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

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Heterogeneity in house price dynamics*

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Abstract

We study the extent to which house price dynamics differ across market segments and possible drivers of this heterogeneity. We construct a data set for individual houses and mortgages, based on a survey of about 500 Dutch households conducted over the period 2003-2016. We estimate a dynamic panel data model of house price dynamics by means of the Arellano-Bond estimator. Three main empirical results emerge. First, we generally find that house price dynamics imply a convergence towards their long-run equilibrium value, as indicated by a low serial correlation coefficient and a positive estimated mean reversion coefficient. Second, there is evidence that the housing market in the Netherlands is inefficient. Third, there is important heterogeneity across different market segments, with some markets being more "cyclical" than others. In particular, the speed of convergence of house price dynamics and the efficiency of housing markets depends on the geographical location, the degree of urbanization, and the type and year of construction of a house. We do not find evidence of significant heterogeneity across different types of mortgage financing and households' income.

Keywords: Housing market dynamics, house prices, heterogeneity, survey data, panel analysis.
JEL classifications: D14, G12, R32.

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1. Introduction

This paper examines heterogeneity in house price dynamics across different segments of the housing market, defined by location, degree of urbanization, age and type of housing, and the type of mortgage finance.

There is a rich literature on the housing market and its role in the economy (Mishkin, 2007), which in recent years has focused on the role of the housing market in the Global Financial Crisis and the Great Recession (see e.g. Mian and Sufi, 2010; Field, 2014). The crisis has underscored the importance of understanding the dynamics of house prices, and of the drivers of booms and busts in the housing market (e.g. Agnello and Schulknecht, 2011).

An important insight gained from empirical work – mostly on US data – is that housing markets tend to be characterized by serial correlation and mean reversion, which can vary significantly across local markets (e.g. Capozza et al., 2004). One conjecture is that there exist two significantly different types of markets – “cyclical” markets, which exhibit pronounced volatility and swings, and “non-cyclical” markets (Gao et al., 2009). As documented by Gao et al. (2009) for the United States over the period 1987-2006, cyclical markets tend to have stronger serial correlation than non-cyclical markets, and therefore tend to deviate further from fundamentals and experience more pronounced house price cycles. This difference is found to not simply reflect the geographic location of real estate but also the cost of mortgages and other factors.

The heterogeneity of housing markets can have important implications for macroeconomic dynamics, e.g. via collateral or wealth effects (see e.g. Calza et al., 2009; Rubio, 2011, 2014). It also matters for policymakers, and in particular for prudential policies targeted to the housing market (Rubio, 2014). This motivates our effort to investigate whether the evidence on this type of heterogeneity is robust to data from other countries, to sample periods that include the Great Recession and to other empirical approaches.

In particular, we examine the heterogeneity of house price dynamics using a large panel of households and mortgages in the Netherlands. Over the past decades, the Dutch housing market has experienced phenomena that were quite common in advanced economies – a rapid increase in housing wealth and household debt, accompanied by a strong growth of mortgage markets which in part reflected financial innovation, and a corresponding rising share of housing loans in bank assets. The strong boom in house prices in the Netherlands that peaked around the time of the global financial crisis and was followed by a pronounced bust, was similar to cycles observed in other countries (Cohen et al., 2012). This suggests that analysing the dynamics of housing markets in the Netherlands can shed light on house price dynamics more generally.

Our data set is based on the DNB Household Survey (DHS), an annual survey of about 2,000 households in the Netherlands that started in 1993. One important advantage of our data set is that it contains information on the official value of a house determined by the municipality in which it is located. In the Netherlands, this value is used to calculate an imputed property value and a residential property tax.

We use a dynamic panel data model by means of the Arellano-Bond panel data estimator to explain the dynamics of individual house prices and to investigate heterogeneity across different segments of the housing market in the Netherlands.

We find three key results. First, house prices generally converge towards their long-run equilibrium value, although this convergence is not very rapid. Second, there is evidence that the housing market in the Netherlands is inefficient. These results are in line with the extensive evidence provided for the United States, based on different types of data and different empirical approaches. Third, we find important heterogeneity in house price dynamics of the type documented for US data by Gao et al (2009) and others. Moreover, house price dynamics are heterogeneous along different dimensions, some of which have not yet been documented in the literature. In particular, the speed of convergence of house price dynamics depends on the geographical region, the degree of urbanization, the type of house and its year of construction. Interestingly, the dynamics of house prices financed by different types of mortgages seem to not differ significantly,

The rest of the paper is organized as follows. The next section surveys the literature on the drivers of house price dynamics. Section 3 documents the characteristics of our panel data set and describes our measure of house prices. Section 4 presents our empirical model and the results. Section 5 concludes.

2. Literature review

A rich literature has investigated the dynamic properties of the housing market and documented that it is generally not efficient, and characterized by serial correlation and mean reversion. Large swings in house prices are typically followed by reversals to the (unobserved) fundamental price level.[1]

The empirical work has generally relied on two types of data. A first set of studies uses cross-sectional data or panel data on regions or metropolitan areas within a country – typically the United States – to investigate housing dynamics and how they differ across market segments.

[11] Cho (1996) provides an early survey of this line of research.

Important contributions to this literature strand include Case and Shiller (1989), Abraham and Hendershott (1993, 1996), Meese and Wallace (1994), Capozza and Seguin (1996), Malpezzi (1999), Kalra et al. (2000), Meen (2002), Capozza et al. (2002), Capozza et al. (2004), Zandi and Chen (2006), and Gao et al. (2009).

A second type of studies uses cross-country data, in an attempt to study the role of macroeconomic drivers along with financial and institutional factors. Tsatsaronis and Zhu (2004) provide an overview of this type of analysis.

One important finding of this literature is that there is significant heterogeneity in house price dynamics across different market segments. The geographical location of houses is typically highlighted as a proximate source of heterogeneity (e.g. Meese and Wallace, 1994; Abraham and Hendershott, 1996; Himmelberg et al., 2005; Zandi and Chen, 2006). A study by Gao et al. (2009) provides a systematic analysis of geographical heterogeneity in US housing markets. The authors use two large panel datasets of house prices from US metropolitan areas – the OFEO and S&P/Case-Shiller house price indices – to cluster market segments depending on their dynamic properties. They first classify housing market segments into "cyclical" (i.e. highly volatile) and "non-cyclical" (i.e. with low volatility) depending on the standard deviation between actual and fundamental house prices over time. They then estimate an asymmetric autoregressive mean reverting model, and find that cyclical markets tend to experience larger house price cycles. They also find evidence of higher autocorrelation of housing prices during upswings compared to downswings.

In turn, geographical differences in house price dynamics have been explained by a number of main factors: income, psychological factors, demographical factors, construction costs, market regulation, mortgage markets and asymmetric information.[2] Income is found to be a key factor determining whether housing market segments exhibit oscillatory or damped, and convergent or divergent price dynamics (Capozza et al., 2004).[3] Serial correlation is higher in metropolitan areas with higher real income (Capozza, 2002). However, as stressed by Case and Shiller (2003), psychological factors may dominate income growth as a driver of house price dynamics and underpin speculative bubbles in geographical segments of the housing market.

There is evidence from both regional data for the United States and cross-country regressions analysis that demographical factors play a significant role (Takáts, 2010). Capozza et al. (2002),

[2] For a rationalization of these types of heterogeneity, see e.g. Glaeser et al. (2014), who explain the dynamics of housing markets in terms of a dynamic, rational expectations version of standard urban real estate models, where house prices are driven by local wages and other local factors.

[3] Related to this finding is research that shows how house prices reflect the cross-sectional dispersion of wages combined with limited land supply (e.g. Van Nieuwerburg and Weill, 2010).

for example, document that serial correlation of house prices is higher in metropolitan areas in the United States with higher population growth. Hiebert and Roma (2010) present evidence that in the United States and a number of euro area countries, income and population differences explain house price differentials.

House price dynamics have been found to be influenced significantly by geographical differences in construction costs. In the United States, higher real construction appear to be associated with higher serial correlation of house prices and lower mean reversion (Capozza et al., 2002). As a result, high real construction cost areas – typically large metropolitan areas and fast growing cities – can witness substantial overshooting of house prices.

Several studies have highlighted that differences in the degree of market regulation may also underpin heterogeneous market dynamics. In the United States, the mean reversion of metropolitan house prices is found to be larger for low-to-moderately regulated markets than for the stringently regulated markets (Malpezzi, 1999). Green et al. (2005) document that differences in supply elasticities – which underpin housing dynamics – are driven by differences in the urban form and in the urban-land use regulation.

The role of mortgage markets and more in general financial factors are documented in a number of studies, most of which rely either on domestic macro time series (Estrella, 2002; McCarthy and Peach, 2002; Peek and Wilcox, 2006) or on cross-country data (Muellbauer and Murphy, 1997; Herring and Wachter, 1999; Hilbers et al., 2001; Swank et al., 2002; Iacoviello and Minetti, 2003; Berger-Thomson and Ellis, 2004; Davis and Zhu, 2004; Hofman, 2004; Tsatsaronis and Zhu, 2004; Egert and Mihaljek, 2007; Warnock and Warnock, 2008; Calza et al., 2009). This line of research suggests that house price dynamics depend importantly on the flexibility and depth of domestic mortgage markets, as well as the tax treatment of homeowners (and in particular the extent to which mortgage payments are tax deductible). The effect of lending practices on house price dynamics in different market segments has also been documented in research based on micro data (e.g. Damianov and Escobari, 2016).

In turn, there is research that relates the influence of mortgage financing on house prices to differences in the degree of informational asymmetries. Using data on 10,000 individual commercial property transactions in the United States, Garmaise and Moskowitz (2004) show that limited participation, selective offering and market segmentation are more important than the use of appropriate forms of financing. Warnock and Warnock (2008) document how the strength of legal rights for borrowers and lenders, through collateral and bankruptcy laws, and the depth of credit information systems underpin the role of housing finance.

Finally, from an international perspective, recent research highlighted the role of monetary policy and macroprudential policy on the behaviour of house prices (Kuttner and Shim, 2012).

3. The data

The existing literature typically relies on data on either regional/metropolitan housing markets or on data aggregated at the country level. An important novelty of our paper is that we use data on a large cross-section of individual houses and households that are available for a number of consecutive years. These data enable us to shed new light on the heterogeneity of the housing market, its sources, and how it affects the dynamics of house prices.

3.1. The DNB Household Survey

Our data source is the DNB Household Survey (DHS), an annual survey of households in the Netherlands that started in 1993 and is run at Tilburg University by CentERdata. The survey is conducted around the start of the year. The DHS consists of a sample intended to be representative of the Dutch population; it covers some 2,000 households in each wave, including refreshment samples compensating for panel attrition. [4] Our dataset covers the period 2003–2016, and has 496 different households and 1,662 point observations.

The DHS provides information on both economic and psychological aspects of financial behaviour: work and pensions, accommodation and mortgages, income and health, assets and liabilities, and economic and psychological concepts.[5]

In this paper we mainly focus on questionnaires related to accommodation and mortgages. In our analysis we use data on home owners, for whom we have information about the value of a house that is determined each year by the municipality in which it is located (the so-called WOZ-value, in Dutch "waardering onroerende zaken"). In determining the value of a house in year t, the municipality uses the price of property with similar characteristics (such as surface area, location, year of construction and lay-out) that has been sold in the vicinity of that house around the start of that year. Figure 1 shows this WOZ-value, which in the Netherlands is used to calculate an imputed home ownership value and a residential property tax. The starting year of our data set and the number of annual observations are dictated by the availability of survey responses about this value in the DHS.

[4] In case of attrition, CentERdata recruits new participants to maintain the panel size and to keep the panel representative with regard to relevant background characteristics such as age, gender, income, education, and region of residence.

[5] For a detailed description of the CentERpanel and the DHS see http://www.uvt.nl/centerdata/dhs and Teppa and Vis (2012).

78 percent of households in our sample reported to have contracted at least one mortgage for house purchase purposes.[6] The mortgage market in the Netherlands is known to be very developed (Andre', 2010).

The DHS contains information that allows to test for the role of main sources of heterogeneity in house market dynamics whose importance has been highlighted in the literature: geographical location and degree of urbanization, income, psychological factors, demographical factors and type of mortgage financing. In addition, we can verify whether house price dynamics depend also on other house-specific characteristics, such as the year of construction or the type of house. Table 1 reports summary statistics on house characteristics (geographical region, year of construction), household specific characteristics, (income, wealth, age), and individual respondents' financial arrangement (types of mortgages).

Table 1 about here

3.2. Measuring house prices

In the DHS, information on our main variable of interest, the house price p of household i at time t, can be gained – for respondents that live in a house they own – from answers to three questions. The first – and our preferred – source of information are the answers to a question on the value of a property for tax purposes (the so-called WOZ), which is determined by the municipality based on the value of property with similar characteristics located in the same neighbourhood. This question reads as follows: *"In order to calculate for example the deemed home ownership value (eigenwoningforfait) and the immovable property tax (OZB) the government uses the WOZ-value of your house (the official value of your house determined by the municipality). What is the determined WOZ-value for your house?".*

An alternative – and more direct – source of information on house prices is a question that asks directly for the actual price that was paid for the purchase of that house. While answers to this question have the advantage of providing information on actual transaction prices, a large majority of households in our data set did not change residence during the sample period. Moreover, when a house was purchased prior to the start of our sample period, the DHS does not provide information on the timing of the transaction. We therefore decided not to use this variable in our empirical analysis.

A third data source consists of answers to the following question: *"About how much do you expect to get for your residence (not including the business part) if you sold it today (empty and not let)?".* Although data on subjective assessments of the current home value are available for a

[6] For information on different types of mortgage contracts in the data set, see Teppa and Vis (2012).

longer period compared to those on the WOZ value, we opted against using this source of information. The main reason is that subjective answers to this question potentially suffer from a persistent bias.[7]

4. Empirical model and main results

4.1 The model

Our empirical model of house price dynamics consists of two equations.[8] The first describes the evolution of the long-term value for house prices P_{it}^* owned by household *i* at time *t*:

$$P_{it}* = X'_{it}\,\delta + c_i + v_{it} \qquad (1)$$

where X_{it} are time-varying house or household characteristics (such as household income or the mortgage rate), c_i is a set of time-invariant house or household specific regressors, and v_{it} is a white noise unobserved residual.[9]

The second equation describes the short-term dynamics of house prices P_{it} for household *i* at time *t*, and is specified in first differences:

$$\Delta P_{it} = \alpha \Delta P_{it-1} + \beta (P_{it-1}* - P_{it-1}) + \gamma \Delta P_{it}* + u_{it} \qquad (2)$$

where the parameter α captures the degree of serial correlation, β the extent of mean reversion to the long-term value, and γ the contemporaneous adjustment to long-term values. u_{it} is a white noise unobserved residual.

This type of model has been used in a number of studies on the dynamics of the housing market (e.g. Capozza et al., 2002; Gao et al., 2009). These studies generally focus on the United States and rely on time series data or on panel data with observations at the regional or municipal level. House prices are typically captured by quarterly data on US house price indices such as the S&P/Case-Shiller index or the actual repeat-transactions house price index. These papers generally follow a two-step estimation strategy. In the first step, an equation for the long-term house price – such as equation (1) – is estimated. In the second step, the dynamic equation (2) is estimated separately, where P_{it}^* is the fitted long-term price from the first step.

[7] In the literature, estimates of the bias of subjective house prices suggest that it can be significant and difficult to pin down (Capozza et al., 2002; Agarwal, 2007; Glindro et al., 2008; Gonzalez-Navarro and Quintana-Domeque, 2009; Bucchianeri and Miron-Schatz, 2011). As shown by Agarwal et al. (2009), an important reason is that the ability to assess the value of one’s home is related to the combined effects of increasing experience and declining cognitive ability.
[8] The model is taken from Galati et al. (2011).
[9] We control for the level of unemployment to capture the role of macroeconomic dynamics. For an overview of the literature on the link between labor markets and real estate markets, see Rogers and Winkler (2013).

This two-step procedure is appropriate in a time series context where a cointegration framework is used to distinguish long-term relationships from short-term dynamics. In principle, it is also appropriate for panel data but only when the time series dimension is large. In our data set however, the time dimension is too small for asymptotic properties to apply in a cointegration-type set up which includes a long-term relationship. To estimate the model consistently, we therefore adopt a different strategy based on estimating in one step a single reduced-form equation that combines equations (1) and (2). In particular, we rewrite equation (2) in levels:

$$P_{it} - P_{it-1} = \alpha P_{it-1} - \alpha P_{it-2} + \beta P_{it-1}* - \beta P_{it-1} + \gamma P_{it}* + \gamma P_{it-1}* + u_{it}$$

$$P_{it} = (1+\alpha-\beta)P_{it-1} + \gamma P_{it}* + (\beta-\gamma)P_{it-1}* - \alpha P_{it-2} + u_{it} \qquad (3)$$

By substituting equation (1) into (3), we get:

$$P_{it} = (1+\alpha-\beta)P_{it-1} + X_{it}'\delta\gamma + X_{it-1}'\delta(\beta-\gamma) - \alpha P_{it-2} + [\beta c_i + \beta v_{it-1} + \gamma\Delta v_{it}] + u_{it}$$

$$P_{it} = (1+\alpha-\beta)P_{it-1} - \alpha P_{it-2} + \Delta X_{it}'\delta\gamma + X_{it-1}'\delta\beta + \beta c_i + \beta v_{it-1} + \gamma\Delta v_{it} + u_{it}$$

$$P_{it} = \theta_1 P_{it-1} + \theta_2 P_{it-2} + \theta_3 \Delta X_{it}' + \theta_4 X_{it-1}' + \varepsilon_{it} \qquad (4)$$

where $\theta_1 = (1+\alpha-\beta)$; $\theta_2 = -\alpha$; $\theta_3 = \delta\gamma$; $\theta_4 = \delta\beta$

Equation (4) can be estimated consistently by means of the Arellano-Bond panel data estimator (Arellano and Bond, 1991). All regressors enter in first differences and in first lags.

Table 2 reports the results from estimating equation (4). In addition to the estimates of α, β and γ – the main parameters of interest – Table 2 also reports F-statistics for the test of equal coefficients and the Hansen-test statistics of overidentifying restrictions.

The first row shows estimates of the baseline specification with the full number of observations. In order to verify the presence of relevant heterogeneity across different house market segments, we also run the baseline regression with data disaggregated along several dimensions: the degree of urbanization, the geographic region, the type of house, the type of mortgage, and the year of construction. In the terminology of Gao et al. (2009), estimates of α, β and γ for these market segments allow us to group them into "cyclical (or volatile)" and "non-cyclical (or tame)" markets.

Table 2 about here

4.2 Results

Table 2 shows that among the parameters of interest (α, β and γ), β is always strongly statistically significant (at the 1% level) and γ is in most cases significant (at least at the 5% level).

We highlight two important results on the dynamics of the Dutch housing market. First, our estimates for α, β and γ show that at an aggregate level, house prices in the Netherlands converge towards their long-term equilibrium value.[10] In terms of speed of convergence, the Dutch housing market as a whole could be characterised as an intermediate case between "non-cyclical" and "cyclical" in the terminology of Gao et al. (2009). We find that α – which measures the degree of serial correlation – is negative and fairly low in absolute terms (-0.16). This indicates that at time *t*, house prices change in the opposite direction with respect to their change at time *t-1*, albeit very slowly. It can be interpreted as suggesting that on average, house prices do not evolve in a persistently adaptive way. This is in contrast with results from studies that, starting from the pioneering work of Case and Shiller (1989), have found significant positive correlations between current and lagged appreciation rates of house prices, particularly in the lead-up to the Global Financial Crisis. This line of research has highlighted how housing markets exhibit an unusually strong autoregressive effect and an unusually long horizon over which it persists (Guren, 2016). The difference of our results with respect to these findings might at least in part reflect the collapse of house prices in the Netherlands in the wake of the Global Financial Crisis, which dominates our sample period.

The parameter β – which measures the degree of mean reversion to the long-term value – is estimated to be positive and fairly high (0.48), implying that a misalignment between long-term house prices and actual house prices induces a change in the same direction of actual house prices in the following period. In other words, if in the previous period house prices are below their long-term value (i.e. $P_{it-1}* - P_{it-1} > 0$), prices will adjust upward in the current period. Conversely, if in the previous period house prices are above their long-term value (i.e. $P_{it-1}* - P_{it-1} < 0$), they will adjust downward in the current period.

The estimate of the parameter γ – which measures the contemporaneous adjustment of house prices to long-term values – is fairly low (0.21), indicating that the housing market in the Netherlands is rather inefficient. This finding can be explained by high transaction costs and the inelastic supply of housing (Swank et al., 2002; IMF, 2010).

A second key observation is that while the dynamics of the Dutch housing market exhibit common features across market segments, there are important heterogeneities. The different housing market segments are all similar in that they are characterised by a low and negative parameter α, a positive parameter β and – in most cases – a fairly low parameter γ. At the same time, the estimated coefficients for α, β and γ change – at times markedly – when we disaggregate our data along different dimensions. In particular, we find evidence of substantial heterogeneity in

[10] This is consistent with evidence from other studies (see IMF, 2010).

the dynamics of house prices across different geographical location or degree of urbanization, type of house and type of mortgage financing. By contrast, we do not find evidence of significant differences in house price dynamics across households of different income or age classes.[11]

More in detail, the relationship between house price dynamics and *degree of urbanization* appears to be U-shaped. House prices in very highly and highly urbanized areas or areas with a very limited degree of urbanization tend exhibit significantly higher parameters of mean reversion (β) and a higher parameter measuring market efficiency (γ) compared to areas that with a moderate or limited degree of urbanization. By contrast, we do not detect major differences in the parameter of serial correlation (α). In terms of *geographic region*, we also find visible differences in mean reversion or market efficiency across the main areas of the Netherlands.

In addition to market segmentation in terms of location, our results also provide evidence on heterogeneity in price dynamics of across different *types of housing*, where we observe a wide range of estimates of the degree of mean reversion and the parameter measuring market efficiency. The same is true for when we distinguish houses by *year of construction*.

Interestingly, the dynamics of the prices of houses financed with different *types of mortgages* seem not to differ significantly, as suggested by similar estimates of the parameters of serial correlation, mean reversion and efficiency across the most used forms of mortgages. We do not find evidence that interest-only mortgages are associated with more pronounced cycles in house price dynamics. Interest-rate mortgages are a financial innovation that became popular in the first decade of this century, and in which borrowers pay only interest during the term of the mortgage and pay back the entire loan the end of the contract.

5. Conclusions

This paper investigates the heterogeneity of house price dynamics across different segments of the housing market, in an effort to verify whether results obtained mainly for the United States also apply to other countries and other empirical approaches. We use a large panel data set of Dutch households that covers the period 2003–2016, which we build based on survey data on housing and mortgages from the DNB Household Survey. In contrast to most existing studies of housing market dynamics we do not use a time-series framework (typically involving cointegrating relationships). Instead, we apply the Arellano-Bond panel data estimator to a reduced-form equation that captures the dynamics of house prices in terms of both micro- and macroeconomic factors.

[11] The latter results are not reported for reasons of space but available upon request from the authors.

Overall, we generally find a low and negative serial correlation coefficient and a positive estimated mean reversion coefficient, implying that house price dynamics lead to a convergence towards their long-run equilibrium value. This is true for the whole sample, as well as for different market segments we investigate. At the same time, the empirical evidence also highlights an important heterogeneity across different market segments defined by geographical location, degree of urbanization and type of housing. Although generally converging to their long-term value, the speed of convergence of house prices, the mean reversion and the degree of market efficiency vary across these market segments. There is evidence that the Dutch housing market has both cyclical and non-cyclical segments, as has been documented for the United States, e.g. by Gao et al. (2009).

We do not find evidence that the dynamics of housing markets diverge across different types of mortgage financing. This is interesting because a particular type of mortgage financing – interest only mortgages – has generally been seen as one factor behind the prolonged boom in the Dutch housing market. An in-depth analysis of the impact of financial innovation in mortgage lending on the dynamics of housing markets is an important avenue of future research.

References

Abraham, J. and Hendershott. P. (1996). Bubbles in metropolitan housing markets. *Journal of Housing Research*, 7, 191-207.

Agarwal, S. (2007). The Impact of Homeowner's Housing Wealth Misestimation on Consumption and Saving Decisions. Real Estate Economics , 35(2), pp. 135-154.

Agarwal, S., Driscoll, J., Gabaix, X. and Liabson, D. (2009). The Age of Reason: Financial Decisions Over the Life Cycle with Implications for Regulation. *Brookings Papers on Economic Activity*, 2, pp. 51-117.

Agnello, L. and Schuknecht, L. (2011). Booms and busts in housing markets: Determinants and implications. Journal of Housing Economics, 20(3), pp. 171-190.

Andre', C. (2010). A bird's eye view of OECD housing markets. OECD Economics Department Working Paper ECO/WKP(2010).

Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. The Review of Economic Studies, 58, pp. 277 – 297.

Berger-Thompson L. and Ellis, L. (2004). Housing construction cycles and interest rates. RBA Research Discussion Paper 08.

Bucchianeri, W.G. and Miron-Shatz, T. (2010). Taking Stock of Housing Wealth: Reported Home Values. Mimeo, Wharton School.

Calza, A., Monacelli, T. and Stracca, L. (2009). Housing finance and monetary policy. ECB Working Paper 1069.

Capozza, D. R. and Seguin, P.J. (1996). Expectations, efficiency, and euphoria in the housing market. Regional Science and Urban Economics, 26(3-4), pp. 369-386.

Capozza, D., Hendershott, P., Mack, C. and Mayer, C. (2002). Determinants of real house price dynamics. NBER Working Paper 9262, October.

Capozza, D., Hendershott, P., Mack, C. (2004). An anatomy of price dynamics in illiquid markets: analysis and evidence from local housing markets. Real Estate Economics 32, pp.1–32.

Case, K. E. and R. J. Shiller (1989). The Efficiency of the Market for Single-Family Homes. American Economic Review, 79 (1), pp. 125-137.

Case, K E and R J Shiller (2003). Is there a bubble in the housing market. *Brookings Papers on Economic Activity*, 2, pp. 299-342.

Chen, C. and M. Zandi, M. (2006). Is the price right?. Regional Financial Review, March, pp. 11–25.

Cho, M. (1996). House price dynamics: a survey of theoretical and empirical issues. Journal of Housing Research, 7 (2), pp.145–172.

Cohen, J., Coughlin C. and D. Lopez (2012). The Boom and Bust of U.S. Housing Prices from Various Geographic Perspectives. Federal Reserve Bank of St. Louis Review, September/October, 94(5), pp. 341-67.

Davis, E. and Zhu, H. (2004). Bank lending and commercial property cycles: Some cross-country evidence. BIS Working Paper 150.

Damianov, D. and D. Escobari (2016). Long-run Equilibrium Shift and Short-run Dynamics of U.S. Home Price Tiers During the Housing Bubble. Journal of Real Estate and Financial Economics, 53, pp.1-28.

Egert, B. and Mihaljek, D. (2007). Determinants of house prices in Central and Eastern Europe. BIS Working Paper 236.

Estrella, A. (2002). Securitization and the efficacy of monetary policy. In *FRBNY Economic Policy Review*, May, pp. 243-55.

Field, A. (2014). The Interwar Housing Cycle in the Light of 2001-2012: A Comparative Historical Perspective. In White, E., Snowden, K. and P. Fishback (eds.) Housing and Mortgage Markets in Historical Perspective . NBER, University of Chicago Press

Galati, G., Teppa, F. and R. Alessie (2011). Micro and macro drivers of house price dynamics. An application to Dutch data. DNB Working Paper No. 288.

Gao, A., Lin, Z. and Na, C. (2009). Housing market dynamics: Evidence of mean reversion and downward rigidity. *Journal of Housing Economics*, 18, pp. 256-266.

Garmaise, M. and Moskowitz, T. (2004). Confronting information asymmetries: Evidence from real estate markets. *Review of Financial Studies*, 17(2), pp. 405-37.

Glaeser, E., Gyourko, J., Morales, E. and Nathanson, C. (2014) Housing Dynamics: An Urban Approach. Journal of Urban Economics, 81 (3), pp. 45-56.

Glindro, E., Subhanij, T., Szeto, J. and Zhu, H. (2008). Determinants of house prices in nine Asia-Pacific economies. BIS Working Papers 263, October.

Gonzalez-Navarro, M. and Quintana-Domeque, C. (2009). The reliability of self-reported home values in a developing country context. *Journal of Housing Economics*, 18, pp. 311–324.

Green, R., Malpezzi. S. and Mayo, S. (2005). Metropolitan-specific estimates of the price elasticity of supply of housing, and their sources. *American Economic Review Papers and Proceedings*, 95(2), pp. 334-39.

Guren, A. (2016). House Price Momentum and Strategic Complementarity. Forthcoming, Journal of Political Economy.

Herring, R. and Wachter, S. (1999). Real estate booms and banking busts: An international perspective. Center for Financial Institutions Working Papers 27, University of Pennsylvania.

Hilbers, P., Lei, Q. and Zacho, L. (2001). Real estate market developments and financial sector soundness. IMF Working Paper 129.

Himmelberg, C., C. Mayer and T. Sinai (2005). Assessing high house prices: Bubbles, fundamentals and misperceptions. NBER Working Paper 11643.

Hofmann, B. (2004) Bank lending and property prices: Some international evidence. Working Paper 222003, Hong Kong Institute for Monetary Research.

Iacoviello, M. and Minetti, R. (2003). Financial liberalization and the sensitivity of house prices to monetary policy: Theory and evidence. *The Manchester School*, 71(1), pp. 20-34.

International Monetary Fund (2010). Dutch Housing Markets: What Went Up Will Come Down?. Analytical Note 1 in Kingdom of the Netherlands – Netherlands: 2009 Article IV Consultation IMF Country Report No. 10/34.

Kalra, S., Mihaljek, D. and Duenwald, C. (2000). Property prices and speculative bubbles: Evidence from Hong Kong SAR. IMF Working Paper 00/2.

Kuttner, K. and I. Shim (2012). Taming the Real Estate Beast. The Effects of Monetary and Macroprudential Policies on House Prices and Credit. Paper presented at the conference on ‘Property Markets and Financial Stability’ organized by the Reserve Bank of Australia and the Bank for International Settlements on 20-21 August 2012.

McCarthy, J. and Peach. R. (2002). Monetary policy transmission to residential investment. *FRBNY Economic Policy Review*, May, pp. 139-158.

Mian, A. R. and Sufi, A. (2010). Household Leverage and the Recession of 2007-2009. IMF Economic Review, 58 (1), pp. 74-117 .

Meen, G. (2002). The time-series behavior of house prices: a transatlantic divide. Journal of Housing Economics 11, pp. 1–23.

Mishkin, F. (2007). Housing and the monetary transmission mechanism. NBER Working Paper No. 13518.

Muellbauer, J. and A. Murphy (1997). Booms and busts in the UK housing market. *Economic Journal*, 107, pp. 1701-1727.

Peek, J. and Wilcox. J. (2006). Housing, credit constraints, and macro stability: The secondary mortgage market and reduced cyclicality of residential investment. *American Economic Review Papers and Proceedings*, May, pp. 135-40.

Rogers, W. and Winkler, A. (2013) The relationship between the housing and labor market crises and doubling up: an MSA-level analysis, 2005–2011. Monthly Labor Review, U.S. Bureau of Labor Statistics.

Rubio, M. (2011). Fixed- and variable-rate mortgages, business cycles, and monetary policy. Journal of Money, Credit and Banking, 43(4), pp. 657-688.

Rubio, M. (2014). Housing-Market Heterogeneity in a Monetary Union. Journal of International Money and Finance. 40(C), pp. 163-184.

Swank, J., Kakes, J. and Tieman, A. (2002). The housing ladder, taxation, and borrowing constraints. DNB Research Report, 9.

Takáts, E. (2010). Ageing and asset prices. BIS Working Paper 318, August.

Teppa, F. and C. Vis (2012). The CentERpanel and the DNB Household Survey: Methodological aspects. DNB Occasional Study, 4.

Tsatsaronis, K. and Zhu, H. (2004). What drives housing price dynamics: Cross-country evidence. *BIS Quarterly Review*, pp. 65-78.

Van Nieuwerburgh, S. and P.O. Weill (2010). Why Has House Price Dispersion Gone Up?. Review of Economic Studies, 77(4), pp. 1567-1606

Warnock, V. and Warnock, F. (2008). Markets and housing finance. *Journal of Housing Economics* 17, pp. 239-251.

Tables and graphs

Table 1: Descriptive statistics of the survey respondents

Characteristic	Mean value	Std.dev.	N.Obs.
Year of birth			
Before 1930 (reference group)	0.02	0.15	1,662
Between 1930 and 1939	0.18	0.38	1,662
Between 1940 and 1949	0.25	0.43	1,662
Between 1950 and 1959	0.26	0.43	1,662
Between 1960 and 1969	0.16	0.36	1,662
After 1969	0.13	0.33	1,662
Level of education			
Low education (ref. group)	0.22	0.42	1,656
Middle education	0.25	0.43	1,656
High education	0.53	0.50	1,656
Geographical region			
Three largest cities (ref.group)	0.13	0.34	1,658
Rest West	0.27	0.44	1,658
North	0.12	0.33	1,658
East	0.22	0.41	1,658
South	0.26	0.44	1,658
Household income classes			
Less than 15,000 euros (reference group)	0.05	0.22	1,662
Between 15,000 and 22,000	0.26	0.44	1,662
Between 23,000 and 40,000	0.47	0.50	1,662
More than 40,000	0.22	0.41	1,662
Mortgage type			
Annuity (reference group)	0.08	0.30	1,605
Traditional life-insurance	0.05	0.24	1,605
Improved tradit. life-insurance	0.20	0.43	1,605
Linear mortgage	0.02	0.13	1,605
Endowment mortgage	0.01	0.10	1,605
Investment mortgage	0.08	0.30	1,605
Interest only mortgage	0.56	0.50	1,605
Type of house			
Detached	0.19	0.39	1,662
Corner	0.13	0.34	1,662
Semidetached	0.18	0.39	1,662
Terraced	0.20	0.46	1,662
Other	0.30	0.35	1,662
Year	2009	2.81	1,662

Specification	α (Std.Err.)	β (Std.Err.)	γ (Std.Err.)	F-test	Hansen-test	N.Obs. (N.hhs.)
Baseline	-0.16 ***	0.48 ***	0.21 ***	0.36	0.13	1662
	(0.04)	(0.05)	(0.02)			(496)
By degree of urbanization						
Very strong	-0.15 **	0.59 ***	0.53 **	0.98	0.33	220
	(0.05)	(0.09)	(0.24)			(62)
Strong	-0.20	0.89 ***	0.50 **	0.42	0.00	386
	(0.13)	(0.13)	(0.18)			(123)
Moderate	-0.21 ***	0.37 ***	0.15 **	0.72	0.49	356
	(0.04)	(0.07)	(0.06)			(109)
Limited	-0.09	0.50 ***	0.20 **	0.85	0.38	380
	(0.06)	(0.10)	(0.07)			(115)
Very limited	-0.11 ***	0.63 ***	0.53 ***	0.90	0.51	275
	(0.03)	(0.07)	(0.11)			(77)
By geographic region						
Three largest cities	-0.12 ***	0.62 ***	0.31 *	0.84	0.21	216
	(0.03)	(0.08)	(0.18)			(63)
Rest West	-0.11 ***	0.60 ***	0.33 *	0.49	0.14	443
	(0.02)	(0.07)	(0.18)			(133)
North	-0.20 ***	0.35 ***	0.18 **	0.58	0.72	199
	(0.03)	(0.05)	(0.10)			(55)
East	-0.09	0.40 ***	0.08	0.95	0.34	356
	(0.09)	(0.11)	(0.17)			(104)
South	-0.38 ***	0.65 ***	0.65 ***	0.80	0.00	426
	(0.08)	(0.11)	(0.14)			(136)
By type of house						
Detached independent	-0.17 ***	0.36 ***	0.18 **	0.77	0.08	339
	(0.03)	(0.09)	(0.07)			(100)
Two-under-one-roof house	-0.01	0.85 ***	0.37 ***	0.61	0.00	315
	(0.06)	(0.11)	(0.21)			(93)
In-between house	-0.16	0.52 ***	0.05	0.36	0.21	415
	(0.04)	(0.07)	(0.15)			(135)
By year of construction						
Before 1945	-0.13 ***	0.51 ***	0.22 **	0.62	0.30	262
	(0.03)	(0.09)	(0.10)			(97)
Between 1960 and 1964	0.07	1.02 **	0.72 **	0.77	0.39	92
	(0.19)	(0.35)	(0.32)			(25)

Table 2: Determinants of house prices – reduced form parameter estimates

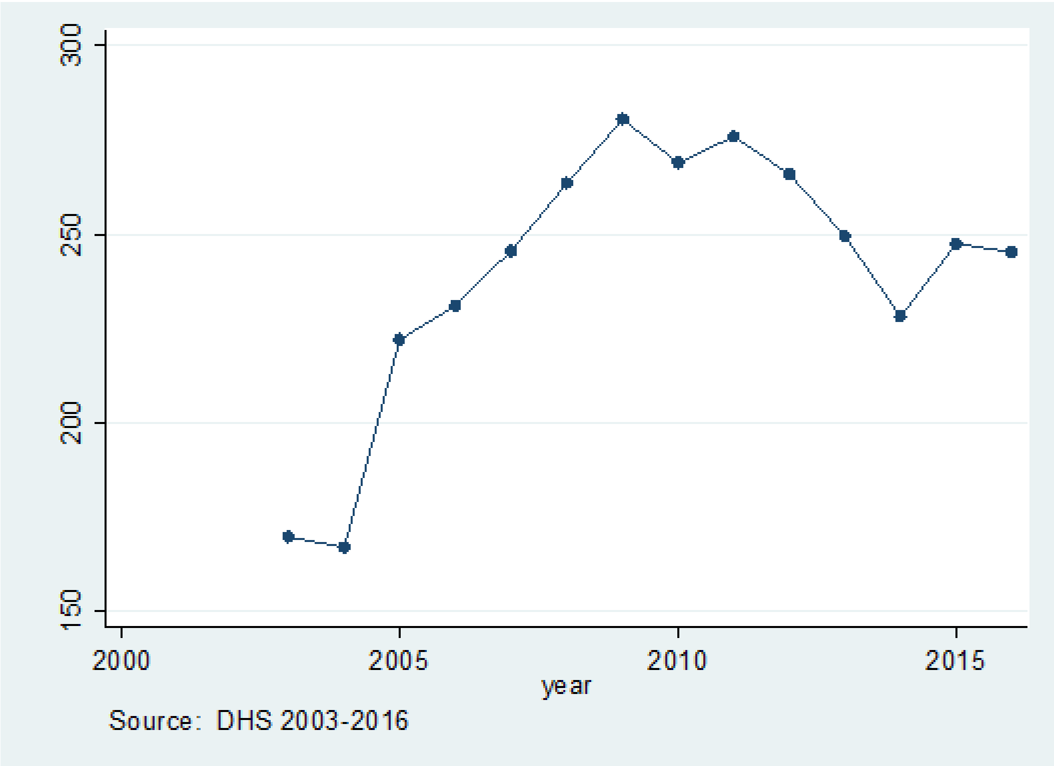
Between 1965 and 1969	-0.64 ***	0.68 ***	0.54 **	0.52	0.09	118
	(0.07)	(0.13)	(0.27)			(37)
Between 1970 and 1974	-0.09 *	0.86 ***	0.44 ***	0.83	0.12	154
	(0.05)	(0.08)	(0.14)			(50)
Between 1975 and 1979	-0.23 ***	0.52 ***	0.13	0.64	0.08	192
	(0.06)	(0.10)	(0.18)			(53)
Between 1985 and 1989	-0.17 ***	0.50 ***	0.18 *	0.40	0.24	199
	(0.04)	(0.06)	(0.10)			(56)
Between 1990 and 1994	-0.31 *	0.60 ***	0.29 **	0.05	0.42	140
	(0.18)	(0.18)	(0.10)			(45)
Between 2000 and 2004	-0.17	0.72 ***	0.32 **	0.18	0.99	39
	(0.11)	(0.10)	(0.12)			(15)
By type of mortgage						
Annuity	-0.11	0.62 ***	0.37	0.96	0.82	95
	(0.07)	(0.13)	(0.40)			(39)
Traditional life-insurance	-0.12 *	0.51 ***	-0.05	0.21	0.83	71
	(0.06)	(0.10)	(0.11)			(25)
Improved life-insurance	-0.14 ***	0.52 ***	0.18 **	0.62	0.28	279
	(0.03)	(0.07)	(0.09)			(90)

Notes:

Estimates from a dynamic model with annual panel data using the Arellano-Bond estimator. The sample period is 2003–2016. The data are taken from the DNB Household Survey. *, ** and *** indicate statistical significance at the 10%, 5% and 1%, respectively.

Degree of urbanization: Very strong: 2000 addresses per km2; Strong: 1500 to 2000 addresses per km2 or more; Moderate: 1000 to 1500 addresses per km2; Limited: 500 to 1000; very limited: less than 500 addresses per km2

Figure 1 Average house prices, 2003-2016



Note: Levels, in thousands of euros.

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