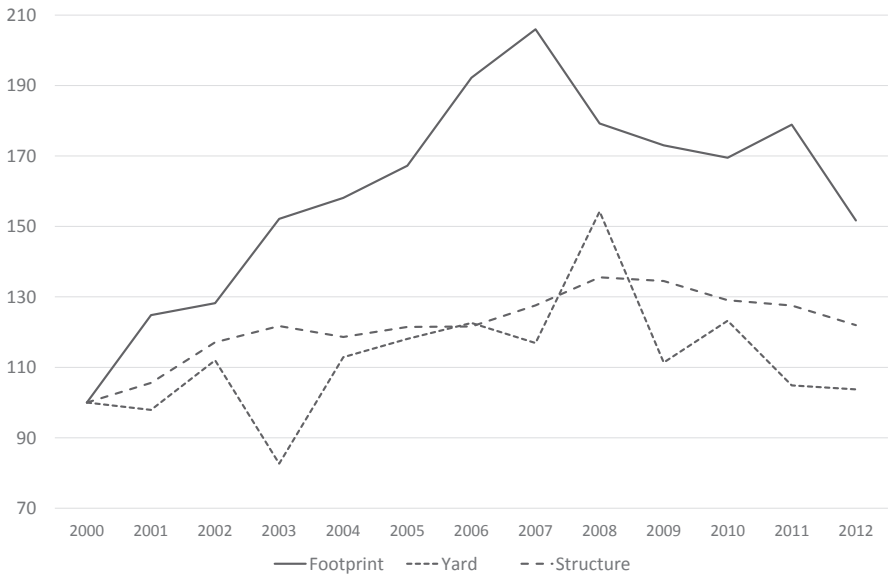
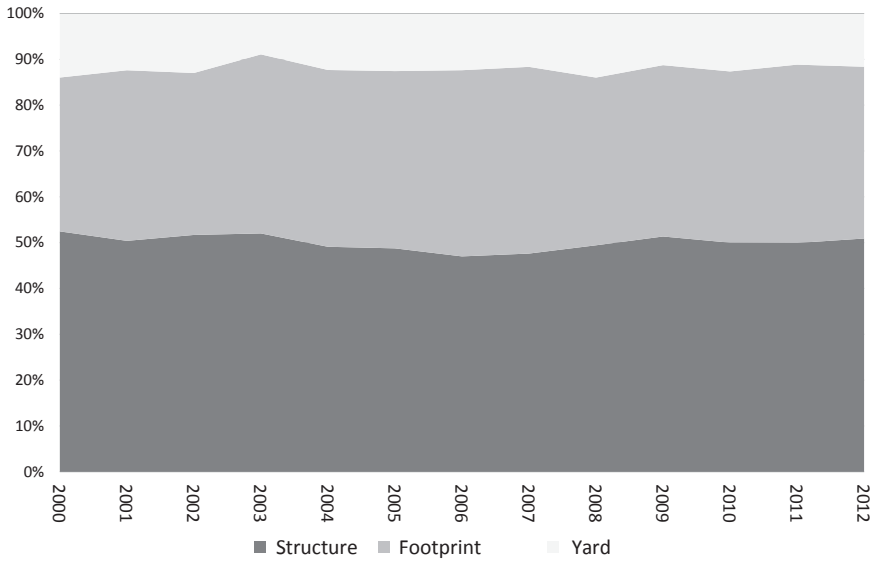


Figure 5.6: Contribution of the individual components to total property value. Expressed as % of total property value.



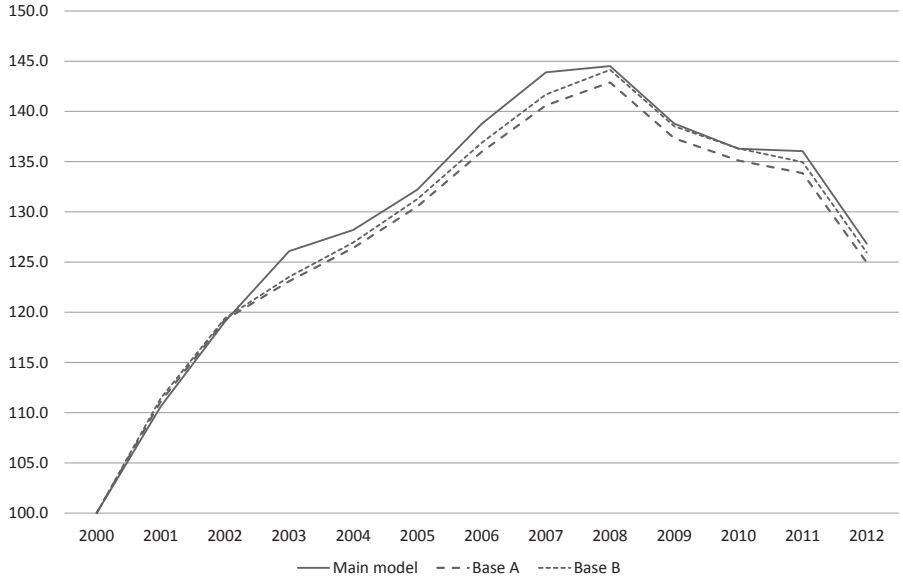
The components are calculated as follows. First the value of each component calculated of all transactions as if they were sold in 2000 using the parameter estimates of the main model. Subsequently the components are multiplied by the indices in Figure 5.5. Also note that do not take into account the cost for site preparation or alternative use of the land. Thus, in reality the fraction of land value to total value is very likely to be lower.

Table 5.10: Statistics and correlation between the land and structure returns.

Mean returns and volatility		
returns	mean	std. dev.
Structure	1.77%	4.68%
Footprint	2.83%	11.28%
Yard	-1.53%	20.53%

Correlations		
	Structure	Footprint
Footprint	0.314	
Yard	0.080	-0.272

Figure 5.7: House price appreciation from 2000 up to 2012 based on the main model and the base-line specifications. The index value in 2000 is 100.



twice as large compared to the linear base-line model (23%). Obviously, homeowners maintain their homes to slow down the rate of decay. Maintaining a home well results in a loss of value of 28% after 50 years (or about 20% and 14% according to the quadratic and linear base-line specifications respectively). Maintaining a home very well results in virtually no physical deterioration in the long run.

The joint impact of vintage and functional obsolescence is quite large. The results (second column in Table 5.9) imply that, apart from the physical deterioration, homes built between 1931 and 1944 sell at a significant premium of 22% compared to new homes. Homes of this era are valued for a distinct (expressionistic) brick architecture, popularized by 'the Amsterdam School' in the 20s and 30s. Prices are lowest (-16%) for homes built between 1960 and 1970. The estimates of the quadratic base-line model for the joint effect of functional obsolescence and vintage are again only half of the estimates of the main model (which was expected considering that the land value is approximately 50% of total property value). Most signs and the ranking of the effects are the same. In most cases, the effect of construction year on prices is twice as large for the linear base-line model, compared to the quadratic base-line model. The ranking of the estimates has changed as well.

The explanatory power and total house price appreciation are comparable between the base-line models and the main model (Figure 5.7). However, this could be attributed to the fact that the percentage of structure value to the total property value is relatively stable in our

application, see Figure 5.6. If this fraction would be volatile, this would affect the precision of the estimated age parameters for the base-line models, but not for the main model.

There does not seem to be an interaction between construction year and location. Leaving out the location dummies in the fourth column of Table 5.9 does not substantially change the coefficients for construction year and the signs remain the same. The age effect (Table D2) does seem to attenuate as the age of the structure increases. Column five of Table 5.9 reveals that the parameter estimates do not change erratically when the reconstruction values are corrected for land prices. This was expected, because the measurement error in replacement costs in the main model will be 'captured' by the land dummies. Thus, the indices, the *average* fraction of land value to total property value and parameter estimates (except for the land dummies), should not change that much. However, if the correction is not considered, on a property level the fraction of land value to total value is structurally over- or undervalued, depending on the location. Better quality data would benefit us greatly in this regard.

The parameter estimates for floor size, γ in Eq. (5.5), show that building costs are approximately proportional to floor size; the estimate is slightly lower than 1 for the main model. The base-line specifications estimate a 0.45% price increase for every 1% increase in floor size. Please note that the number of rooms is also entered in the base-line models. Omitting this variable from the regression increases the effect of floor size on house prices.

Structures have the lowest annual average return of all indices (1.8%). The correlation between the structure returns and the returns for the footprint and yard is relatively small (Table 5.10). This was expected, since construction is supplied elastically, hence, its costs do not vary greatly with demand, while land is in fixed supply and it residually captures almost all the longitudinal movement in property asset market values. The volatility of the structure returns is - indeed - almost half of the volatility of the footprint returns. Both figures are consistent with empirical work and theory of earlier research in land pricing (Bostic, Longhofer, and Redfearn 2007; Davis and Heathcote 2007; Davis and Palumbo 2008; Bourassa et al. 2011). Around 2003 the structure price index goes down, whereas the index of the footprint goes up. The correlation between the structure returns and the returns on the footprint is, therefore, even lower for the period after 2003, namely 0.11.

5.5.2 Land variables

The parameter estimates of the land variables for the main model in Table 5.9 show that, *ceteris paribus*, the square meter footprint price for detached housing is higher than the square meter prices of terraced and semi-detached housing. The square meter price of the footprint for semi-detached and terraced housing is roughly the same. The base-line specifications find a premium for semi-detached housing, but this can be attributed to a higher square meter reconstruction value for said type of housing (Table 5.5). Thus, that premium is part of the structure value and not the land value.

It is expected that the marginal price per square meter land decreases when the size of the land increases, so $0 < \alpha_l < 1$ and $0 < \delta_l < 1$ in Eqs. (5.7) and (5.8). The estimated coefficient α_l is about 0.15, implying that every square meter footprint larger than 75m^2 is approximately 15% of the price per m^2 for the first 75m^2. The estimated coefficient δ_l is about 0.40, implying that every square meter yard after 75m^2 is approximately 40% of the price per m^2 for the first 75m^2. The value of the footprint is more than twice the value of the yard (€808 versus €328 for the reference home). The base-line specification estimates a 0.25% price increase for every 1% increase in footprint size for the first 75m^2. The effect of the yard size and the splines (both footprint and yard) on house prices are negligible / non-significant, according to the base-line models.

The volatility of the yard returns is much larger than that of the footprint and structure returns (Table 5.10). Still, because of the relative low value of the yard, the price range per square meter yard for the reference home is only €250 – €460 between 2000 and 2012; a difference of €210. The range of the footprint square meter price, on the other hand, is approximately €800 – €1,600 between 2000 and 2012; a difference of €800. In other words, the high volatility of the yard returns hardly contributed to the total value of the property, see Figure 5.6 as well.

5.6 Concluding Remarks

The focus of this Chapter is the measurement of depreciation of houses. The main contribution is that we show that it *is possible* to simultaneously estimate age, construction year and time of sale, in a nonlinear hedonic price model, by attributing the age and construction year effects to the structure value and the time of sale effect to the land value. Physical deterioration is measured by age and maintenance level, functional obsolescence and vintage by construction year and external obsolescence by year of sale. Compared to traditional hedonic models our model (1) gives less biased estimates for physical deterioration and vintage, (2) is free of the multicollinearity issues between age, time of sale and construction year, without imposing any structure on the functional form of said variables and, (3) can easily be applied in markets in which the percentage of structure value to total property value is volatile.

The proposed model circumvents the typical problem of perfect collinearity between time of sale, age and construction year in hedonic price models, by making some appropriate assumptions: physical deterioration (age and maintenance), vintage and functional obsolescence (construction year) only affect the structure value and external obsolescence (time of sale) only the land value.

The proposed model explicitly assumes that land and structure values are additive. In the case of the Netherlands this is a plausible assumption. However, in regions with less rigid zoning restrictions it will be more important to use a proxy for option value and control for the

endogenous effect of maintenance.

Using reliable data from a region in the Netherlands we show that maintaining a structure poorly results in an annual physical deterioration of more than 1.5% for the first 20 years and almost 1% for the first 50 years. Maintaining a home well reduces the effective age considerably. However, it shold be noted that our depreciation estimates are probably conservative due to missing renovation data.

Chapter 6

Conclusion

In conclusion, this thesis outlines multiple important issues related to house price dynamics and its determinants. This dissertation focusses on changing determinants of house prices in the long-run (Chapter 2), the effect of credit conditions on house prices (Chapter 3), the effect of demographic growth and decline on house prices (Chapter 4) and finally the effect of depreciation on house prices (Chapter 5). Even though we limited ourselves to the housing market in the Netherlands, the findings might be relevant for other sectors in the real estate market or even any other market that is characterized by (heavy) supply constraints.

Chapter 2 examines the determinants of house prices using almost 200 years of data from the Amsterdam housing market. In total we focus on seven major determinant of house prices: housing supply, construction costs, income per capita (GDP), the opportunity cost of capital (interest rates), the percentage of working age population to total population, unemployment, and population growth. One main contribution of this study is that we allow for the determinants to be time-varying. Parameters are likely time-varying in the long-run because of (long) real estate cycles and (political and economic) regime shifts. A yearly rolling regression with changing combinations of covariates is used, because it allows us to estimate a series of parameter estimates without imposing any particular structure on the way in which conditional covariates change over time. Since the long-run time-series are non-stationary, the model is estimated using a rolling (Engle and Granger 2 step) error correction model. We fix the window length at 30 years as this is the average length of a real estate cycle according to literature and, in addition, because it resulted in the largest number of cointegrating relationships. The results imply that the determinants of house prices are, indeed, *not fixed* but change over time and reflect the economic state of affairs in each different era.

During the 19$^{\text{th}}$ century population growth, housing supply and construction costs are the main drivers of house prices in Amsterdam. At the start of the 20$^{\text{th}}$ century GDP per capita starts to play a role. After World War II there is a time period in which housing supply and population growth determine house prices. This reflects the post-war reconstruction efforts in the Netherlands and increases in housing demand as a result of the baby-boom generation and

subsequent decrease in housing demand due to the large scale deurbanization of Amsterdam. Finally, from the 1970s onwards, income and interest rates (co-jointly with construction costs) start to have a large impact on house prices, most likely due to financial innovation and liberalization. During this time period financing a house through mortgage debt became more and more popular. It also signals the beginning of a remarkable period in time in which house prices start to increase rapidly in many countries (i.e. the 1990s).

In Chapter 3 we focus on the effects of the mortgage market on house prices in more detail for the period 1995 – 2012. We first introduce a new method to estimate a credit condition index (CCI). The CCI represents changes in the supply of credit over time, apart from changes in interest rates and income. It is estimated by an unobserved component in an error correction model in which the average amount of new provided mortgages per period is explained by the borrowing capacity (which is a function of variables like interest rates and household income) and additional control variables. By controlling mortgage lending for different demographic and economic variables the unobserved component should capture the credit conditions. The unobserved component itself is modelled as a local-linear trend (LLT), random walk (RW) and as linear splines (LS), resulting in three CCIs. The model has been estimated on data representing first time buyers (FTB). For FTB we can assume that the housing and non-housing wealth is essentially zero. This makes FTB more reliant on the supply of mortgage debt, as they do not have any liquid funds themselves. This reduces some demand side effects which could 'contaminate' the unobserved component.

In all models the credit conditions reveal a steady growth until 2009 with a small interruption in 2007, during the credit crunch. The increasing levels of mortgage lending can be attributed to more households taking an interest only mortgage and the growing popularity of the NHG product which made mortgages less risky investments from a bank's perspective. After 2010 however, there was a steady decline, probably mostly fuelled by more stringent liquidity ratios on banks (Basel accords), the 'de facto' abolishment of interest only type mortgages and lower LTV caps allowed by the Dutch government. In 2012.$Q4$ the supply of credit is on the same level as it was during the period 2003 – 2004. The estimated CCI has a high correlation with the Bank Lending Survey, a quarterly survey in which banks are asked whether there is a tightening or relaxation of (mortgage) lending standards compared to the preceding period.

The CCI has subsequently been used as an explanatory variable in an error correction model for house prices representing not only FTB, but all households. The models have been estimated on quarterly data from 1995 to 2012. The CCI has explanatory power in the error correction model for house prices. In real terms house prices declined about 25% from 2009 to 2012. The estimation results show that about half of this decline can be attributed to a decline in the CCI.

The focus of Chapter 4 is the asymmetry between the effect of population growth and decline on housing prices taking into account local (municipalities) supply constraints in the Netherlands. This asymmetry arises in the first place, because of the durable nature of houses.

Homes are built to last for decades if not centuries. The durability of housing means that it can take decades for negative urban shocks to be fully reflected in housing supply levels. This slow adaptation of existing stock during decreasing demand results in disproportionally large house price decreases. A city will start to decline when housing prices are below construction costs, because investments in housing will stop being feasible. When urban productivity falls, the most active members of the labor force will naturally flee; but durable housing ensures that their homes will then be occupied by those that are less connected to the labor market.

Demographic growth on the other hand has a more ambiguous effect on house prices, depending on the local supply constraints. When supply is unable to keep pace with demand shocks quickly and cheaply, more of the demand shocks carry through into prices. Usually, whenever a city grows, delivery lags and imperfect foresight of agents will enable housing price increases on the short-run, until a new long-run equilibrium is reached. However, in some instances supply will not even react to house prices in the long-run due to (local) supply constraints. These supply constraints can be caused by physical space constraints or by regulatory constraints. Physical space constraints refers to the scarcity of land (amount of developable land) and uneven topography (steep slopes etc.). The main regulatory constraints in the Netherlands are the zoning plans made on municipality level.

To estimate the effect of demographic decline and growth (taking into account supply constraints) we utilize a panel data set with 15 years of data on municipality level in the Netherlands. The data is differenced over the full 15 years, so we only capture long-run effects. Population change is entered in piecewise linear form to allow for differential effects in expanding versus declining municipalities. We subsequently interact population growth with a measure for local supply constraints (which we estimate from the data). To construct this index, we first regress house prices on new housing permits, using an IV approach. We rank order the municipalities from the most supply constraint to the municipality with the least supply constraints and subsequently group them in categories ranging from 'no supply constraints' to 'heavy supply constraints'.

Every 1% decrease in population results in a housing price decrease of 1.9%, *ceteris paribus*. In the most constraint markets a 1% increase in population results in a 0.4% price increase on average. Population growth barely (or even slightly negatively) affect house prices for the least constraint municipalities.

The focus of Chapter 5 is the measurement of depreciation of houses, where we define depreciation as *"to be the decline in asset values (or shadow price) due to ageing"*. Depreciation consists of three parts: (1) physical deterioration, (2) functional obsolescence and (3) external obsolescence. Physical deterioration is the simple wear and tear of the structure. Functional obsolescence is caused by the evolution in technologies (building quality) and preferences for residential living. External obsolescence encompasses changes, not to the property itself, but to the area surrounding the property. Apart from depreciation it is important to distinguish the vintage effect: a preference for specific structure characteristics. Physical deterioration can be

retarded by maintenance activities. Functional obsolescence, on the other hand, is much more difficult (if even possible) to cure.

In this study we measure physical deterioration by the age of the structure, the joint effect of functional obsolescence and vintage by the construction year and the external obsolescence by the time of sale in a (non-linear) hedonic framework. We also interact the age of the property (as proxy for physical deterioration) with the level of maintenance. There are two difficulties regarding depreciation studies. Firstly, there is perfect collinearity between key variables: age, construction year and time of sale. Secondly, regressing age on the property value will always bias the estimate downward. The size of the bias depends on the fraction of structure value to total property value.

The proposed model circumvents these typical problems by making the following assumptions: physical deterioration (age and maintenance), vintage and functional obsolescence (construction year) only affect the structure value and external obsolescence (time of sale) only the land value. Another important assumption we make is that there is no (redevelopment) option value in structures in the Netherlands due to heavy zoning restrictions. The structure is a function of its reconstruction value, the structure size, the age (interacted with maintenance level) and the construction year of the structure. The land value is disentangled in a yard value and a footprint value. The land values are functions of the location, time of sale, size of the land and the property types allowed on the land.

The model is non-linear in its parameters and is therefore estimated with non-linear least squares. The NVM made the data available to us for a region in the Netherlands called 's-Hertogenbosch. After the filters were applied we were left with more than $9,000$ individual transactions of homes between 2000 and 2012. Data on reconstruction values are obtained from the website of Bouwkostenkompas.

Our findings show that maintenance has a substantial impact on the rate of physical deterioration. After 50 years of not or barely maintaining a home a typical structure has lost around 43% of its value. In contrast, maintaining a home very well results in virtually no physical deterioration in the long run. The findings also suggest that land prices are more volatile than structure prices. Both indices are barely correlated, indicating that the market for structures and land are separate ones. Compared to traditional hedonic models our model (1) gives unbiased estimates for physical deterioration and vintage, (2) is free of the multicollinearity issues between age, time of sale and construction year, without imposing any structure on the functional form of said variables and, (3) can easily be applied in markets in which the percentage of structure value to total property value is volatile.

Appendix A

Appendix for Chapter 2

A.1 Transaction Data Herengracht

Data description is provided in Tables A1 – A3 and Figure A.1.1. The descriptives are based on the data after filters were applied. If a home was converted to an office or if the home was combined with a neighboring home the sale was removed from the data.

After the filters were applied we end up with 580 different homes and about 3,000 transactions. Table A1 also reveals that the average time between repeat sales is 34 years. Most homes were sold 6 times in our data. One specific home was sold 17 times during the 350 year period (Table A2). The average number of transactions per year is approximately 10. However, in some years there are no transactions (see Figure A.1.1). Table A3 provides the yearly log nominal returns subdivided in different quantiles. The average yearly log nominal return is a little under 2%. The mode is lower with 0.05%.

Table A1: Descriptive statistics Herengracht data.

Description	
Number of transactions	3,416
Number of transactions (with at least two sales)	2,953
Number of different homes	580
Minimum year of sale	1628
Maximum year of sale	1972
Average years between repeat sales	34

Figure A.1.1: Number of transactions per year, Herengracht data.

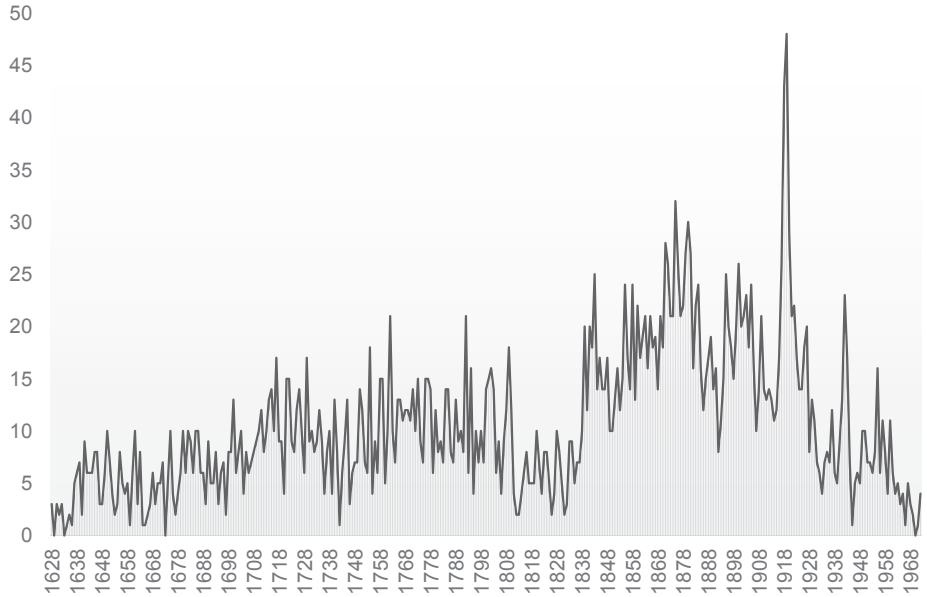


Table A2: Number of sales of the same property

Number of sales	**Number of observations**
2	66
3	54
4	62
5	68
6	95
7	61
8	55
9	41
10	24
11	16
12	12
13	5
14	4
15	2
17	1

Table A3: Log nominal return statistics

Quantile	**Annual log nominal returns**
average	0.018
0.025	-0.052
0.05	-0.033
0.1	-0.019
0.5	0.005
0.9	0.059
0.95	0.104
0.975	0.185

A.1.1 Constructing a House Price Index

The methodology to estimate the price index using the Herengracht data is described extensively in Francke (2010). Here we give a brief description of the model and some descriptive statistics of the data. The 'standard' Case and Shiller repeat sales is given by:

$$\ln\left(\frac{P_{i,t}}{P_{i,s}}\right) = \beta_t - \beta_s + \alpha_{i,t} + \epsilon_{i,t}, \qquad \epsilon_{i,t} \sim N(0, \sigma_\epsilon^2), \tag{A.1}$$

$$\alpha_{i,t+1} = \alpha_{i,t} + \eta_{i,t}, \qquad \eta_{i,t} \sim N(0, \sigma_\eta^2), \tag{A.2}$$

for $t = 1, \ldots, T$ and $i = 1, \ldots, M$, where T is the number of years and M is the number of houses. P are house prices sold at time t (sale) and s (buy), with $t > s$. Subscript i is for the individual properties. The coefficient β_t is the logarithm of the cumulative price index at time t. The random walk component (α) is the cumulative idiosyncratic drift of each property (Case and Shiller 1987), since the variance of the error term is related to the interval between time of sales.

In the repeat sales model it is typically assumed that the β_t's are fixed unknown parameters. In the methodology described by Francke (2010), it is assumed that β_t is a scalar stochastic trend process in the form of a local linear trend model, in which both the level and slope can vary over time. The local linear trend model is given by:

$$\beta_{t+1} = \beta_t + \kappa_t + \zeta_t, \qquad \zeta_t \sim N(0, \sigma_\zeta^2), \tag{A.3}$$

$$\kappa_{t+1} = \kappa_t + \xi_t, \qquad \xi_t \sim N(0, \sigma_\xi^2). \tag{A.4}$$

The local linear trend model 'in differences' is estimated with the Bayesian procedure described in Francke (2010), avoiding the somewhat more usual ad hoc two-step procedure. The model can be expressed as a linear regression model with a prior for β, induced by the local linear trend model. Estimates of parameters are obtained by maximizing the likelihood of the 'differenced' data.

A.1.2 Estimation Results

The results of the model are given in Table A4. The standard deviation (σ) is relatively high with approximately 30%. This could be because of the large average time of sale (34 years, Table A1). Taking into account the large average time between sales and the large variance in time between sales (Table A2), it is surprising to note that the standard deviation for the individual random walks (σ_η) is near 0. The price level of the next year is best explained by taking the price level of this year, with a standard deviation of 8.3% per year (σ_ζ), plus a drift. The drift of next year is best explained by taking the drift of this year plus a small standard deviation of 0.3% (σ_ξ).

Table A4: Estimation results

	Estimate	**Log estimate**	**Std. error.**	**t-value**
σ	0.310	-1.171	0.015	84.28
σ_η	0.000	-10.471	1.688	6.20
σ_ζ	0.083	-2.492	0.162	15.39
σ_ξ	0.003	-5.936	2.325	2.55

A.1.3 Long-run time series: Macro Determinants

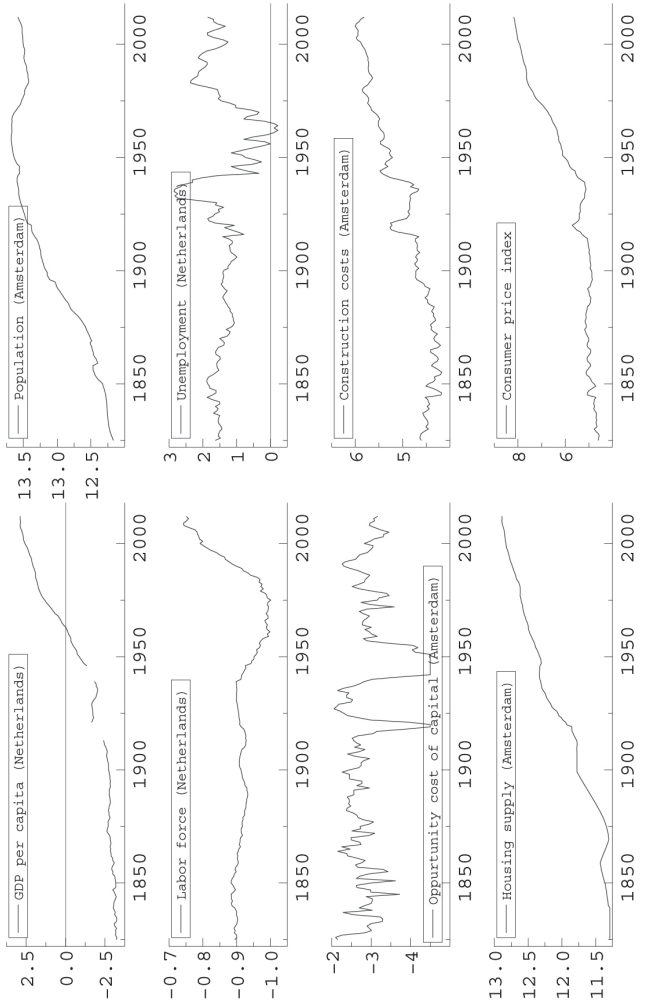


Figure A.1.2: Time series in Log levels.

A.1.4 Order of Integration

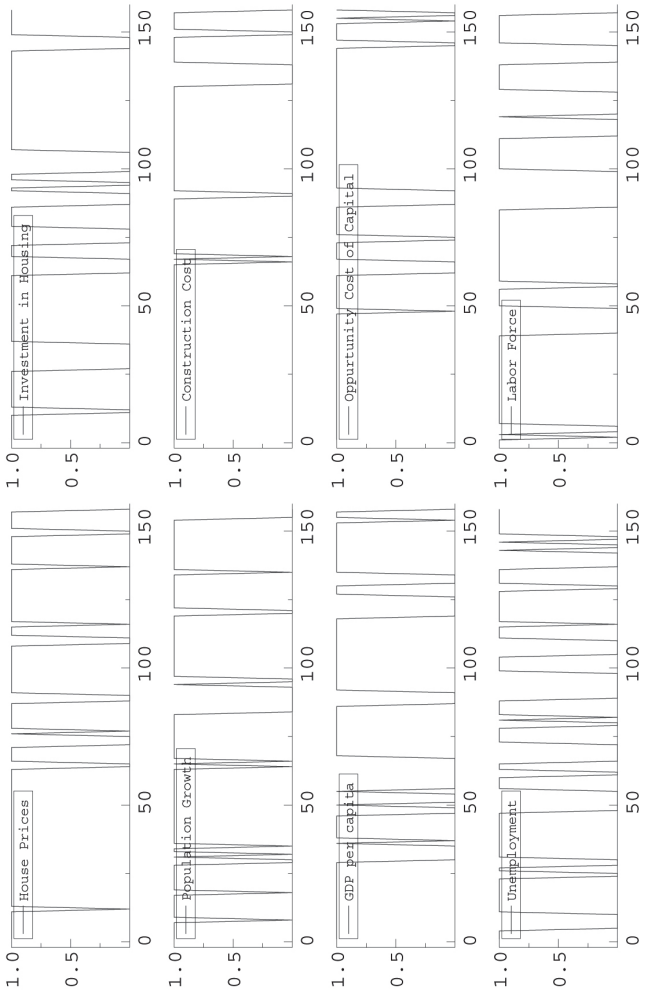


Figure A.1.3: Order of integration of the variables.

Note. Order of integration: 1 means I(1), which is necessary for the R-ECM framework. We only use I(1) variables in the regressions. The x-axis is the number of years starting from 1825.

Appendix B

Appendix for Chapter 3

B.1 Financial Liberation in the Netherlands

Table B1: Dating of financial liberalisation in the Netherlands.

Year	**Event**
1990	Change that allowed households to use a share of other household members' income as a basis for obtaining mortgage credit.
2001	The first restriction to the deductibility of mortgage payments on income was made in 2001. Here it was determined that after a period of 30 years, households were no longer entitled to deduct the interest payments.
2004	The so-called 'bijleenregeling' assumes that households use all their positive equity (if present) built up in their former property and use it to finance the new property in case of a move. If households decide to finance this amount through a mortgage anyway, this is no longer deductible.
2011	Banks themselves agreed (GHF) that at most 50% of the assessed value of the home may be financed through an interest-only mortgage.
2011	The maximum allowed LTV for new mortgages decreased from 110% to 106%. The main reason being the lowering of transfer tax from 6% to 2%.
2012	Maximum allowed LTV for new mortgages is lowered even further. From 2012 onwards the maximum allowed LTV is lowered with 1%-point until it is 100% in 2018.
2013	From 2013 the deductibility of interest payments on income is limited. Interest rate deductibility is applicable to annuity and linear mortgage products only.

B.2 Granger Causality Tests

Table B2: Granger causality test (1995.$Q1$ – 2012.$Q4$, with 4 year lags), between house prices p and mortgage levels m for first time buyers.

Granger Causality		F-test	P-values
$p_{ftb,t}$	$\rightarrow m_{ftb,t}$	1.723	0.114
$m_{ftb,t}$	$\rightarrow p_{ftb,t}$	2.137	0.047
$\Delta p_{ftb,t}$	$\rightarrow \Delta m_{ftb,t}$	1.352	0.252
$\Delta m_{ftb,t}$	$\rightarrow \Delta p_{ftb,t}$	1.997	0.066
$\Delta p_{ftb,t}$	$\rightarrow m_{ftb,t}$	1.464	0.201
$m_{ftb,t}$	$\rightarrow \Delta p_{ftb,t}$	2.581	0.020
$p_{ftb,t}$	$\rightarrow \Delta m_{ftb,t}$	1.497	0.187
$\Delta m_{ftb,t}$	$\rightarrow p_{ftb,t}$	2.165	0.047

Table B3: Granger causality test (1995.$Q1$ – 2012.$Q4$, with 4 year lags), between house prices p and credit conditions cci (RW model) for all households.

Granger Causality		F-test	P-value
p_t	$\rightarrow cci_t$	1.367	0.302
cci_t	$\rightarrow p_t$	2.825	0.040
Δp_t	$\rightarrow \Delta cci_t$	0.768	0.706
Δcci_t	$\rightarrow \Delta p_t$	2.702	0.054
Δp_t	$\rightarrow cci_t$	0.897	0.602
cci_t	$\rightarrow \Delta p_t$	2.477	0.071
p_t	$\rightarrow \Delta cci_t$	0.689	0.771
Δcci_t	$\rightarrow p_t$	2.435	0.075

B.3 Test for Cointegration

Table B4: Tests for cointegration in CCI models

	ρ	critical value (k)	$\rho \leq k$
Model I	0.500	0.522	Yes
Model II	0.504	0.522	Yes
	ADF		$ADF \leq k$
Model III	-4.049	-3.967	Yes

Note. All critical values are obtained from (MacKinnon 2010). The critical values for the Unobserved Error Correction Models are computed by multiplying the standard deviation of ρ by the critical values, plus 1.

B.4 Long-run time series Macro Determinants

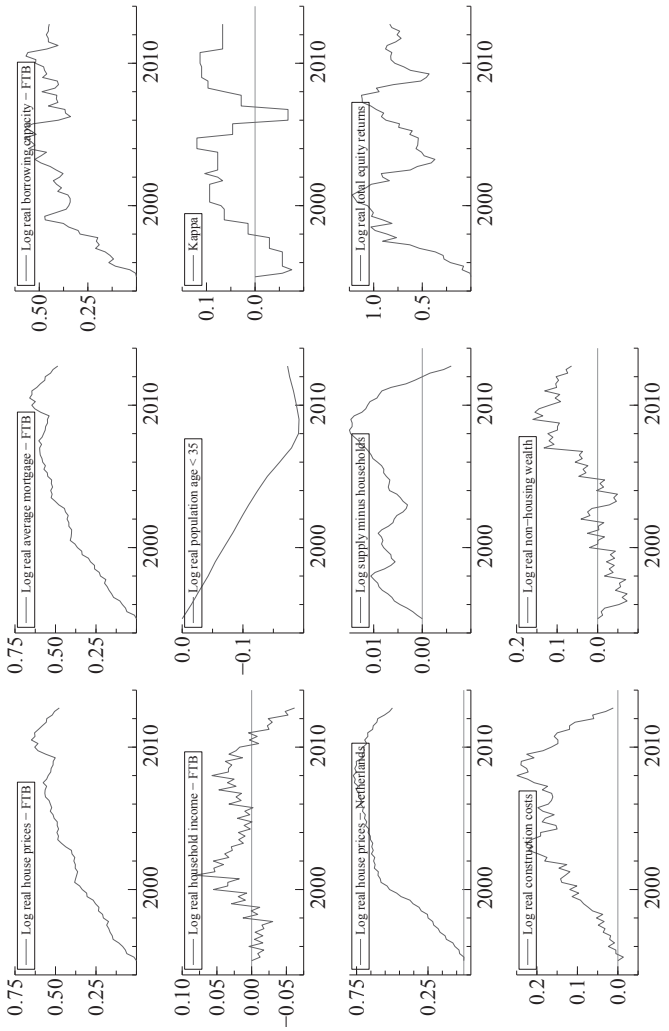
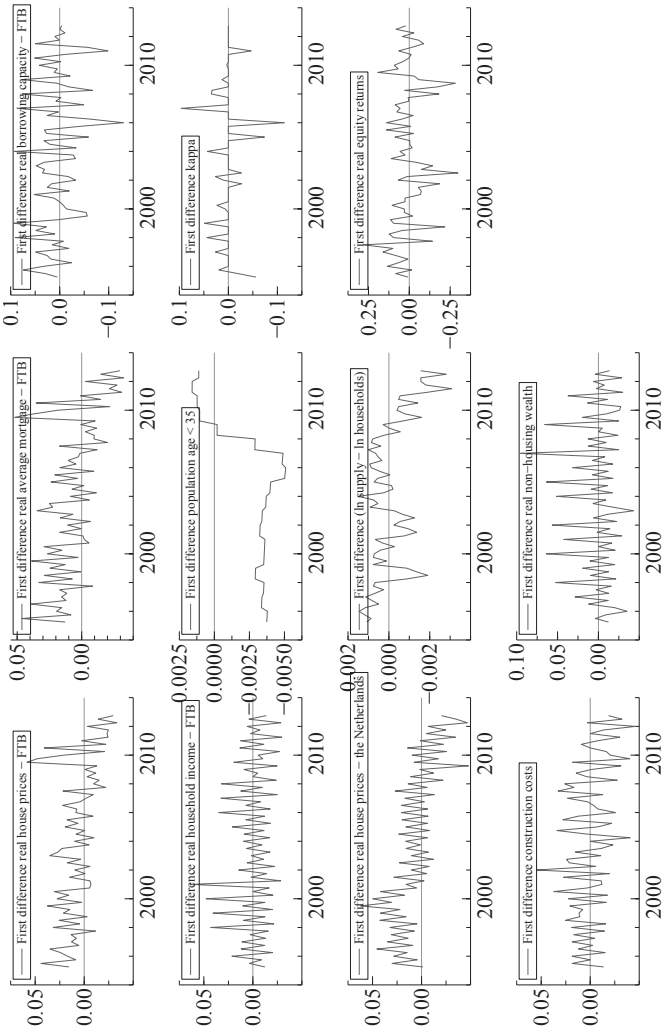


Figure B.4.1: Time series indices in log levels. 1995.Q1 = 0.

Figure B.4.2: Time series indices (*Continued*), First-differences.



Appendix C

Appendix for Chapter 4

C.1 Municipalities in the Netherlands

Table C1: List of absent municipalities

Aalten	Leidschendam-Voorburg
Bergeijk	Middelburg (Z)
Berkelland	Midden-Delfland
De Bilt	Moerdijk
Boxtel	Nieuwkoop
Breda	Nijmegen
Bronckhorst	Ommen
Coevorden	Oost Gelre
Cranendonck	Pijnacker-Nootdorp
Dinkelland	Rijswijk (ZH)
Echt-Susteren	Roermond
Emmen	Sittard-Geleen
Ferwerderadiel	Steenbergen
Geldrop-Mierlo	Tilburg
Goirle	Utrechtse Heuvelrug
s-Gravenhage	Waalwijk
Gulpen-Wittem	Woensdrecht
Heeze-Leende	De Wolden
Hof van Twente	Zundert
Horst aan de Maas	



Figure C.1.1: Distribution of the municipalities in the Netherlands. End of 2009.

C.2 Results and Descriptives of the Supply Equations

Table C2: Subdivision municipalities in three types, used for the 'simple' model. Period 1995 - 2009.

Housing Market	Variable	Average increase	N x Cases
	Growing municipalities		
Inelastic supply	Population	$> 0.00\%$ per year	86
	Housing stock	$< 0.75\%$ per year	
Medium elastic supply	Population	$> 0.00\%$ per year	171
	Housing stock	$>= 0.75\%$ and $< 1.25\%$ per year	
Elastic supply	Population	$> 0.00\%$ per year	87
	Housing stock	$> 1.25\%$ per year	
Subtotal			344
	Declining municipalities		
Inelastic supply	Population	$< 0.0\%$ per year	24
	Housing stock	$< 0.50\%$ per year	
Elastic supply	Population	$< 0.0\%$ per year	34
	Housing stock	$>= 0.50\%$ per year	
Subtotal			87
Total			402

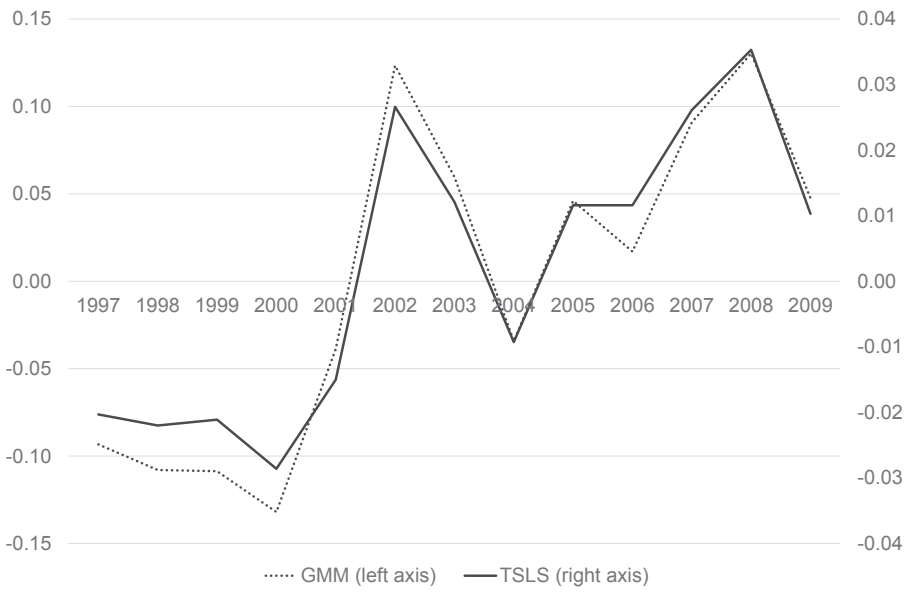


Figure C.2.2: Time fixed effects of the myopic and forward looking model.

Table C3: Estimation results for the Myopic and Forward Looking models. The (log) ranking of the Location Fixed effects are entered in the main model.

Description	**Parameter**	**Myopic**	**Forward**
Log price	γ_1	0.007	
		(4.25)**	
Marginal cost of investment	γ_1		0.059
			(1.71)*
Density	γ_2	-0.001	-7.673
		(-3.07)***	(2.24)**
Method		TSLS	GMM
Location FE		Yes	Yes
Time FE		Yes	Yes
Adj. R^2		0.284	0.211
Sigma		0.010	0.088
N		5,625	5,625
P(J-stat)		0.766	0.680

Note. IV estimates of variants of Eq. (4.3) using linear projections onto *industry* and *age distribution* instruments, as described in the text. In both cases the instruments are appropriately uncorrelated with the error term. Unfortunately the density parameter is not significant in the myopic model. The probably reason is that overall housing stock changes is quite slow (only 1%). Heteroskedasticity-robust standard errors in parenthesis.

C.3 Detailed description of the Variables

Detailed description of the variables as seen in Table 4.1:

- **B:** Someone belonging to the population living in a given area.
- **HH:** Group of people living in one accommodation who provide for their own housing and daily needs or whose housing and daily needs are provided for by others.
- **HS:** Number of people in a private household.
- **U:** Unemployment benefits are based on one of the following regulations: Unemployment insurance act (WW), Unemployment Provisions Act (WWV), State Group Regulation for unemployed Persons (RWW), Act on Income Provisions for Older or Partially Disabled Unemployed Persons (IOAW), Civil Service Redundancy Payment Scheme (WRO).
- **P:** Housing prices are based on data provided by the Land Registry Office (Kadaster) which are calculated by Ortec Finance (OF) by a repeat sales method.
- **K:** A housing unit indented to be lived in and that, from a building technical point of view, is meant to permanently function as a dwelling for households. It suffices all the criteria applicable to housing, except for a kitchen and toilet. However the housing unit must be in a building which compensates for these short comings.
- **A:** all measurements are in square kilometres. Included are area used for traffic (railways, roads, airport), buildings (housing, retail, catering, public, social cultural, business), semi-built (dump, wrecks repository, graveyard, mineral extraction site, building site, semi solidified other area), recreational (park, plantation, sports ground, allotment, recreation [short stay], tourism [long stay]). The sum of the square kilometres is multiplied by the highest density achieved in the Netherlands.
- **CC:** The construction cost index from 1995 onwards is based on analysed permits of all homes in the Netherlands. Price changes resulting from changes in quality have been eliminated as much as possible.
- **I:** All permits for houses or apartments on the owner-occupier market which are intended - from a building technical perspective - for permanent living by a single household.

Appendix D

Appendix for Chapter 5

Table D1: Estimation results period dummies. Results are in log.

	House price						Footprint			
	(I)		(II)		(III)		(IV)		(V)	
	Base A		Base B		Main model		Robustness			
year	estimate	t-value	estimate	t-value	estimate	t-value	estimate	t-value	estimate	t-value
2001	0.106	17.556	0.108	18.163	0.222	5.109	0.140	1.871	0.230	5.200
2002	0.176	29.943	0.177	30.385	0.248	5.662	0.268	3.345	0.250	5.591
2003	0.208	35.554	0.211	36.393	0.420	8.882	0.341	4.065	0.416	8.668
2004	0.234	40.307	0.239	41.255	0.458	9.578	0.481	5.464	0.462	9.470
2005	0.267	45.684	0.272	46.853	0.514	10.443	0.536	5.977	0.524	10.401
2006	0.307	51.690	0.314	52.958	0.653	12.284	0.690	7.201	0.662	12.153
2007	0.341	56.500	0.349	57.906	0.723	13.017	0.703	7.282	0.735	12.945
2008	0.357	55.148	0.366	56.577	0.583	10.512	0.767	6.920	0.594	10.452
2009	0.317	45.003	0.326	46.364	0.548	9.788	0.461	4.607	0.551	9.678
2010	0.301	42.115	0.310	43.441	0.528	9.649	0.653	6.382	0.533	9.565
2011	0.292	39.361	0.300	40.612	0.582	10.453	0.640	6.290	0.598	10.495
2012	0.223	30.109	0.231	31.289	0.417	8.182	0.538	5.681	0.426	8.170
							Yard			
year					estimate	t-value	estimate	t-value	estimate	t-value
2001					-0.021	-0.245	0.202	1.173	-0.042	-0.493
2002					0.113	1.194	0.069	0.413	0.109	1.155
2003					-0.191	-2.398	0.048	0.282	-0.170	-2.108
2004					0.121	1.316	0.242	1.332	0.116	1.263
2005					0.166	1.753	0.219	1.228	0.145	1.545
2006					0.204	2.100	0.243	1.354	0.181	1.886
2007					0.156	1.587	0.278	1.521	0.126	1.297
2008					0.433	3.588	-0.009	-0.046	0.404	3.382
2009					0.108	1.008	0.229	1.082	0.096	0.904
2010					0.209	1.956	-0.047	-0.263	0.195	1.841
2011					0.048	0.474	-0.099	-0.570	0.008	0.084
2012					0.037	0.378	-0.254	-1.651	0.014	0.148

Table D2: Estimation results of the log age variables.

	(I) Base A		(II) Base B		(III) Main model		(IV) Robustness		(V) Robustness	
Variable	estimate	t-value	estimate	t-value	estimate	t-value	estimate	t-value	estimate	t-value
Age × M(-1)	-0.005	-16.45	-0.011	-18.138						
Age^2 × M(-1)			0.000	9.978						
Age × M(0)	-0.003	-9.03	-0.008	-15.450						
Age^2 × M(0)			0.000	12.489						
Age × M(+1)	-0.001	-3.36	-0.006	-10.267						
Age^2 × M(+1)			0.000	8.857						
Age[05,10]					-0.117	-1.79	-0.106	-1.55	-0.120	-1.82
Age[11,15]					-0.330	-5.59	-0.188	-3.47	-0.324	-5.64
Age[16,20]					-0.299	-6.46	-0.239	-5.19	-0.296	-6.41
Age[21,25]					-0.322	-7.65	-0.230	-5.65	-0.318	-7.62
Age[26,30]					-0.306	-8.51	-0.232	-6.48	-0.310	-8.52
Age[31,35]					-0.426	-11.65	-0.350	-9.63	-0.430	-11.61
Age[36,40]					-0.524	-12.70	-0.371	-9.56	-0.532	-12.72
Age[41,45]					-0.556	-12.62	-0.352	-8.78	-0.564	-12.66
Age[46,50]					-0.555	-10.87	-0.282	-6.46	-0.549	-10.84
Age[51,-]					-0.621	-13.84	-0.357	-8.92	-0.617	-13.83
Age[05,10] × M(-1)					-0.036	-2.75	-0.029	-2.13	-0.036	-2.68
Age[11,15] × M(-1)					-0.090	-6.01	-0.077	-5.06	-0.091	-6.02
Age[16,20] × M(-1)					-0.147	-8.57	-0.111	-6.47	-0.148	-8.59
Age[21,25] × M(-1)					-0.154	-7.95	-0.104	-5.38	-0.155	-7.95
Age[26,30] × M(-1)					-0.187	-8.63	-0.141	-6.46	-0.188	-8.64
Age[31,35] × M(-1)					-0.225	-9.52	-0.167	-7.00	-0.226	-9.49
Age[36,40] × M(-1)					-0.265	-10.10	-0.187	-7.12	-0.267	-10.11
Age[41,45] × M(-1)					-0.330	-11.02	-0.178	-6.09	-0.334	-11.07
Age[46,50] × M(-1)					-0.336	-9.78	-0.135	-4.18	-0.341	-9.91
Age[51,-] × M(-1)					-0.236	-6.32	-0.074	-2.10	-0.240	-6.44
Age[05,10] × M(+1)					-0.016	-1.02	-0.020	-1.22	-0.016	-1.06
Age[11,15] × M(+1)					-0.022	-1.20	-0.019	-1.01	-0.024	-1.29
Age[16,20] × M(+1)					-0.056	-2.45	-0.040	-1.67	-0.059	-2.56
Age[21,25] × M(+1)					-0.113	-3.92	-0.064	-2.20	-0.116	-4.03
Age[26,30] × M(+1)					-0.125	-3.99	-0.084	-2.61	-0.128	-4.07
Age[31,35] × M(+1)					-0.120	-3.82	-0.077	-2.38	-0.120	-3.79
Age[36,40] × M(+1)					-0.124	-3.13	-0.059	-1.48	-0.127	-3.21
Age[41,45] × M(+1)					-0.118	-2.58	-0.006	-0.14	-0.126	-2.76
Age[46,50] × M(+1)					-0.189	-3.10	-0.134	-2.21	-0.197	-3.22
Age[51,-] × M(+1)					-0.052	-1.21	0.036	0.87	-0.057	-1.32

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Samenvatting (Summary in Dutch)

Woningprijsdynamieken

Het effect van krediet, demografie en depreciatie

Vaak wordt het eigenwoningbezit gezien als een solide investering. De kredietcrisis en de daar op volgende woningprijsdalingen hebben echter laten zien dat het eigenwoningbezit ook risico's met zich meebrengt. Dit proefschrift bevat vier empirische onderzoeken met betrekking tot woningprijsdynamieken en woningprijsdeterminanten. Dit proefschrift analyseert veranderende woningprijsdeterminanten over de tijd heen (Hoofdstuk 2), het effect van 'kredietvoorwaarden' op woningprijzen (Hoofdstuk 3), het effect van bevolkingsgroei en krimp op woningprijzen (Hoofdstuk 4) en het laatste hoofdstuk behandelt de gevolgen van depreciatie op woningprijzen (Hoofdstuk 5). Al beperkt dit proefschrift zich tot de Nederlandse woningmarkt, de resultaten kunnen relevant zijn voor andere sectoren binnen de vastgoedmarkt of zelfs voor andere markten die gekenmerkt worden door aanbod dat slecht reageert op prijzen.

Hoofdstuk 2 bestudeert de determinanten van woningprijzen gebruik makende van 200 jaar aan (voornamelijk) Amsterdamse data. Zeven verschillende woningprijsdeterminanten worden behandeld: woningvoorraad, constructiekosten, bruto nationaal product (BNP) per capita, de (gecorrigeerde) hypotheekrente, beroepsbevolking als percentage van de gehele populatie, werkloosheid en bevolkingsgroei. Een belangrijk onderdeel van deze studie is dat de woningprijsdeterminanten tijds-variant verondersteld worden. Parameters moeten tijds-variant worden verondersteld vanwege (lange) vastgoedcycli en door veranderingen in (politieke en economische) regimes. Een jaar-op-jaar rollende regressie, met daarin alle mogelijke combinaties van woningprijsdeterminanten, is gebruikt om woningprijzen te analyseren. Het voordeel van zo'n model is dat er geen a priori structuur opgelegd wordt aan de manier waarop de woningprijsdeterminanten veranderen over de tijd heen. Aangezien de tijdreeksen niet-stationair zijn, wordt het model geschat in een foutencorrectieraamwerk. De lengte van het raam is vastgezet op 30 jaar, aangezien dit de gemiddelde lengte is van een vastgoedcyclus en omdat dit resulteert in het grootst aantal coïntegrerende relaties. De resultaten laten zien dat de woningprijsdeterminanten inderdaad veranderend zijn en dat deze de economische werkelijkheid van dat tijdperk weergeven.

Gedurende de 19^{e} eeuw zijn bevolkingsgroei, woningvoorraad en constructiekosten de hoofddeterminanten van woningprijzen. Aan het begin van de 20^{e} eeuw wordt het BNP per capita

steeds belangrijker. Na de Tweede Wereldoorlog is er een korte periode waarin woningbouwinvesteringen en bevolkingsgroei belangrijk zijn. Dit is een afspiegeling van de naoorlogse wederopbouw van Nederland en de groeiende vraag naar woonruimte door de geboorte van de babyboom-generatie. Na 1970 zijn BNP per capita en de hypotheekrente de belangrijkste woningprijsdeterminanten. Dit is op zijn beurt weer een afspiegeling van de eenvoudige toegang tot de hypotheekmarkt in deze periode. Deze bijzondere periode wordt (wereldwijd) tevens gekenmerkt door enorme woningprijsstijgingen.

In Hoofdstuk 3 testen we in meer detail wat het effect is van de hypotheekmarkt op woningprijzen voor de periode 1995 – 2012. Eerst construeren we een 'kredietvoorwaardenindex' (CCI). De CCI geeft het aanbod van krediet op de hypotheekmarkt weer, los van de rentestand en het inkomen van leners. De index wordt geschat als een niet-geobserveerde component in een foutencorrectiemodel waarin de gemiddeld verkregen hypotheek verklaard wordt aan de hand van variabelen als de leencapaciteit van huishoudens (berekend gebruik makende van de Nibud normen) en andere controle-variabelen. Het idee is dat als we woningprijzen verklaren aan de hand van economische en demografische variabelen, de overgebleven niet-geobserveerde component de CCI moet zijn. De niet-geobserveerde component is gemodelleerd als 'local linear trend', 'random walk' en als 'linear splines'. Het model wordt geschat op data voor starters. Het voordeel is dat starters geen eigen vermogen uit de vorige woning mee kunnen nemen en dat ze daardoor (bijna) in zijn geheel afhankelijk zijn van de banken. Hierdoor verdwijnen enkele vraagzijde factoren die de niet-geobserveerde component zouden kunnen vervuilen.

In alle modellen stijgt de CCI tot en met 2009, met een kleine interruptie tijdens de kredietcrisis in 2007 – 2008. Het feit dat steeds meer huishoudens een aflossingsvrije hypotheek namen en de groeiende populariteit van de Nationale Hypotheek Garantie zijn belangrijke verklaringen voor de stijging van het kredietaanbod op de hypotheekmarkt in deze periode. Echter, na 2010 zien we een sterke daling van het kredietaanbod op de hypotheekmarkt. De reden moet waarschijnlijk gezocht worden in de strengere kapitaaleisen voor banken, de afschaffing van aflossingsvrije hypotheekproducten en de strengere Loan-to-Value eisen, opgelegd door de overheid. Aan het einde van 2012 is het aanbod van krediet op de hypotheekmarkt ongeveer zo hoog als in 2003 – 2004. De geschatte CCI is hoog gecorreleerd met de 'Bank Lending Survey' (BLS). In de BLS wordt medewerkers van banken elk kwartaal gevraagd of zij denken dat de hypotheekverstrekking is verscherpt of juist is versoepeld ten opzichte van de vorige periode.

De CCI is vervolgens opgenomen in een foutencorrectiemodel waarin Nederlandse woningprijzen verklaard worden (niet specifiek voor starters) op kwartaalbasis tussen 1995 en 2012. De verklaringskracht van de foutencorrectiemodellen stijgt na het opnemen van de CCI. In reële termen zijn woningprijzen tussen 2009 en 2012 met 25 procent gedaald. Ongeveer de helft van deze woningprijsdalingen kunnen verklaard worden door de daling van de CCI.

Hoofdstuk 4 richt zich op het asymmetrische effect van bevolkingsgroei en krimp op woningprijzen, waarbij expliciet rekening gehouden wordt met het feit dat woningaanbod niet of nauwelijks meteen kan reageren op veranderingen in de vraag naar woonruimte. Door de

duurzame aard van woningen – ze worden immers gebouwd met het idee tientallen jaren mee te gaan – duurt het zeer lang voordat het aanbod van woningen zich heeft aangepast aan de vraag in het geval van krimp (er wordt nauwelijks tot sloop overgegaan). Door deze vraaguitval zullen woningprijzen disproportioneel hard dalen. Een regio raakt in verval als woningprijzen lager zijn dan de herbouwwaarde van diezelfde woningen, aangezien investeringen dan geen economisch nut meer hebben. Op het moment dat een regio in verval raakt zullen huishoudens met het meeste 'menselijk kapitaal' als eerste verhuizen naar een andere regio. Huishoudens met een lager menselijk kapitaal zullen hun plaats innemen.

Woningprijzen reageren anders op demografische groei. Het effect van demografische groei op woningprijzen is namelijk sterk afhankelijk van hoe snel het aanbod van woningen reageert op de vraag. Als het aanbod niet kan inspelen op de vraag, dan zal de vraag zich vooral vertalen in hogere prijzen. Op de korte termijn zal er altijd enige discrepantie zitten tussen vraag en aanbod aangezien het ontwikkelen van woningen enige tijd in beslag neemt. Echter, het kan ook zo zijn dat het aanbod van woningen zich zelfs niet of nauwelijks aanpast op de lange termijn. Dit kan komen door een fysiek tekort aan ruimte of door regelgeving. Regelgeving in Nederland met betrekking op woonaanbod is vooral te vinden in de Wet Ruimtelijke Ordening. Het belangrijkste uitvoerende orgaan in de geanalyseerde periode is de gemeente met haar bestemmingsplannen.

Om het effect te schatten van demografische groei en krimp op woningprijzen gebruiken we een panel data set op gemeenteniveau voor de periode 1995 – 2009. De bevolkingsgroei of -krimp moet echter langdurig zijn wil die de woningprijzen structureel beïnvloeden. Om deze reden is er gekozen om te modelleren naar het langst mogelijke tijdsinterval: 15 jaar. Aangezien we vooral geïnteresseerd zijn in het asymmetrische effect van bevolkingsgroei en -krimp wordt de variabele bevolkingsmutatie opgesplitst in een variabele met bevolkingstoename en in een variabele met bevolkingsafname. De variabele met bevolkingstoename wordt bovendien verder opgesplitst in categorieën die aangeven hoe eenvoudig het aanbod zich kan aanpassen aan de vraag in desbetreffende gemeente. Om deze categorieën aan te maken verklaren we eerst woningprijsontwikkelingen aan de hand van het aantal nieuwbouwvergunningen. De categorieën zijn een ordening van gemeentes waarbij het aantal nieuwbouwvergunningen weinig reageert op woningprijzen tot en met gemeentes waar het aantal nieuwbouwvergunningen zeer goed reageert op woningprijzen.

Elke 1% bevolkingskrimp resulteert in $1,9\%$ lagere woningprijzen. In de gemeentes waar het aanbod het minst reageert op vraag zullen prijzen met $0,4\%$ stijgen bij elke procent bevolkingstoename. Bevolkingsgroei zal woningprijzen echter niet of nauwelijks beïnvloeden in gemeentes waar het aanbod zich relatief snel aanpast aan de vraag. Voorbeelden hiervan zijn de gemeentes Barendrecht, Houten en Almere.

Hoofdstuk 5 analyseert het effect van depreciatie op woningprijzen. Via depreciatie wordt rekening gehouden met het waardeverlies van de woning als gevolg van het feit dat de woning ouder wordt. Depreciatie bestaan uit drie onderdelen: (1) fysieke slijtage, (2) functionele

veroudering en (3) externe veroudering. Fysieke slijtage is de slijtage van de opstal naarmate deze ouder wordt. Onder functionele veroudering verstaan we de vermindering van de door de woning geleverde woondiensten door de tijd heen. Externe veroudering is de waardeverandering van de grond, bijvoorbeeld omdat de lokale voorzieningen door de tijd heen kunnen veranderen. Daarbij zijn er ook nog zogenoemde 'vintage' of 'jaargang' effecten. Dit is een extra prijseffect (positief of negatief) op de opstal die enkel en alleen voorkomt omdat de woning in een bepaalde periode is gebouwd (denk in de breedste zin aan architecturale stijl). Fysieke slijtage kan tegengegaan worden door goed onderhoud te plegen. Functionele veroudering kan alleen tegengegaan worden door (grote) renovaties.

We gebruiken de leeftijd van de opstal om de fysieke slijtage te meten, het bouwjaar van de opstal om het gezamenlijke effect van de functionele veroudering en 'vintage' te meten en het verkoopjaar om de externe veroudering te meten in een (niet-lineair) hedonisch model. Daarbij kijken we specifiek naar het effect van fysieke slijtage (leeftijd) *per* onderhoudsniveau.

In het algemeen zijn er twee grote problemen bij studies over depreciatie. Ten eerste is er een identificatieprobleem tussen de belangrijkste variabelen: leeftijd, bouwjaar en verkoopjaar. Ten tweede zal men altijd een onderschatting vinden van de leeftijdseffecten op het moment dat de grondprijzen groter zijn dan nul. Ons model omzeilt deze problemen door ervan uit te gaan dat de fysieke slijtage (gemeten als leeftijd) en het gezamenlijke effect van fysieke veroudering en 'vintage' (gemeten als bouwjaar) alleen invloed hebben op de opstal. De externe veroudering (verkoopjaar) daarentegen heeft alleen invloed op de grondprijs. De enige input in het model is de herbouwwaarde van de opstal. De opstalwaarde is nu een functie van de herbouwwaarde van de opstal, de leeftijd en het bouwjaar van de opstal en de grootte (aantal vierkante meters) van de opstal. De grondwaarde wordt opgesplitst in tweeën: een waarde van de grond waar de woning op staat en een tuinwaarde. De waardes van de grond zijn functies van de locatie, grootte, verkooptijd en het type opstal dat op de grond staat.

De Nederlandsche Vereniging van Makelaars (NVM) heeft ons data geleverd van meer dan 9.000 woningtransacties in de regio 's-Hertogenbosch in de periode 2000 – 2012. Data over herbouwwaardes zijn verkregen van de website Bouwkostenkompas.

De resultaten laten zien dat de staat van onderhoud een belangrijke effect heeft op de fysieke slijtage van de opstal. Na 50 jaar van geen of nauwelijks onderhoud zal een opstal 43% in waarde zijn verminderd. Een goed onderhouden opstal zal daarentegen nauwelijks in waarde verminderen. De resultaten laten tevens zien dat grondprijzen een stuk volatieler zijn dan opstalprijzen. Daarbij zijn de grondprijzen- en opstalindex nauwelijks gecorreleerd. Vergeleken met traditionele hedonische modellen heeft het beschreven model drie voordelen. Ten eerste geeft ons model geen onderschatting van de leeftijdseffecten. Ten tweede is ons model niet gevoelig voor het eerdergenoemde identificatieprobleem. Als derde en laatste is de precisie van de leeftijdsschattingen niet gevoelig voor volatiele grondprijzen.

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