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The effect of Credit Conditions on the Dutch Housing Market

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Abstract

It is widely perceived that the supply of mortgages, especially since the extensive liberalization of the mortgage market since the 1980s, has had implications for the housing market in the Netherlands. In this paper we 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 has been 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 and additional control variables. The model has been estimated on data representing first time buyers (FTB). For

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FTB we can assume that the housing and non-housing wealth is essentially zero. 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 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 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 12% point of this decline can be attributed to a decline in the CCI.

KEYWORDS: Lending Standards, Financial Liberation, Housing Prices.
JEL-codes: C32, E44, E51, G21.

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 (De Greef and De Haas, 2000). 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. Therefore knowing the workings of the mortgage market becomes imperative for policy makers and households alike (Fernandez-Corugedo and Muellbauer, 2006).

Increasing levels of income and lower interest rates greatly facilitates the ability of financial institutions to advance higher levels of credit to households. However, developments within credit markets themselves also fueled 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 *risk-perception* by financial intermediaries due to changes in the macro-economic environment, like the unemployment rate[1]; (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 et al., 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 article is to derive an index representing the credit conditions. 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 amount of mortgage, both for first time buyers (henceforward FTB), and the unobserved component

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

is specified as a stochastic trend. The dependent 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 article is to measure the impact of credit conditions on all house prices. We include the CCI in an error-correction model for all house prices.

The contribution of this paper 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, amoung 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. As of 2012 the availability of credit on the mortgage market is on the same level as it was in the period 2004 – 2005. 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. The estimation results show that 12% point of this decline can be attributed to a decline in the CCI.

The setup of this paper is as follows. Section 2 gives a short description of the mortgage market in the Netherlands. Section 3 provides a literature review on credit conditions in mortgage markets. Section 4 provides a detailed description of the empirical model. Section 5 describes the dataset and provides some statistics. Section 6 provides the estimation results and finally Section 7 concludes.

2 Dutch Mortgage Market

As of 2012 housing accounts for 60% of Dutch household wealth (source: Statistics Netherlands). In total Dutch households have €1,157 billion in housing wealth and €639 billion 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 were first time buyers 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 defaulting in 2012 (Francke and Schilder, 2014).

Almost 90% of the €639 billion mortgage debt is financed by one of the three largest banks in the Netherlands (ABN AMRO, Rabobank and ING). Not surprisingly, our calculations reveal a relative high Herfindahl measure of almost 0.30. As of now there is a debate in the Netherlands if the lack of competition between banks does not restrict the supply of mortgage credit (Schilder and Conijn, 2012). Indeed, international evidence that lack of competition influences (negatively) the amount credit borrowed in other markets is plentiful (see Claessens and Laeven, 2004; Rice and Strahan, 2010).

As a result of high collective (second pillar) pension savings, Dutch households have relatively low banking deposits[2]. 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 did start to securatize 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 consists of mortgages. The large funding gap also make banks vulnerable for 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) sells insurances and reimburses 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 it is 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 ia 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 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 in total an insured mortgage debt of over €154 billion.

The maximum allowed LTV in the Netherlands has always been among the highest worldwide (Andrews et al., 2011) in modern history, with 112%. However, starting from 2010 the Dutch government started gradually lowering the maximum allowed LTV on a yearly basis

[2] 70% of all Dutch savings is in either a retirement fund or in a life insurance.

until it is 100% in 2018. 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.

Financial institutions regulate themselves as well. In the 'Codes of Conduct Mortgage Loans' (GHF)[3] Dutch banks agree on for example how to calculate the borrowing limit of consumers. An example 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. An international example of self-regulation by financial institution are the Basel accords. Other examples of financial liberation in the Netherlands are given in Table 8.

3 Literature Review of Credit Models

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 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 et al. (2011) and Van der Veer and Hoeberichts (2013), who both use the Bank Lending Survey (BLS[4]) for their research on credit conditions[5].

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.

A recent and 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),

[3]'Gedragscode Hypothecaire Financieringen' in Dutch.

[4]In Section 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.

[5]Please revisit Section 1 were one of the definitions of credit conditions was the bank lending standards in any given year.

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 et al., 2006) and Australia (Williams, 2009).

Using FTB only in the analysis has two 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 invest in the home, so we can disregard housing and non-housing wealth in the analysis. 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.

Secondly, in countries where the interest payments are deductible from income (like the Netherlands[6] and the US), theory predicts that the demand for mortgage debt will increase considerably (Brueckner, 1994; Ling and McGill, 1998; Hendershott et al., 2002). If mortgage interest rates are lower or on the same level as the interest rate on savings, households will not save up money to invest in a home, but purchase the home outright using the highest mortgage debt possible[7]. Together with the fact that FTB have no notable savings or liquid funds the relative low mortgage interest rate 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 et al. (2009) use a slightly different setup. Firstly the 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;

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

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 an 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

[6]Even though the rules changed after 2013 (revisit Section 1) interest deductability for FTB is still 100%. The only thing that changed is that non annuity type mortgages ar not allowed anymore.

[7]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 deductable from your income (lowest tax bracket in the Netherlands is around 30%), making the 'net' mortgage interest rate lower than the rate on savings. It should be noted that the interest payments on deposits with a maturity less than one year is on a historic low, with less than 1%. Also interesting to note is that every Euro above €20,000 on a savings account is taxed with 1.2% per annum, giving further disincentive to use save up money instead of taking up more home equity.

mortgage level (M_t) is above the equilibrium mortgage levels based on the borrowing capacity (B_t) are regarded as periods of excess credit and vice versa.

Addison-Smyth et al. (2009) also simultaneously estimate a house price equation. In the house price 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 et al. (2009) estimate that house prices in Ireland were 24% overvalued at the end of their sample (2008) due to over-crediting. The effect was approximately -30% in 1994.

Estimation results of Cameron et al. (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.

4 Model

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

$$M_t = f(B_t, CCI_t, W_t), \tag{1a}$$

$$P_t = g(M_t, X_t), \tag{1b}$$

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) 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. B is the borrowing capacity. It is given by

$$B_{ftb,t} = \kappa_{ct} I_{ftb,t} \left(\frac{1-(1+R_t)^{-\tau}}{R_t} \right), \tag{2}$$

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 spend 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 spend on housing - κ - is based on the income of the main earner (subscript c) and not on the income of the entire household (I) and is given to us by the Nibud[8]. This calculation method is also in accordance with the guidelines issued by the Nibud to financial intermediaries, government and families. Every year the Nibud calculates κ for different income categories. The percentages are based on a residual method, were 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 en 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 spend 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) 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. (1a) in (1b). The mortgage and price equations (1a)–(1b) can be simplified as

$$M_{FTB,t} = f(B_{FTB,t}, CCI_t), \tag{3a}$$

$$P_{FTB,t} = g(B_{FTB,t}, CCI_t, X_t), \tag{3b}$$

In this paper we will use a specification of the error-correction model (ECM) with an unobserved component (Francke et al., 2009) to extract the credit conditions index. The specification is given by

$$\Delta y_t = \sum_{j=1}^{r} \phi \Delta y_{t-j} + \sum_{j=0}^{s-1} \sum_{i=1}^{k} \beta_{ij} \Delta x_{i,t-j} + (1-\phi)\Big(y_{t-1} - \mu_t - \sum_{i=1}^{k} \delta_i x_{it-1}\Big) + \epsilon_t, \tag{4}$$

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

[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.

random walk (RW), a local linear trend model (LLT) and linear splines (LS), given by

$$\text{RW: } \mu_{t+1} = \mu_t + \eta_t, \qquad \eta_t \sim NID(0, \sigma_\eta^2), \tag{5a}$$

$$\begin{aligned} \text{LLT: } \mu_{t+1} &= \mu_t + \gamma_t + \eta_t, & \eta_t &\sim NID(0, \sigma_\eta^2), \\ \gamma_{t+1} &= \gamma_t + \zeta_t, & \zeta_t &\sim NID(0, \sigma_\zeta^2), \end{aligned} \tag{5b}$$

$$\text{LS: } \mu_t = \lambda_1 t + \sum_{w=2}^{W} \lambda_w (t - t_w^*)^+, \tag{5c}$$

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 can be formulated in state-space form and estimated by the Kalman filter (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 6.1.

Note that we do not take the mortgage requests into account 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. 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. Section 5 reviews this topic in more detail.

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 (1987) framework (Malpezzi, 1999). The results of this stage of the research are presented in Section 6.2.

5 Data and Descriptive Statistics

We obtain our data from five 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) and Ortec Finance (OF). All variables are available for the period 1995 – 2012. Some data is on a yearly basis (Y), quarterly basis (Q) and even monthly basis (M). 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[9]. 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[10]. All variables and sources used in this paper are presented in Table 1. Some descriptives of the variables in (real) levels are given in Table 2 and in first differences ($\Delta \ln$) in Table 3. For comparability, all (ln) time series are indexed, with 1995.$Q1$ as 0 in Figure 5 in the Appendix. A graphical representation of the first-differenced time series ($\Delta \ln$) is given in Figure 6.

Table 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	M	NVM
$B_{FTB,t}$	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	OF
W_t	Non-housing wealth index	1995 – 2012	Y	OF
CC_t	Construction costs index	1995 – 2012	Q	CBS
κ_t	% of I which can be spend on housing	1995 – 2012	Q	Nibud
S_t/HH_t	Housing supply / Households	1995 – 2012	Y	CBS

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

In Tables 1 – 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 et al., 2006) from the Statistics Netherlands is used as the measure for national house prices (P_t). House prices for first time buyers ($P_{FTB,t}$) specific is calculated as the average sales price per period observed by the NHG for households of age 35 or younger. 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 –

[9] Salary for the next year per branch is determined by a collective labor agreement (in Dutch CAO).
[10] 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 housing expenditure is a component in the latter.

Table 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
$B_{FTB,t}$	€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	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
S_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. Critical values are taken from MacKinnon (2010).
The lag lengths differ per variable and is based on the Akaike Information Criterion.

Table 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
$\Delta b_{FTB,t}$	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	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
$\Delta(s-hh)_t$	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 is a period of large national (FTB specific) house price appreciation in real terms of +86% (+40%) between 1995 – 2001, then from 2001 – 2008 house prices increases more or less stalls with +14% (+16%) and finally from 2008 onwards house prices are decreasing with -22% (-5%).

M 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 deductability 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). Also interesting is that the Granger causality (see Table 9 in the Appendix) 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 9 also further reduces the endogeneity criticism discussed in Section 3.

B is the calculated borrowing capacity using Eq. (2). The borrowing capacity was mainly fuelled by the real (5-year annuity) mortgage interest rates (R), which dropped sharply for the analyzed period. The other variables to calculate borrowing capacity B are income for first time buyers and κ.

F is the population of age > 20 and ≤ 35 years[11], I is the real gross average household income level, EQR are the real total equity returns of Dutch businesses (stock value + dividend), W is real total non-housing wealth in the Netherlands, and CC are the real construction costs (as proxy for structure values, Bostic et al., 2007). Figures 5 and 6 reveal that the average household income, the construction costs and non-housing wealth are decreasing - in real terms - from 2009 onwards. In Tables 1 – 3 the variable S_t/HH_t is a proxy variable for excess supply relative to demand, where S 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). There is however one caveat to this measurement.

The problem is that housing units are also included in the supply variable (S). By

[11] 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.

definition[12] these housing units *can* contain multiple households. This becomes especially apparent in student cities, where we find more households than houses. Still, taking this caveat into account we assume S_t/HH_t to be a sufficient proxy for excess levels of supply.

All variables are I(1) except for F and I. However, we still treat them as if they are I(1). Also note that income is used to compute B, which is I(1) in itself.

In Section 4 we already noted that we do not observe data on households which mortgage requests were denied, which could bias our estimates downwards or upwards. One simple - albeit rough - way to measure whether or not the group of first time buyers is of constant quality is by looking at the inflow of FTB. If this is inflow is constant over time, this could suggest that that the group is more or less 'constant quality'. If we compare the number of households of age < 35 who own a home compared to all households of age < 35 we find that this fraction is between 51% and 52% for almost all years between 1998 and 2012 (source: Statistics Netherlands[13]).

6 Results

This Section contains the results for both the unobserved error-correction models which gives us a measure for the credit conditions (Section 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 6.2).

6.1 The Credit Conditions Index.

In total four models are presented in this Section. In Model I the (log) mortgage levels (m) is explained by the (log) borrowing capacity (b) and the (log) income (i). In this model the unobserved component is specified as a Random Walk (RW). In model II (log) house prices (p) are explained by the (log) borrowing capacity (b) and (log) population of age between 20 and 35 (f). Here income (i) has a significant effect on house price in the short-run only. The unobserved component is specified as a Random Walk as well. Model III has the same specification as Model II, only the unobserved component is specified as a Local Linear Trend model (LLT). Model IV has the same specification as Model I with the exception that the unobserved component is specified as a linear spline (LS). Insignificant splines were excluded piecewise until a parsimonious model was found.

[12] 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.

[13] Only in the years 2000 and 2009 this number was slightly higher with 55% and 54% respectively.

The estimation results are presented in Table 4 The unobserved components (i.e. the CCI) are presented in Figure 1. Additional model diagnostics are found in Figure 2. Tests for co-integration are found in the Appendix in Table 10. For the Unobserved ECM models (Models I through III) 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.

Table 4: Main results unobserved ECM models, FTB only

	Model I	**Model II**	**Model III**	**Model IV**
dep.var.	$\Delta m_{ftb,t}$	$\Delta p_{ftb,t}$	$\Delta p_{ftb,t}$	$\Delta m_{ftb,t}$
μ_t	RW	RW	LLT	LS
	Short-run model estimates			
$\Delta i_{ftb,t}$	-0.449	-0.287	-0.254	-0.233
	(-6.21)***	(-4.49)***	(-4.48)***	(-2.06)**
$\Delta b_{ftb,t}$	-0.080	-0.110		0.071
	(-1.88)**	(-2.37)***		(1.72)*
ECT_{t-1}	-0.354	-0.490	-0.708	-0.433
	(-4.37)***	(-5.04)***	(-6.28)***	(-3.41)***
	Long-run model estimates			
$b_{ftb,t}$	0.299	0.227	0.113	0.265
	(4.03)***	(5.00)**	(10.07)***	(4.62)***
$i_{ftb,t}$	0.756			0.612
	(3.79)***			(2.44)**
f_t		0.575	0.657	
		(12.21)***	(6.42)***	
Std. Error	0.014	0.015	0.015	0.013
R^2	0.492	0.425	0.638	0.584
LogLikelihood	275,991	269,457	269,005	254,515
p.e.v.	0.000	0.000	0.000	
DW	1.971	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 III. The long run coefficients and t-values for Model IV are given by PCGive (Doornik and Hendry, 2007).

Applying the test for co-integration on Model I reveals that the null hypothesis of no co-integration is not rejected. We do find a co-integrated relationship for the other 3 models. Therefore we will not discuss the results of Model I in great detail from here onwards. We will also not use the said CCI in Section 6.2 to explain house prices.

The estimation results in Table 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 IV. 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

Figure 1: Unobserved components for the different models

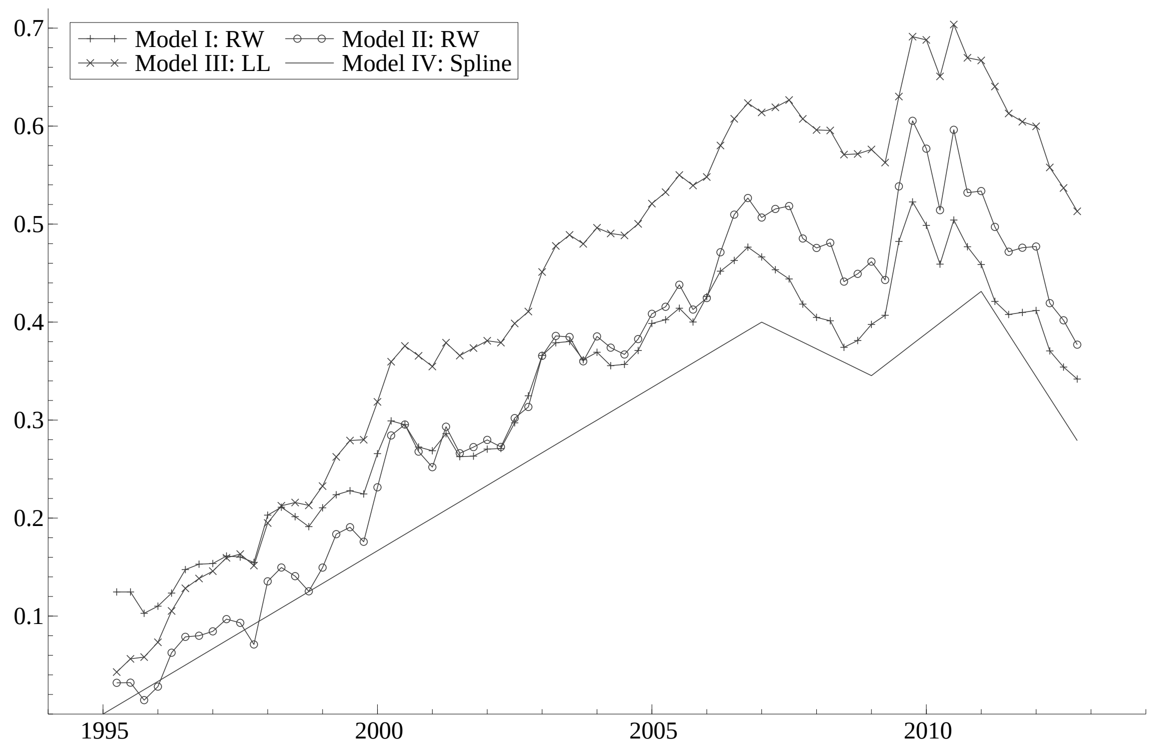
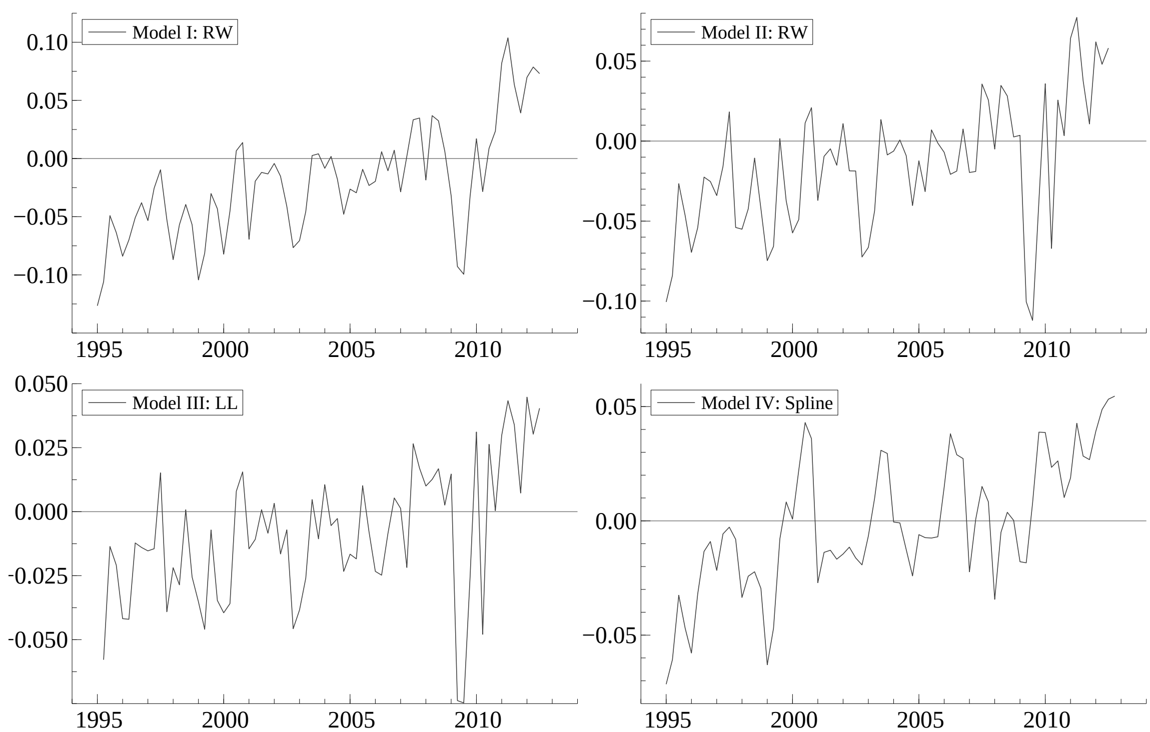


Figure 2: Error-correction terms for all models



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. The increasing levels of mortgage lending can be attributed to more households taking a 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. As of 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 temporary relaxed. This meant that banks could lend credit with less risk involved to a wider audience decreasing the total mortgage portfolio risk.

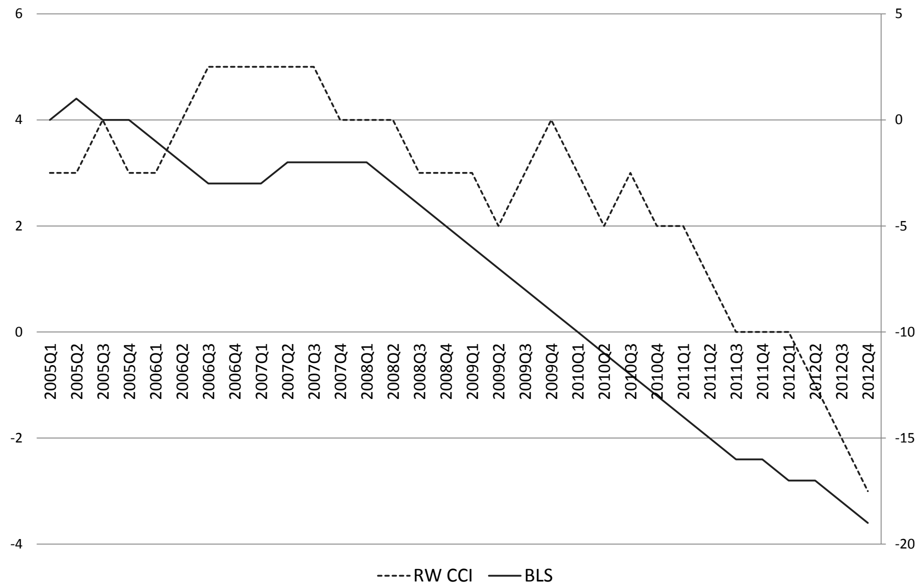
Next we compare our measures for credit conditions with the outcome of the Bank Lending Survey (BLS) for Dutch banks. The BLS is a quarterly survey among representatives of banks. A main question in the BLS is whether there was a tightening or relaxation of lending standards compared to the period before. This question is also specifically asked for mortgage lending, which we will 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. Although 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: DNB).

To make the BLS comparable to our measure for credit conditions, we first construct a variable for the level of bank's lending standards by coding the qualitative answers given in the BLS in the same way as Van der Veer and Hoeberichts (2013); Del Giovane et al. (2011) 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[14]. We do the exact same for our CCIs so the magnitude of the level index will be the same. So 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 from 2005 onwards[15]. The indices are presented in Figure 3.

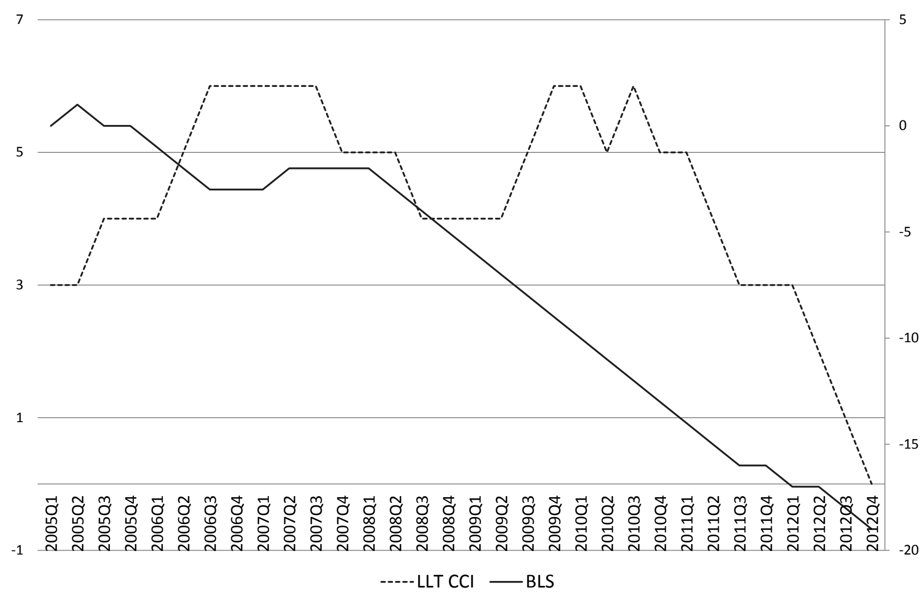
[14] Please note that in the BLS the signs are the other way around. So an relaxation of lending values actually gets "-1", etc. However, to make the BLS comparable to our study we inverted the signs first.

[15] 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

Figure 3: 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.

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 relatively comparable to the BLS.

6.2 House prices and the supply of credit.

In this Section we regress our measures for the credit conditions found in Section 6.1 on the log real house prices in the Netherlands in a 2-step Engle and Granger framework. In the first model we include the RW CCI (resulting from Model II in Section 6.1), in the second model we include the LLT CCI (resulting from Model III in Section 6.1) and the third model includes the CCI based on the splines of Model IV in Section 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 5 and Figure 4 and for the short term model in Table 6.

In Table 5 *cci* is the credit conditions, *cc* is the real construction costs (which is seen as a proxy for structure values, Bostic et al., 2007), i is the real household income, w is real non-housing wealth, *eqr* are the total real equity returns, b is the real borrowing capacity (see Eq. (2)) and $(s - hh)_t$ is a rough measure for vacancy. Subscript t denotes time and lower case letter denotes a variable in natural logarithm.

From the ADF tests shown in Table 5 it can be concluded that all model are I(1) except for model IV which is spurious. 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, likelihood are higher, the standard error of regression is lower and the results of the aforementioned co-integration test (especially for

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. Also we do not take the LS CCI into account since the structure of this index in completely different. More specifically, there is no "0" value.

Table 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)***
$(s - hh)_t$	-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					0.786
					(6.39)***
b_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

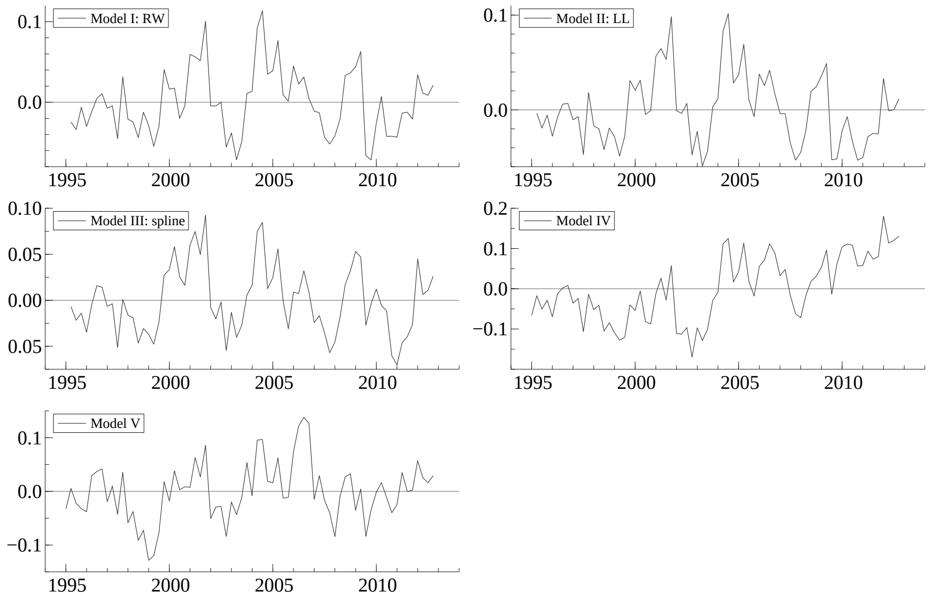
Note. Coefficient (t statistic),*** sig. within 99% prob.
Critical values for ADF test taken from MacKinnon (2010), with T = 70 and a constant.

Table 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 4: Error-correction terms for all models.



Model I) are better. Shocks out of equilibrium are observed in approximately 9 periods (little over 2 years) for the models with a measure for credit conditions and 21 periods (little over 5 years) for models without a measure for credit conditions.

Housing prices increased from 1995.$Q1$ to 2009.$Q4$ with over a 100% and subsequently decreased with 17% in the next three years to the end of our sample in nominal term. The contribution of the different measures of the credit conditions (Models I though III) + the explanatory variables on house price appreciation is presented in Table 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 +32% for the period 1995.$Q1$ – 2009.$Q4$ on average and −12% for the period 2010.$Q1$ – 2012.$Q4$ on average.

One other large contributor to the house price decreases after 2010 has been the drop in structure values, proxied by construction costs. The reason can be a decrease in labor costs and material costs (Davis and Heathcote, 2007). If new investment in housing compared to demand (poxied by $s - hh$) 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 the total equity returns.

Table 7: Contribution 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%

7 Conclusions

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. However, the housing market and the supply of credit have contracted sharply in the period after 2008.

This paper 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 and the interest rate deductibility 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 32% 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 12% on average.

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Appendix

Figure 5: Time series indices in log levels. 1995.Q1 = 0.

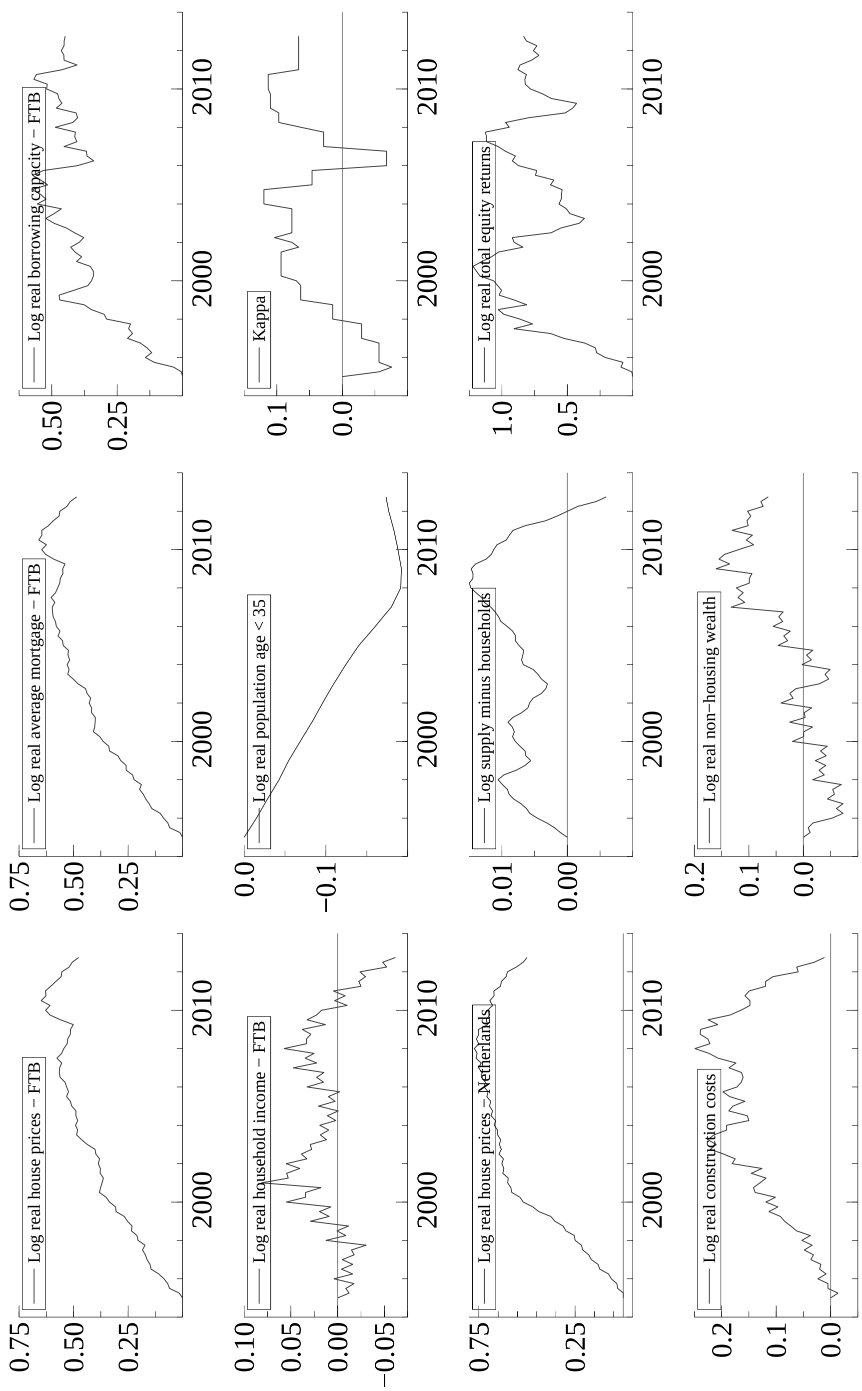

Figure 6: Time series indices (*Continued*), First-differences.

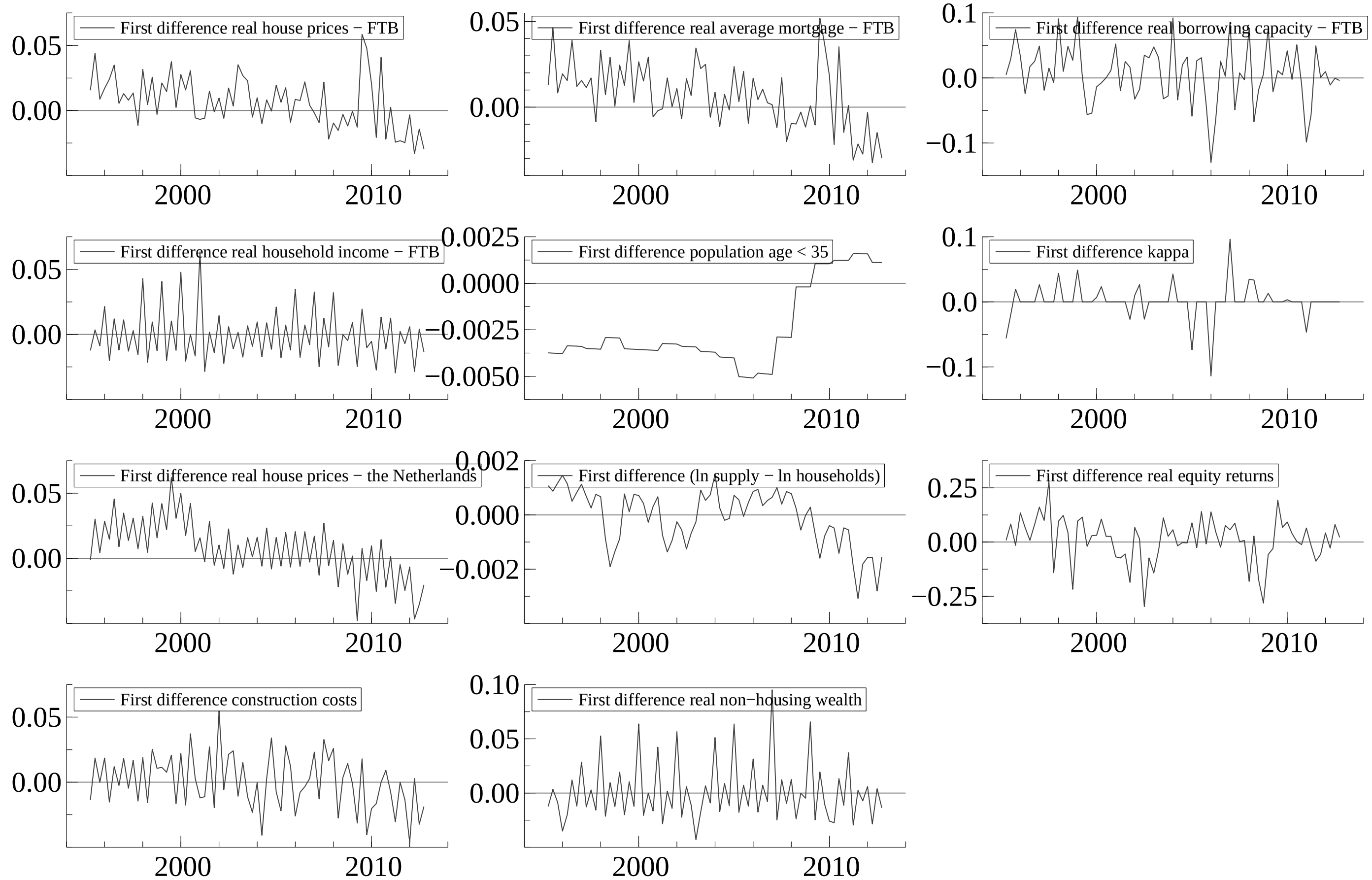

Table 8: Dating of financial liberalisation in the Netherlands.

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 deductability 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 'bijleenregeling' assumes that household 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 anyways, 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 decreased from 112% to 106%. The main reason being the lowering of transfer tax from 8% to 2%.
2012	Maximum allowed LTV 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 deductability of interest payments on income is limited. Interest rate deductability is applicable to annuity and linear mortgage products only.

Table 9: 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 10: Tests for cointegration in CCI models

	ρ	critical value (k)	$\rho \leq k$
Model I	0.745	0.597	**No**
Model II	0.500	0.522	Yes
Model III	0.504	0.522	Yes
	ADF		$ADF \leq k$
Model IV	-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.