Semi-Structural Credit Gap Estimation

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Abstract

This paper proposes a semi-structural approach to identifying excessive household credit developments. Using an overlapping generations model, a normative trend level for the real household credit stock is derived. Semi-structural household credit gaps are obtained as deviations of the real household credit stock from this fundamental trend level. Estimates of these credit gaps for 12 EU countries over the past 25 years yield credit cycles that last between 15 to 25 years with amplitudes of around 20%. The early warning properties for financial crises are superior compared to credit gaps that are obtained from purely statistical filters. The proposed semi-structural household credit gaps could therefore provide useful information for the formulation of countercyclical macroprudential policy.

Keywords: equilibrium credit, credit cycle, financial crises, macro-prudential analysis, early-warning models

JEL classification: E32, E51, E21

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Non-Technical Summary

This paper proposes a theory-based approach to identifying excessive household credit developments. In particular, we derive an equilibrium-relationship for the level of household credit using a structural economic model that takes into account the demographic age structure of the economy. In the scope of this framework we show that potential GDP, a measure of the equilibrium real interest rate, information about the debt distribution by cohorts and the level of institutional quality are important determinants of the trend household credit stock. The resulting model is estimated as an unobserved components system for 12 EU countries (Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, and Great Britain) using quarterly data for the period 1980 - 2015. We draw on existing empirical frameworks for estimating potential GDP and equilibrium real interest rates and the respective gaps. Focussing our analysis on household credit, which was one of the major drivers sparking the global financial crisis that in turn led to the great recession, we also contribute to a better understanding of the interaction between financial cycles and business cycles.

Since we spell out the driving factors of the credit trend we can attach economic interpretation to the estimated credit gap, as opposed to purely statistical credit gaps like the Basel total credit-to-GDP gap, where the trend is computed with a statistical smoothing method.

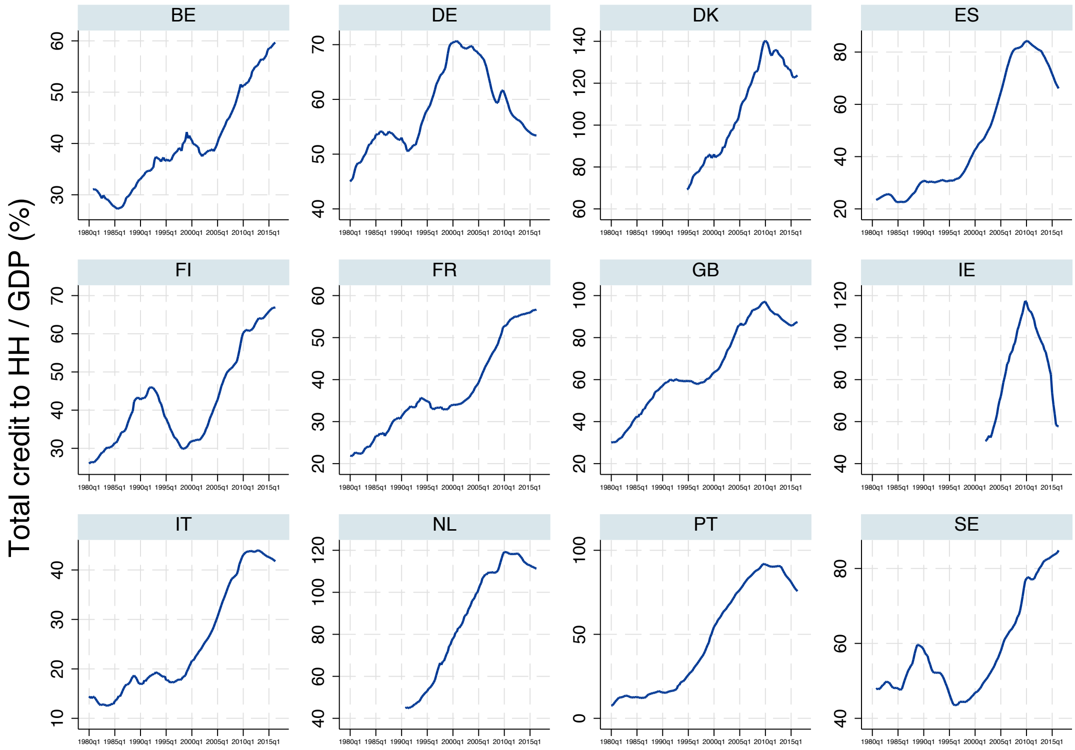
Without imposing a priori information on the cycle length the estimated credit gaps display long credit cycles that last between 15 to 25 years with substantial amplitudes of around 20% across time and countries. The estimated credit gaps possess superior early warning properties for financial crises relative to a number of established statistical credit gaps, notably the commonly used Basel total-credit-to-GDP gap and its household credit-to-GDP gap variant. The theory-based gaps, while increasing well ahead of financial crises, do not tend to increase over excessively long periods of time before such crises. In addition, our estimated gaps do not tend to fall to as large negative values in the aftermath of financial booms and/or crises as, for example, those currently observed for Basel credit gaps in a number of euro area countries. This property should mitigate the risk of underestimating cyclical systemic risks.

Theory-based credit gaps could therefore provide a useful complement to purely statistical measures of credit excesses, thereby helping to inform the setting of countercyclical macroprudential policy.

1 Introduction

Excessive credit growth and leverage were identified as key drivers of the recent global financial crisis and of many other historic episodes of financial instability.[1] However, ex ante identification of periods with excessive leverage and credit growth is difficult. This becomes apparent in the developments of credit-to-GDP ratios, commonly used as a broad measure of leverage, over the last 35 years and as illustrated for 12 EU countries in Figure 1.

Figure 1: Household credit to GDP ratios across selected EU countries



Sources: See Table B1 in Appendix B.

Oftentimes ratios have trended upwards for a long time after which they turned rapidly, reflecting in many cases financial turmoil. The swift increases in credit relative to GDP could to some extent be justified in periods of economic transition, e.g. after deregulation in certain economic sectors [2] or due to political reform. For example, it could be argued that, in part, the long phases of credit growth rates exceeding GDP growth rates in Ireland and Spain were justified by the economic

[1]See e.g. Schularick and Taylor (2012), Borio and Lowe (2002), Borio and Drehmann (2009), Detken et al. (2014).
[2]Deregulation in the financial sector may however have triggered periods of financial exuberance in some cases.

development in these countries, but at some point credit developments became unsustainable.

This paper makes an attempt to address such questions. We derive a model-based equilibrium-relationship for the level of household credit that depends on economic fundamentals. In particular, the overlapping generations model by Eggertsson and Mehrotra (2014) serves as the basis for deriving an equation for the trend of the household credit stock. We show that potential GDP, a measure of the equilibrium real interest rate, demographic information and the level of institutional quality are important determinants of the trend household credit stock. The resulting semi-structural model is estimated as an unobserved components system for the 12 EU countries shown in Figure 1 for the period 1980 - 2015. In that respect we draw on existing empirical frameworks for estimating potential GDP and the equilibrium real interest rate and the respective gaps. In this paper we focus our analysis on household credit, which was one of the major drivers sparking the global financial crisis that in turn led to the great recession. We therefore also contribute to a better understanding of the interaction between financial cycles and business cycles (see e.g. Mian et al. (2015), Mian and Sufi (2014), International Monetary Fund (2012) Glick and Lansing (2010)).

Many empirical researchers rely on purely statistical methods to find normative benchmarks for credit, e.g. by removing smooth and persistent statistical trends (see e.g. Aikman et al. (2015), Drehmann et al. (2011), Borio and Lowe (2002) or as recommended by the Basel Committee on Banking Supervision (2010) and the European Systemic Risk Board (2014)) or by investigating tails of the empirical data density. While statistical approaches to identifying excessive credit growth and leverage seem to work to some extent, they have various drawbacks. For example, they cannot account for structural shifts in an economy or capture catch-up processes in economic development that would warrant higher leverage or credit growth. In addition, the longer credit booms last the more will elevated credit levels transmit to the underlying statistical trend thereby contaminating the trend with possibly excessive developments. If such a period ends with a rapid credit contraction, large negative gaps will open because of the a priori assumed persistent trend that will remain at its inflated level for a long time. Indeed, currently large negative credit-to-GDP gaps are observed for more than half of the euro area countries with values ranging between -30 percentage points and -50 percentage points. Therefore, purely statistical credit gaps are vulnerable to underestimating cyclical systemic risk, in particular in a recovery period after a credit boom or financial crisis as is currently the case.[3] The statistical methods themselves have also been criticised on methodological grounds e.g. by Hamilton (2017) and van Norden and Wildi (2015).

[3] See Lang and Welz (2017) for a more detailed discussion and possible implications for macroprudential policy.

There are a few papers that try to measure equilibrium credit with a structural approach, usually in a co-integration framework, but none of the approaches is fully convincing so far.[4] One reason is that the empirical model specifications often lack clear derivations from economic theory. Another more important shortcoming is that observed variables such as GDP, interest rates and asset prices are commonly used as explanatory variables, although these variables themselves should be affected by credit booms. This is problematic if the co-integration system does not feature an additional mechanism that pulls all variables back to their long-run equilibrium. Our approach uses explanatory variables that are less susceptible to the impact of excessive credit growth.

We estimate long cycles for household credit without imposing any ex-ante restrictions on the frequency of the cyclical component as is often done in statistical approaches.[5] In addition, the amplitude of household credit (stock) cycles is large and ranges between +/- 20 % in most of the countries that are studied. The semi-structural credit gaps tend to increase well before financial crises and decrease afterwards. The early warning signalling power of our estimated credit gap for financial crises is superior to that of the Basel total credit-to-GDP gap and a Basel-type household-credit-to GDP. Our semi-structural credit gaps do not seem to suffer from the undesirable property of excessively persistent positive gaps that are observed for the Basel credit-to-GDP-gap for some euro area countries.[6] In addition, our credit gaps have decreased much less since the onset of the global financial crisis than the standardised Basel credit-to-GDP gaps.

Our paper connects to various strands of the theoretical and empirical literature. On the theoretical side our paper relates to the literature on secular stagnation (Eggertsson and Mehrotra (2014)), exogenous borrowing constraints (Aiyagari (1994), Kiyotaki and Moore (1997)), endogenous borrowing constraints due to limited commitment and enforcement in debt contracts (Kehoe and Levine (1993), Kocherlakota (1996), Alvarez and Jermann (2000)), and the role of institutions for economic and financial development (Acemoglu et al. (2005)). On the empirical side our paper contributes to the literature on equilibrium credit estimation (see e.g. Cottarelli et al. (2005) Buncic and Melecky (2014), Juselius and Drehmann (2015), Albuquerque et al. (2015)) and the still nascent literature on financial cycles (Schüler et al. (2015), Rünstler and Vlekke (2016)). We contribute to the recent empirical literature that relates demographic developments to economic developments and (real) interest rates as in Ferrero et al. (2017) and Favero et al. (2016). The paper also stands in

[4]See for example Cottarelli et al. (2005) Buncic and Melecky (2014), Juselius and Drehmann (2015), Albuquerque et al. (2015).

[5]For example, the assumption behind the total credit-to-GDP gap as recommended by the Basel Committee on Banking Supervision (2010) and the European Systemic Risk Board (2014) is that cycles last up to 40 years.

[6]Notably for Spain, Italy, and Portugal, see e.g. Detken et al. (2014)).

the context of early warning models (e.g. Alessi and Detken (2011), Borio and Lowe (2002), Kaminsky et al. (1998)) and makes use of techniques from the reduced form estimation of output gaps (Clark (1987) and Blagrave et al. (2015)) and the equilibrium real interest rate (Laubach and Williams (2003), Holston et al. (2016), Hamilton et al. (2015)) in an unobserved components setting.

The remainder of the paper is structured as follows. In Section 2 we use the overlapping generations model by Eggertsson and Mehrotra (2014) to derive a simple structural equation for the trend of household credit. Section 3 introduces our empirical modeling framework. Section 4 presents the dataset used for estimation, while Section 5 shows estimation results for the semi-structural credit gaps with additional robustness analysis presented in Section 6. Section 7 provides a brief conclusion with an outlook on further research.

2 A structural model for the credit trend

We use a slightly modified version of the overlapping generations model developed by Eggertsson and Mehrotra (2014) for the analysis of secular stagnation in order to motivate the factors that should affect the trend component of household credit. We deem the model useful for our purposes due to the following three reasons: first, heterogeneity in terms of age and income should be important determinants of household credit because of the different preferences across cohorts and income levels that guide households' credit demand and supply decisions. Second, borrowing constraints should affect the level of household credit and these should be subject to long-lasting changes over time. Third, it appears more important to have a theory of the trend in household credit rather than of cyclical credit fluctuations, as the level of household credit relative to GDP has increased significantly over the last 35 years in most EU countries. Hence, in our view an overlapping generations model that allows for the study of all of these features appears better suited than a DSGE model that in most cases assumes stochastic processes for its trend components and might be better suited to study credit fluctuations at business cycle frequency.

The baseline model by Eggertsson and Mehrotra (2014) consists of a simple endowment economy with overlapping generations where households go through three stages of life:[7] young, middle-aged, and old. Given the endowment structure in the model, young agents borrow from middle-aged agents who save for retirement. Young agents face a debt limit that is assumed as exogenous

[7] For details of the model set-up, see pages 5-11 of Eggertsson and Mehrotra (2014). In the remainder of the paper the set-up will only be briefly touched upon in order to focus on the main insights of the paper that are useful in the context of estimating semi-structural household credit gaps.

and to be binding in the model. All borrowing and lending takes place via a one period risk-free bond. In an extension to their baseline model Eggertsson and Mehrotra (2014) also incorporate a simple form of income inequality by assuming that a certain fraction of middle-aged households has low income and will therefore remain credit constrained and borrow.

In equilibrium, credit demand from young households and middle-aged low-income households needs to balance with the credit supply from middle-aged high-income households, to jointly pin down the equilibrium real interest rate. Given the equilibrium real interest rate and the exogenous binding borrowing limit, the aggregate equilibrium quantity of household credit can be easily obtained from the credit demand equation, and is given by:[8]

$$C_t^{d*} = \left(1 + \frac{\eta}{1+g_t}\right) N_t \frac{D_t}{1+r_t^*} \tag{1}$$

where C_t^{d*} is aggregate equilibrium household credit demand in period t, N_t is the size of the generation born in period t, the variable $g_t = (N_t/N_{t-1} - 1)$ is the population growth rate from one cohort to the next, η is the fraction of low income middle-aged households (proxy for income inequality), D_t is the exogenous debt limit, and r_t^* is the equilibrium real interest rate. We take this equation as a starting point and impose some additional assumptions and modifications to derive a slightly richer specification that can be taken to the data.

Eggertsson and Mehrotra (2014) take the debt limit D_t as exogenous, but argue that they think of it as reflecting some form of incentive constraint. The literature on endogenous borrowing constraints[9] has shown that limited commitment or limited contract enforcement provide micro-foundations for collateral-based or income-based borrowing constraints. We make use of the latter within the context of equation (1) to gain further insights into the driving factors of equilibrium household credit. There are two main reasons for this choice. First, if income is not sufficient to service debt obligations in the long run, incentives to default should be high. Second, history has shown that credit excesses often go hand in hand with asset price booms and collateral-based borrowing constraints should therefore be based on the fundamental asset price rather than the observed price. This however, would greatly complicate the endeavor to determine the trend of household credit empirically. For the remainder of the paper we therefore assume a borrowing constraint where the

[8] Let the (binding) borrowing constraint be $(1+r_t)B_t^i = D_t$. Aggregate credit demand is given by demand from young (y) and low-income middle-aged (m, L) households, or $C_t^d = N_t B_t^y + \eta N_{t-1} B_t^{m,L}$. Using the borrowing constraint with the equilibrium real interest rate in the credit demand equation and rearranging, yields equation 1.

[9] See e.g. Kehoe and Levine (1993), Kocherlakota (1996), and Alvarez and Jermann (2000).

maximum borrowing capacity for a household is limited to a certain fraction of its expected future income (Y_{t+1}^{hh}), or:

$$D_t = \Theta_t \mathbb{E}_t[Y_{t+1}^{hh}] \tag{2}$$

Note that the fraction Θ_t of expected future income that can be borrowed is explicitly indexed by time, reflecting that the tightness of the borrowing constraint should vary with the economic environment. In particular, the level of economic development, the economy's structural characteristics and the level of institutional quality should affect the tightness of borrowing constraints, and these factors can change profoundly over time. For example, the efficiency of the legal system and notably the level of financial regulation, the existence and quality of credit registers, the regime for tax deductability of interest payments, the costs of liquidating assets or the prevalence of full recourse compared to non-recourse credit contracts should all affect how tight borrowing constraints are in equilibrium. The parameter Θ_t can therefore be best thought of as a reduced-form function of institutional quality and other structural factors that determine the level of equilibrium leverage (debt relative to income) in an economy.

For tractability, we assume that there is a non-linear relationship between institutional quality and the tightness of the borrowing constraint. A non-linear relationship can be motivated by the fact that a household's borrowing capacity in terms of expected future income should be bounded below at zero and should reach an upper limit $\bar{\Theta}$, once institutional quality has reached a certain saturation level (akin to an S-curve). As an absolute maximum, the entire amount of expected future income should determine the borrowing constraint. Therefore, a logistic function transformation of institutional quality (IQ_t) is used to model the tightness of the borrowing constraint, where the parameters k and x_0 determine the slope and the midpoint of the resulting S-curve:[10]

$$\Theta_t = \bar{\Theta} \frac{1}{1 + e^{-k(IQ_t - x_0)}} \tag{3}$$

The income-based borrowing constraint in equation (2) and the mapping of institutional quality into the tightness of the borrowing constraint in equation (3) can be used in equation (1) to rewrite aggregate equilibrium household credit demand. Taking the natural logarithm, we arrive at the following equilibrium relationship for real household credit:

$$ln(C_t^{d*}) \quad = \quad ln\left(1 + \frac{\eta}{1 + g_t}\right) + ln\left(\frac{1}{1 + e^{-k(IQ_t - x_0)}}\right) +$$

[10]For a similar idea see Ugarte Ruiz (2015).

$$ln(N_t) + ln(\mathbb{E}_t[Y^{hh}_{t+1}]) + ln(\bar{\Theta}) - ln(1+r^*_t) \quad (4)$$

Equation (4) can be rewritten further if we assume that aggregate household disposable income is a fraction (λ_t) of aggregate GDP (Y_t) and equally distributed amongst all households that receive income (i.e. $Y^{hh}_t = \lambda_t Y_t / P_t$) and that the natural logarithm of aggregate GDP follows a local linear trend model with an AR(2) cyclical component.[11] Although the assumption of equally distributed income across households is not fully consistent with the structural model and clearly not realistic, it is a useful simplification that allows us to write down an equilibrium condition for aggregate household credit that incorporates aggregate macroeconomic concepts, such as potential output, the trend growth rate of output and the output gap:

$$\begin{aligned} ln(C^{d*}_t) &= ln\left(1 + \frac{\eta}{1+g_t}\right) + ln\left(\frac{1}{1+e^{-k(IQ_t - x_0)}}\right) + ln\left(\frac{N_t}{P_{t+1}}\right) + \\ &\quad ln(Y^*_t) + d_t + \alpha_1 ln(\hat{Y}_t) + \alpha_2 ln(\hat{Y}_{t-1}) + \frac{\sigma^2_{\epsilon^*}}{2} + \frac{\sigma^2_{\hat{\epsilon}}}{2} + \\ &\quad ln(\lambda_{t+1}) + ln(\bar{\Theta}) - ln(1+r^*_t) \end{aligned} \quad (5)$$

The equilibrium condition for aggregate household credit in equation (5) stipulates that the real household credit stock is a function of population growth (g_t), income inequality (η), institutional quality (IQ_t), demographics or equivalently the share of young people (borrowers) relative to all people receiving income (N_t/P_{t+1}), potential output (Y^*_t), trend output growth (d_t), the output gap ($\hat{Y}_t$), the disposable income share in GDP (λ_{t+1}), and the equilibrium real interest rate (r^*_t).[12] In particular, the effect from all of these variables on the aggregate real household credit stock should be positive, with the exception of the equilibrium real interest rate and population growth. In the next section we use a simplified version of this structural equilibrium equation as the basis for specifying an empirical trend equation for aggregate real household credit.

[11] It is a standard assumption in the literature on output gap estimation to model output as a local linear trend with an AR(2) component for the cycle (See for example Clark (1987) or Laubach and Williams (2003)). The local linear trend AR(2) model for the natural logarithm of output can be written as:

$$\begin{aligned} y_t &= y^*_t + \hat{y}_t = ln(Y_t) \\ y^*_t &= y^*_{t-1} + d_{t-1} + \epsilon^*_t \\ d_t &= d_{t-1} + \epsilon^d_t \\ \hat{y}_t &= \alpha_1 \hat{y}_{t-1} + \alpha_2 \hat{y}_{t-2} + \hat{\epsilon}_t \end{aligned}$$

[12] The terms $\frac{\sigma^2_{\epsilon^*}}{2}$ and $\frac{\sigma^2_{\hat{\epsilon}}}{2}$ refer to the variances of the shocks to trend output and to the output gap. To the extent that these variances do not change over time, they will show up as constants in the equation for equilibrium household credit.

3 A theory-based empirical model for credit gaps

As shown in the introduction of the paper, it appears that large parts of the variation in household credit over time are due to changes in the trend rather than in the cyclical component. In order to estimate household credit gaps, we therefore adopt an approach where the trend in real household credit is modeled explicitly with fundamental economic factors as derived in Section 2 and the real household credit cycle is modeled as a residual statistical process. For this purpose, a simplified version of the theory-based trend equation (5) for real household credit is used in an unobserved components model.

Our semi-structural system for real household credit consists of three equations. First, the logarithm of observed real household credit (c_t) is decomposed into the sum of a trend (c_t^*) and a cyclical component ($\hat{c}_t$). Second, the trend of the logarithm of real household credit is modeled to be driven by four factors: the logarithm of real potential GDP (y_t^*), the equilibrium real interest rate (r_t^*), the logarithm of the share of young/middle-aged people relative to all people that receive income (dem_t), and the logarithm of a non-linear transformation of institutional quality (γ_t). These fundamental economic drivers of the household credit trend are taken one-for-one from the theoretical model described in section 2. Third, it is assumed that the cycle of the logarithm of real household credit follows an AR(2) process, which is a common assumption in the empirical literature on output gap estimation. Hence, the following semi-structural system of equations is used to estimate household credit gaps:

$$c_t = c_t^* + \hat{c}_t \tag{6}$$

$$c_t^* = \alpha_0 + y_t^* + \gamma_t + \alpha_1 r_t^* + \alpha_2 dem_t + \epsilon_t^{c^*} \tag{7}$$

$$\hat{c}_t = \beta_1 \hat{c}_{t-1} + \beta_2 \hat{c}_{t-2} + \epsilon_t^{\hat{c}}, \tag{8}$$

where γ_t is defined as $ln\left(\frac{1}{1+e^{-k(IQ_t - x_0)}}\right)$.

Compared to the structural household credit trend equation (5), the empirical trend equation has been simplified along a number of dimensions.[13] First, the term related to income inequality was dropped due to practical reasons, as it is impossible to obtain long time series for measures of income inequality, especially at higher (quarterly or annual) frequencies. Second, the terms related to trend output growth and the output gap were dropped, as the former would need to be estimated

[13]Note that the term for the equilibrium real interest rate has been linearized around 0, to simplify the trend equation.

and the latter appears conceptually of minor importance to determine the medium-term trend in household credit. Third, we dropped the disposable income share from our empirical specification of the real household credit trend. There are two main reasons for this. First, as long as the share of household disposable income in GDP is rather stable over time, it is not necessary to explicitly model this determinant of the household credit trend. As shown in Figure A1 in Appendix A, this has indeed been the case over the last 35 years for most of the EU countries in our sample.[14] Second, long time series for household disposable income are not available for all of the EU countries that we study.

Our household credit trend equation is similar in spirit to the one used by Castro et al. (2016) for total credit. We differ from these authors by modeling the credit stock instead of the credit-to-GDP ratio. We use an equilibrium real interest rate measure instead of the nominal rate and a non-linear transformation of potential GDP per capita instead of GDP per capita. Finally, we add a population ratio to the list of explanatory variables and we explicitly model the dynamics of the credit cycle instead of assuming an i.i.d error structure.

Estimation of the semi-structural system of equations is performed in a state-space set-up by means of maximum likelihood, where the Kalman filter is used to compute the likelihood function. The flexible unobserved components approach that we employ facilitates the incorporation of insights from economic theory, at least in a semi-structural manner: the approach has long been prominent in the business cycle literature for estimating potential GDP and output gaps as in Clark (1987) and Blagrave et al. (2015), and more recently for estimating natural real interest rates (Laubach and Williams (2003), Mésonnier and Renne (2007), Holston et al. (2016)). Our empirical approach makes explicit use of variables that embed an interpretation of the long-run equilibrium, such as potential output and the equilibrium real interest rate. In contrast, existing empirical approaches to identify equilibrium credit with the use of co-integration techniques often use variables that are themselves affected by credit booms (e.g. real estate prices, or observed GDP) so that long-run equations for credit may not accurately capture deviations from equilibrium (see e.g. Albuquerque et al. (2015), Buncic and Melecky (2014) or Juselius and Drehmann (2015)).

The next section discusses in detail the data sources and measurement of the variables that enter our semi-structural system of equations to estimate household credit gaps.

[14]The intercept term α_0 in the empirical trend equation will therefore capture the effect of four constant terms from the theoretical trend equation: $\frac{\sigma^2_{\epsilon*}}{2}, \frac{\sigma^2_{\hat{\epsilon}}}{2}, ln(\lambda_{t+1}), ln(\bar{\Theta})$.

4 Data and descriptive statistics

We estimate the model given by equations (6) to (8) for the 12 EU countries shown in Figure 1 using quarterly data from 1980 to 2015.[15] The data is obtained from various sources such as the ECB, Eurostat, BIS, OECD and the European Commission. Details regarding all of the data sources and variables can be found in Table B1 of Appendix B. The main data series of interest for our framework are real total household credit, a population ratio (young/middle-aged cohort compared to all people with income), a proxy for institutional quality/development of a country, the equilibrium real interest rate, and real potential GDP. Time series charts for the main variables of interest are shown in Figures A2 - A6 of Appendix A.

In principle, real potential GDP and the equilibrium real interest rate are both unobserved, endogenous variables and should be jointly estimated alongside the real household credit trend. However, both concepts are assumed to be observed for the purpose of this paper to keep the empirical system of equations parsimonious and the number of parameters to estimate as small as possible. The measurement of real potential GDP is taken from the European Commission's annual AMECO database and is linearly interpolated to arrive at a quarterly frequency. The equilibrium real interest rate is approximated by means of an HP-filtered trend component of the real interest rate with a smoothing parameter of 1,600.

We use 10-year government bond yields provided by the ECB as the relevant interest rate for our model, because household credit is usually longer-term (related to housing) and therefore debt sustainability should be related to long-term interest rates rather than to short-term interest rates.[16] In order to compute the real interest rate, we subtract the average inflation rate that actually materialized over the subsequent 10-years for all of the periods up to 2005Q1 and subtract 1.9 for all periods after that. This way of constructing real interest rates can be motivated by rational expectations, as on average realized inflation should be equal to expected inflation under rational expectations.[17] Moreover, under the assumption that the ECB's monetary policy framework is credible, long-term inflation expectations should be close to but below 2% in all euro area countries.

Household credit is obtained from the Quarterly Sectoral Accounts (QSA) statistics provided by

[15]These 12 countries are Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, and Great Britain.

[16]We acknowledge that there is some heterogeneity in interest rate fixation periods across EU countries.

[17]In practice, expectations could deviate from rational expectations, in which case the proxy for the real 10-year interest rate that is used in the model could deviate from the real interest rate that is expected by households. However, given that long time series for inflation expectations are not available across EU countries, the proposed method constitutes a simple, transparent and theoretically justified way to construct real interest rates.

Eurostat and is backcasted using long time series for household credit from the BIS. The nominal household credit series are deflated with the consumer price index from the OECD's Main Economic Indicators (MEI) to obtain real household credit. The different population ratios of young/middle-aged people to all people with income are constructed from detailed demographic data provided by Eurostat. Again, the annual demographic series are linearly interpolated to arrive at a quarterly frequency.

In order to determine the relevant age cohorts to be used for the population ratios, detailed micro data on household debt holdings by age is used from the second wave of the Household Finance and Consumption Survey (HFCS) for all euro area countries (See Household Finance and Consumption Network (2016) and Household Finance and Consumption Network (2017)). For Denmark, Sweden and the Great Britain, data on debt holdings by age are taken from Christensen et al. (2013), Ölcer and van Santen (2016), and Office for National Statistics (2015) respectively. As shown in Table 1, the structure of debt holdings across different age cohorts varies considerably across euro area countries, which suggests that country-specific population ratios should be used in the household credit trend equation (7). For the baseline household credit gap estimates that are presented in Section 5, the relevant country-specific cohorts are comprised of all age groups that have approximately a share of more than 1.5%.[18]

As it is not possible to obtain long time series for variables that capture the institutional quality/development of a country[19] we need to resort to a proxy variable. Since good institutions should increase the productive potential of an economy (see e.g. Acemoglu et al. (2005)), we opt for real potential GDP per capita as our proxy variable. Since we only look for for an instrumental variable and we are not interested in the causal relationship between institutional quality and economic development, it is sufficient that real potential GDP per capita exhibits a high positive correlation with measures of institutional quality. This indeed seems to be the case both across countries and across time as suggested in Figure 2.

[18]The population aged 20 and older is taken as the relevant group of people that receive some form of income (i.e. the denominator of the population ratio).

[19]Many datasets that provide time series on institutional quality, such as the World Bank's Doing Business database, only start in the 2000s and therefore do not lend themselves to being used in our empirical models that cover household credit data going back to the early 1980's.

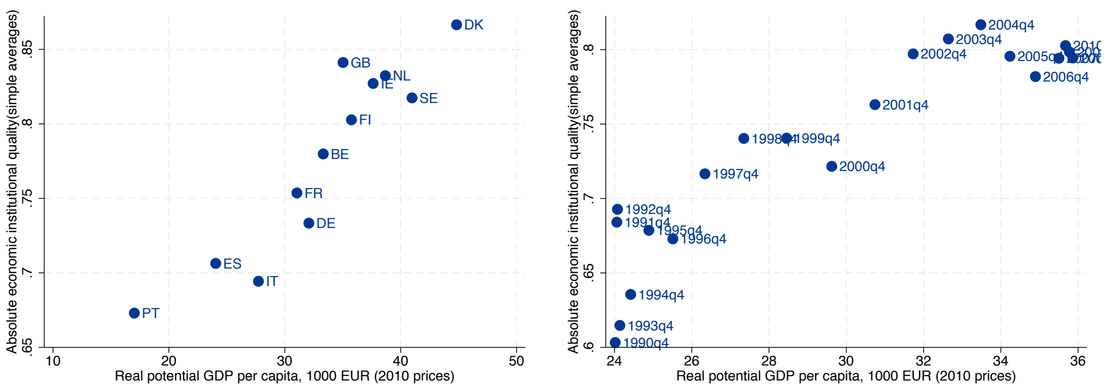
Table 1: Proxy shares of aggregate household debt held across different age cohorts

	BE	DE	ES	FI	FR	IE	IT	NL	PT	Euro Area
Less than 30	15.6	1.7	10.4	3.3	2.0	0.4	2.3	3.0	13.8	2.3
30-34	26.0	3.6	33.0	21.9	23.8	22.7	25.1	21.9	22.7	17.4
35-39	25.0	17.1	17.0	24.6	30.0	26.9	26.9	11.7	22.8	25.5
40-44	13.4	22.6	10.3	20.2	18.6	19.4	15.1	11.4	16.5	18.0
45-49	11.0	18.2	10.3	11.5	11.3	16.8	12.1	16.0	9.8	14.2
50-54	4.4	17.5	10.7	8.0	6.9	7.5	10.0	10.0	7.5	11.1
55-59	3.0	8.7	4.6	5.4	3.9	4.8	4.2	8.8	4.1	5.8
60-64	1.4	6.4	2.4	2.6	2.1	1.1	2.2	6.2	1.5	3.3
65-69	0.3	3.7	0.9	2.0	1.1	0.4	1.7	6.7	1.2	1.8
70 or more	0.1	0.6	0.5	0.5	0.2	0.1	0.4	4.3	0.2	0.5
Relevant cohort	20 - 59	20 - 69	25 - 64	25 - 69	20 - 64	30 - 59	25 - 69	25 - 74	25 - 59	30 - 64
Debt share (%)	98.3	99.4	98.6	99.5	98.7	97.9	99.6	100.0	97.1	95.3

Source: Household Finance and Consumption Survey Wave 2; Authors' calculations.
Notes: The table displays proxy values for the share of aggregate household debt that is held by each age cohort. The proxy values for each age cohort are calculated by multiplying the percentage of households holding debt by the conditional median debt holding and dividing by the sum of this product across all age cohorts. The relevant country-specific cohorts are comprised of all age groups that have a proxy share of more than 1.5%, except for the euro area for which all age groups with a proxy share of more than 2.5% are taken. The underlying data is taken from more granular age breakdowns of tables E5 and E6 in Household Finance and Consumption Network (2017). The Household Finance and Consumption Survey does not cover Denmark, Sweden and the Great Britain.

Figure 2: Correlation between institutional quality and potential GDP per capita

(a) Across EU countries (b) Across time (example Finland)



Sources: Kuncic (2014) obtained via the dataset of Teorell et al. (2016); Eurostat.

Notes: (a) Data points are for 2010. (b) Data points are for Finland

5 Estimates of semi-structural credit gaps

In the actual estimation of the model we split the set of parameters into three groups: parameters that we calibrate as implied by the theoretical model in Section 2, parameters that we calibrate on the basis of a priori-estimations outside the complete model and those that we estimate directly in the model with maximum likelihood.

Regarding the group of calibrated parameters, the coefficients for the logarithm of real potential GDP and for the logarithm of the non-linear transformation of institutional quality are set to unity.[20] Moreover, for the baseline estimation results in this section, the coefficient for the logarithm of the share of young/middle-aged people relative to all people that receive income is also set to unity. This is intuitive as the aggregate household borrowing capacity should increase one-for-one with every additional unit of aggregate future expected income that belongs to the class of borrowing households. In Section 6, robustness tests are performed and a version of the model is estimated where this assumption is relaxed.

Pre-estimated parameters occur in the non-linear transformation of the institutional quality proxy, γ_t. We choose the two parameters x_0, a location parameter, and k, a slope parameter, with the following algorithm where we allow for country-specific measurements of institutional quality and age cohorts. First, we select the country-specific measurement of young/middle-aged people relative to all people that receive income based on micro data on household debt holdings from the Household Finance and Consumption Survey (HFCS).[21] Conditional on the selected age share, we estimate many single equation models with different non-linear transformations of the institutional quality proxy (i.e. x_0, k pairs), where the logarithm of real household credit is regressed on the factors that drive the household credit trend in equation (7).[22] We then select the country-specific model specifications that yield the lowest root mean squared error for each country.[23] In Section 6 we show that the baseline results are qualitatively robust to using common measurements across countries, to using different country-specific age shares and non-linear transformations, as well as

[20]Note that the fraction of future expected income that can be borrowed enters the trend equation in logs. Hence, the parameter $\bar{\Theta}$ of the non-linear mapping of institutional quality shows up as a separate constant term and the coefficient for the non-linear transformation of institutional quality should be unity.

[21]Details on the relevant micro data and age shares are contained in section 4 and Table 1.

[22]These simple single equation models are akin to assuming i.i.d household credit cycles and can be estimated by simple maximum likelihood, which is computationally much less costly than estimating an unobserved components model.

[23]One additional condition for the selection of the appropriate country-specific model is that the estimated interest rate coefficient in the single equation regression is lower or equal to -1, as this is implied by the structural model. This additional condition is only relevant for the selection of models for Finland, Germany, and Ireland.

to estimating the coefficient for the age share alongside the interest rate coefficient. Table B2 in Appendix B provides an overview of all model specifications across the 12 EU countries.

The remaining parameters that need to be estimated are the intercept term, the coefficient for the equilibrium real interest rate and the standard deviation of transitory shocks in the credit trend equation (7) as well as the shock standard deviation of the cyclical component in equation (8).

5.1 Baseline estimation results for EU countries

Table 2 shows the estimated coefficients for the baseline specification of equations (6) - (8) across the 12 EU countries, along with information on the number of observations and the value of the maximised log-likelihood function. Starting with the household credit trend equation, it can be seen that the estimated coefficients for the equilibrium real interest rate are negative for all countries, which is in line with economic theory and intuition: Higher equilibrium real interest rates should increase the debt service burden for a given stock of credit and ceteris paribus should therefore reduce the trend level of household credit. The estimated interest rate coefficients are statistically significant for most of the countries. The exceptions are Finland, Germany, Ireland, and Spain.

Table 2: Coefficient estimates for the baseline household credit gap system

	(1) BE	(2) DE	(3) DK	(4) ES	(5) FI	(6) FR	(7) GB	(8) IE	(9) IT	(10) NL	(11) PT	(12) SE
CREDIT TREND												
Real interest rate	-5.121***	-0.845	-11.786***	-1.436	-2.356	-2.497*	-5.288***	-3.654	-4.987***	-8.828**	-6.310***	-4.874***
	(0.948)	(1.550)	(1.586)	(1.837)	(3.035)	(1.441)	(1.193)	(2.895)	(1.923)	(4.108)	(1.598)	(1.831)
Intercept	-0.155***	-0.252***	0.618***	0.382***	-0.326**	-0.282***	0.260***	0.372***	-0.496***	0.395***	2.154***	-0.055
	(0.046)	(0.068)	(0.045)	(0.089)	(0.130)	(0.084)	(0.057)	(0.140)	(0.106)	(0.113)	(0.083)	(0.087)
Shock SD	0.009***	0.006***	0.007***	0.011***	0.006***	0.004***	0.006***	0.013***	0.018***	0.011***	0.008***	0.004***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
CREDIT GAP												
AR(1) coefficient	1.907***	1.912***	1.958***	1.920***	1.906***	1.710***	1.914***	1.957***	1.920***	1.962***	1.799***	1.906***
	(0.041)	(0.041)	(0.028)	(0.032)	(0.048)	(0.087)	(0.035)	(0.026)	(0.041)	(0.029)	(0.068)	(0.037)
AR(2) coefficient	-0.919***	-0.916***	-0.971***	-0.929***	-0.912***	-0.716***	-0.926***	-0.963***	-0.925***	-0.967***	-0.819***	-0.913***
	(0.041)	(0.041)	(0.028)	(0.033)	(0.049)	(0.088)	(0.035)	(0.026)	(0.042)	(0.029)	(0.067)	(0.037)
Shock SD	0.004***	0.002***	0.003***	0.005***	0.006***	0.007***	0.004***	0.005***	0.005***	0.002***	0.010***	0.005***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	137	140	81	137	140	140	140	140	140	97	128	137
Log likelihood	389.472	449.825	246.413	361.654	414.409	443.023	444.541	349.420	316.437	267.392	337.984	442.417

Notes: Details on the country-specific model specifications are given in Table B2. Standard errors are in parentheses. Stars indicate significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Moreover, the magnitudes of the estimated interest rate coefficients imply reasonable responses of the trend level of household credit to economic fundamentals. The estimated interest rate coefficients are in the range of -2.4 to -6.3 for most of the countries, suggesting that for a 1 percentage point reduction in the equilibrium real interest rate, the trend level of household credit increases by around 2.4% to 6.3%. To put these magnitudes into perspective, the simple structural overlapping generations model in Section 2 that is used to derive the trend equation for household credit implies a coefficient for the equilibrium real interest rate of -1. Given that the structural model is fairly simple and abstracts from many aspects of reality, it is reasonable to assume that estimated coefficients deviate somewhat from the values implied by the model.

The estimated coefficients of the household credit gap equation are all statistically significant at the 1% level and imply stationary processes for the household credit gaps. The standard deviation of shocks to the household credit gaps is between 0.004 and 0.008 in most of the countries, which can be interpreted as shocks in the range of 0.4% to 0.8% of the real household credit trend. The next subsection discusses in detail what these estimated coefficients imply for the amplitude and cycle length of household credit gaps across the 12 EU countries.

5.2 Time-series properties of semi-structural credit gaps

The baseline estimation results for our semi-structural model produce fairly long cycles for household credit gaps. This property of the semi-structural credit gaps can be seen from Panel (a) of Figure 3 which plots the cross-country distribution of household credit gaps over the last 35 years. The estimated household credit cycles have an average length of around 20 years across the 12 EU countries and varies between 15 and 25 years. For example, the time from one peak in the household credit cycle to the next one is around 15 years for Belgium and around 25 years for Finland, as shown in Figure 4.

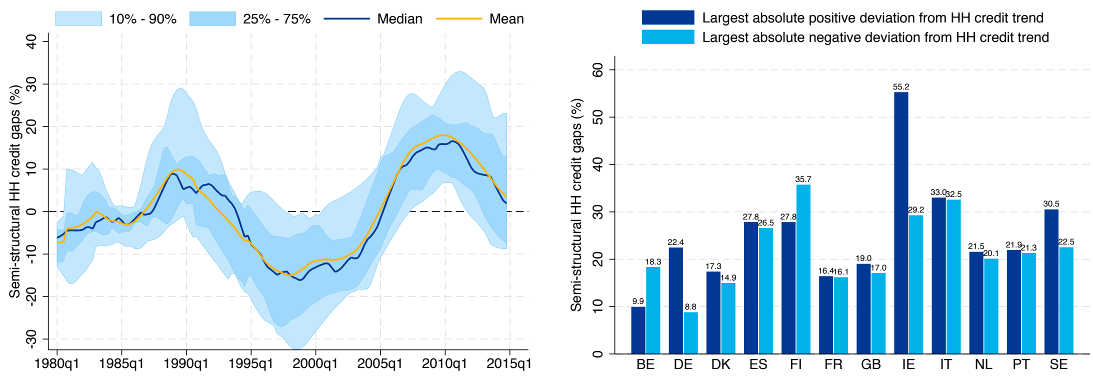
This feature of long cycles for household credit gaps is in line with the literature on financial cycles that has found long cycles for total credit and real estate prices based on statistical filters.[24] In contrast to purely statistical approaches, no ex-ante restrictions are imposed on the properties of the semi-structural household credit gaps, except that they follow AR(2) processes. The main identifying information for the semi-structural household credit gaps comes the credit trend.

In addition to long cycle lengths, we estimate substantial booms and bust episodes in a number of countries of the past 35 years as reflected in large (and heterogenous) amplitudes around the trend, ranging between +/- 15% and +/- 30% (see Panel (b) in Figure 3). In some of the countries that experienced particularly pronounced credit booms, such as for example Ireland, the semi-structural credit gaps reach levels of more than + 50% of the real household credit trend.

[24] See for example Drehmann et al. (2012) or Schüler et al. (2015).

Figure 3: Properties of semi-structural household credit gaps across EU countries

(a) Evolution of credit gaps over time (b) Maximum amplitudes of credit gaps



Notes: (a) The chart shows the mean, median, interquartile range, and 90-10 percentile range of the semi-structural household credit gaps across 12 EU countries (Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden and the Great Britain). (b) The largest absolute positive and negative deviations of the household credit gaps from the credit trend are computed for the sample Q1 1981 to Q4 2014.

Figures 4 and 5 further illustrate the properties of the semi-structural household credit gaps. In most countries the household credit gaps display two to three peaks since the beginning of the 1980s. The difference between one-sided (filtered) and two-sided (smoothed) estimates of the household credit gaps is negligible, given that most of the identifying information for the household credit gaps enters through the specification of the household credit trend.[25] Figures 4 and 5 also show that the semi-structural household credit gaps tend to be positive and at rather high levels at the start of systemic financial crises. The next subsection analyses in more detail the behaviour of the semi-structural household credit gaps around systemic financial crises.

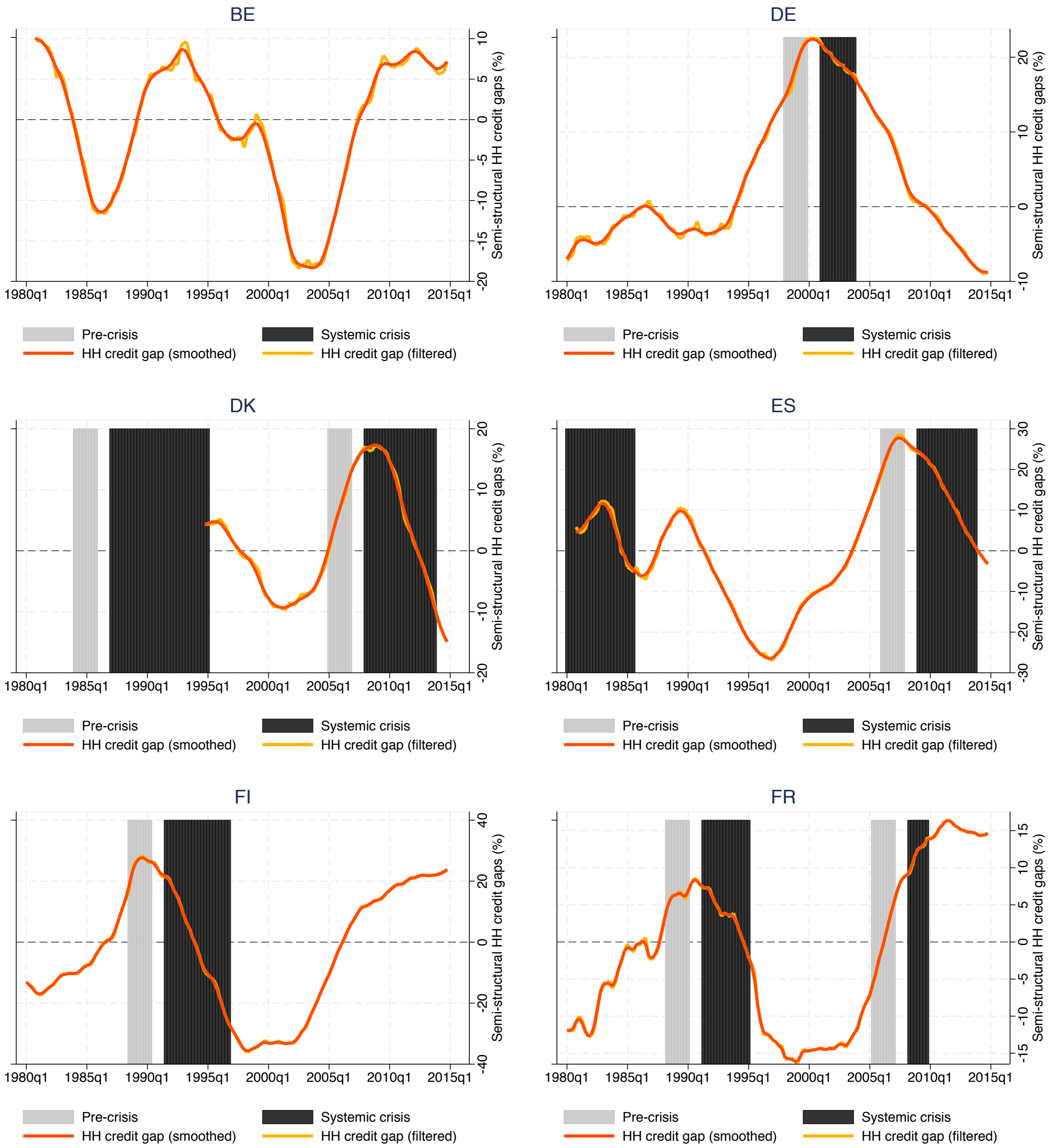
5.3 Signalling properties for systemic financial crises

Since the onset of the global financial crisis, the interest in early warning models for systemic financial crises has grown substantially. Most papers have found that in a univariate signalling approach various statistical transformations (e.g. changes, growth rates, or filtered cycles) of credit aggregates and asset prices have good early warning properties.[26] In a univariate signalling approach, which was originally applied by Kaminsky et al. (1998) in the context of currency crises, the patterns of an

[25]Given that all fundamental drivers of the household credit trend are assumed to be observed, there is little uncertainty about the true state apart from a transitory shock, once coefficients are estimated. If the equilibrium real interest rate and potential output were treated as unobserved endogenous variables, and were jointly estimated with the household credit trend, uncertainty about the true underlying states of household credit would increase.

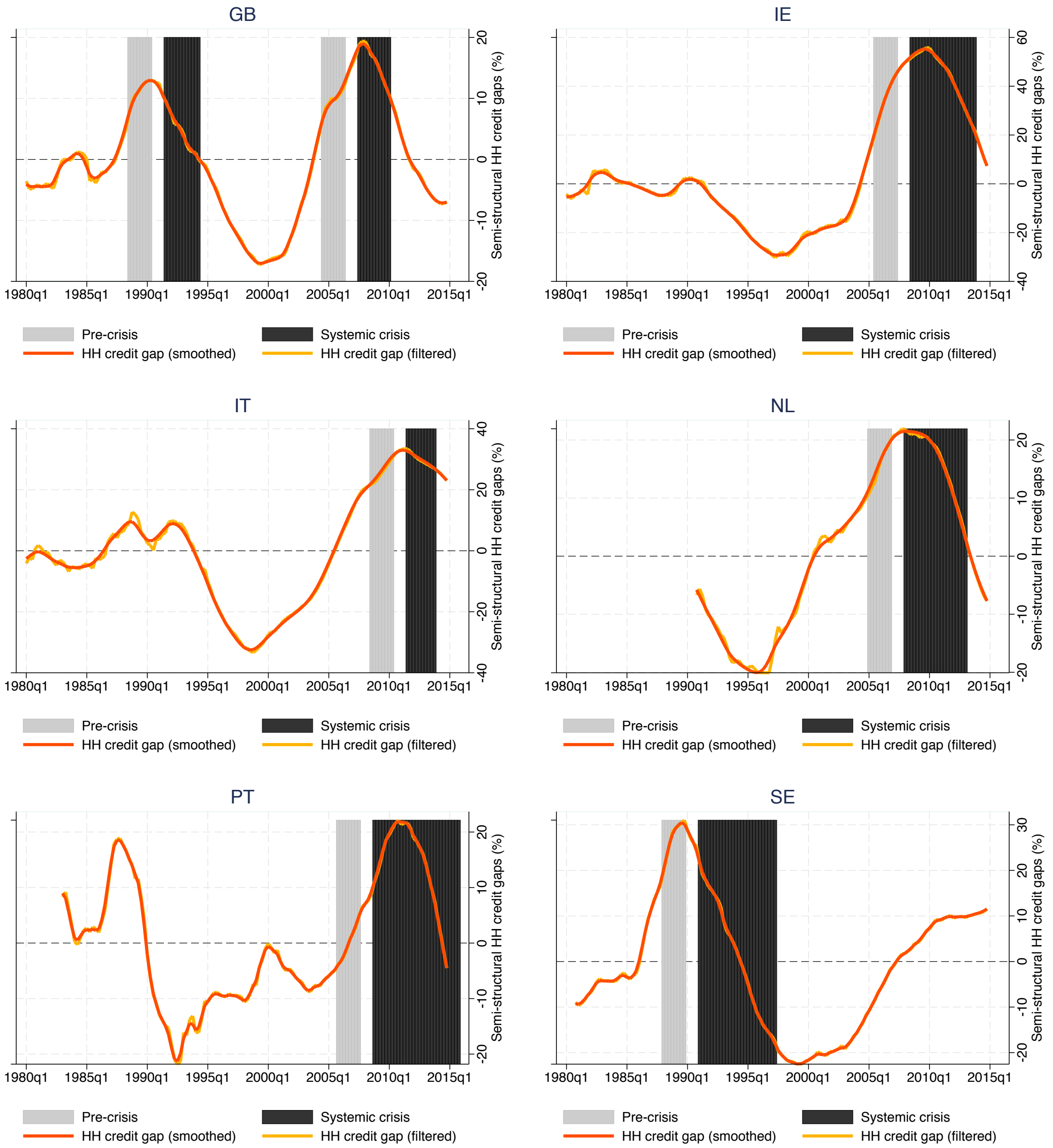
[26]See for example Borio and Lowe (2002), Borio and Drehmann (2009), Schularick and Taylor (2012), Detken et al. (2014), or Lo Duca et al. (2017).

Figure 4: Baseline household credit gap estimates across EU countries I



Notes: Details on the country-specific model specifications underlying the baseline household credit gap estimates are contained in Table B2. The systemic crisis events in the Figure are based on the definition and dating of systemic financial crises with either a domestic origin or a combination of a domestic and foreign origin contained in Lo Duca et al. (2017). The pre-crisis horizon is defined as 12 to 5 quarters prior to a systemic financial crisis.

Figure 5: Baseline household credit gap estimates across EU countries II



Notes: Details on the country-specific model specifications underlying the baseline household credit gap estimates are contained in Table B2. The systemic crisis events in the figure are based on the definition and dating of systemic financial crises with either a domestic origin or a combination of a domestic and foreign origin contained in Lo Duca et al. (2017). The pre-crisis horizon is defined as 12 to 5 quarters prior to a systemic financial crisis.

indicator before crisis events are used to distinguish pre-crisis episodes from normal episodes. We use both a univariate and a bivariate[27] signalling approach to evaluate the early warning properties of the semi-structural household credit gaps for systemic financial crises. For this purpose we use the definition and dating of systemic financial crises with either a domestic origin or a combination of a domestic and foreign origin contained in the novel crisis database for EU countries by Lo Duca et al. (2017). In total there are 13 relevant crisis events in the sample. As has become common practice in the early warning literature on financial crises, we do not try to predict the beginning of a crises but instead try to predict vulnerability periods prior to a crises. For that purpose we study four specifications: 16-9 quarters prior to a crisis, 12 to 5 quarters, 8 to 1 quarters and 4 to 1 quarters.[28]

The baseline semi-structural household credit gaps tend to increase well before systemic financial crises and decrease slowly afterwards, as shown in panel (a) of Figure 6. On average across the 12 EU countries, the semi-structural household credit gaps start to become positive more than four years prior to the start of a systemic financial crisis. Moreover, the credit gaps tend to increase continuously during the period leading up to a systemic financial crisis to reach levels of around +20% of the real household credit trend on average across the EU countries that are studied. Once a systemic financial crisis materialises, a slow deleveraging process usually starts that takes on average more than 4 years to bring real household credit back to its trend level that is determined by economic fundamentals. These dynamics indicate that the baseline semi-structural household credit gaps could be useful to identify periods when excessive leverage builds up in the household sector that could threaten financial stability.

Panel (b) of Figure 6 further shows that there seems to be information content in both the level and the change of the credit gaps. In the vast majority of cases, both the level and the 2-year change of the credit gaps display high positive values during the 12 to 5 quarters prior to systemic financial crises. If either the level or the 2-year change of the credit gaps is negative, this tends to signal that the current period is tranquil, i.e. not leading up to a systemic financial crisis. This result is not surprising given that panel (a) of Figure 6 shows that before systemic financial crises the semi-structural credit gaps tend to be positive and increasing, while immediately after systemic financial crises they tend to be positive but decreasing.

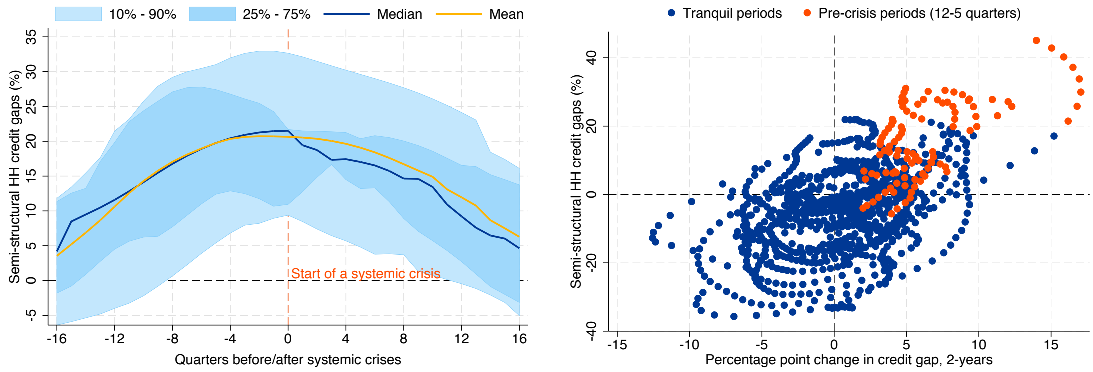
Table 3 shows more formally that the semi-structural household credit gaps have very good early

[27] In a bivariate signalling approach the joint patterns of two indicators before crisis events are used to distinguish pre-crisis episodes from normal episodes, see Detken et al. (2014).

[28] See e.g. Detken et al. (2014) for a detailed discussion.

Figure 6: Patterns of semi-structural household credit gaps around systemic crises

(a) Distribution around systemic crises (b) Level and change before systemic crises



Notes: Details on the country-specific model specifications underlying the baseline household credit gap estimates are contained in Table B2. The systemic crisis events in the figure are based on the definition and dating of systemic financial crises with either a domestic origin or a combination of a domestic and foreign origin contained in Lo Duca et al. (2017). In total there are 13 systemic financial crisis events in the sample across the 12 EU countries. (a) The chart shows the cross-country mean, median, interquartile range, and 90-10 percentile range of the baseline semi-structural household credit gaps before and after the start of the 13 systemic financial crisis events in the sample. (b) The chart shows all realisations of the level and 2-year change of the baseline semi-structural household credit gaps for the 12 EU countries since 1980q1. The pre-crisis horizon is defined as 12 to 5 quarters prior to a systemic financial crisis. The 2-year percentage point change in the semi-structural household credit gaps is expressed as an annual average.

warning properties for systemic financial crises. The Area Under the Receiver Operating Characteristics Curve (AUROC)[29], which is a global measure of the early warning quality of an indicator, is 0.90 for prediction horizons of 12 to 5, 8 to 1, and 4 to 1 quarters before systemic financial crises respectively. For a prediction horizon of 16 to 9 quarters before systemic financial crises the AUROC is 0.80. To put these numbers into perspective, the AUROC values for the Basel total credit-to-GDP gap[30], which is usually considered as one of the best univariate signalling indicators for systemic financial crises[31], are in the range of 0.72 - 0.78 for these prediction horizons. The early warning properties of the semi-structural household credit gaps also compare favourably to other purely statistical early warning indicators, notably the Basel household credit-to-GDP gap, the Basel bank

[29]The AUROC is computed as the area under the Receiver Operating Characteristics (ROC) curve, which plots the noise ratio (false positive rate) on the x-axis against the signal ratio (true positive rate) on the y-axis for every possible signalling threshold value that can be applied to an early warning indicator. For a given noise ratio, a higher signal ratio implies that an early warning indicator is better able to classify between pre-crisis and tranquil states of the world. Usually, there is a trade-off between the noise and the signal ratio, so that higher signal ratios are associated with higher noise ratios. The ROC curve is therefore upward sloping. A perfect indicator would imply a noise ratio of 0 and a signal ratio of 1 for the optimal signalling threshold. For other signalling thresholds, the signal ratio would stay at 1, but the noise ratio would start to increase until it also reaches 1. The ROC curve for such a perfect early warning indicator would look like an "L" switched upside down and the area under this curve would be equal to 1. Hence, An AUROC value of 1 indicates a perfect early warning indicator, while an AUROC value of 0.5 indicates an uninformative indicator.

[30]The Basel total credit-to-GDP gap is defined as the difference between the total credit-to-GDP ratio and its long-run statistical trend, which is computed with a recursive Hodrick-Prescott (HP) filter applying a smoothing parameter of 400,000, in line with the guidance in Basel Committee on Banking Supervision (2010).

[31]See for example Borio and Lowe (2002), or Detken et al. (2014)

Table 3: Overview of early warning properties of semi-structural HH credit gaps

	Semi-structural HH credit gap	Basel total credit-to-GDP gap	Basel bank credit-to-GDP gap	Basel HH credit-to-GDP gap	3-year Δ in HH credit-to-GDP ratio	3-year growth rate of real HH credit
Pooled results						
AUROC 16-9q	0.80	0.72	0.76	0.78	0.80	0.69
AUROC 12-5q	0.90	0.78	0.79	0.77	0.84	0.74
AUROC 8-1q	0.90	0.75	0.74	0.72	0.76	0.66
AUROC 4-1q	0.90	0.74	0.72	0.66	0.72	0.60
Pseudo R2 12-5q	0.39	0.14	0.15	0.09	0.22	0.07
Observations	1,204	1,196	1,204	1,116	1,055	1,055
Country results 12-5 quarters						
AUROC BE	-	-	-	-	-	-
AUROC DE	0.99	1.00	0.96	0.98	0.95	0.75
AUROC DK	0.94	1.00	1.00	1.00	1.00	0.96
AUROC ES	1.00	1.00	1.00	1.00	1.00	0.93
AUROC FI	0.99	0.75	0.63	0.62	0.79	1.00
AUROC FR	0.78	0.80	0.88	0.81	0.84	0.95
AUROC GB	1.00	0.82	0.81	0.91	0.89	0.85
AUROC IE	1.00	1.00	1.00	0.68	1.00	1.00
AUROC IT	1.00	0.93	0.83	0.89	0.90	0.45
AUROC NL	1.00	0.21	0.39	0.61	0.75	0.31
AUROC PT	0.70	0.66	0.64	0.57	0.67	0.27
AUROC SE	1.00	0.90	0.97	0.49	0.81	0.97
Average AUROC	0.95	0.82	0.83	0.78	0.87	0.77

Notes: The results are based on a sample of 12 EU countries (Belgium, Germany, Denmark, Spain, Finland, France, Ireland, Italy, Netherlands, Portugal, Sweden, and the Great Britain). AUROC stands for Area Under the Receiver Operating Characteristics Curve and it is a global measure of the signalling performance of an early warning indicator. An AUROC value of 0.5 indicates an uninformative indicator and a value of 1 indicates a perfect early warning indicator. The AUROC is computed for various pre-crisis horizons (indicated e.g. by "12-5q"), based on the definition and dating of systemic financial crises with either a domestic origin or a combination of a domestic and foreign origin contained in Lo Duca et al. (2017). The Pseudo R-square is obtained for a logit model that has the relevant early warning indicator on the right hand side and a binary vulnerability indicator on the left hand side, that takes a value of 1 during the 12 to 5 quarters before systemic financial crises, and is zero otherwise, except during the 4 quarters before a crisis and during actual crisis quarters, when it is set to missing. The various credit-to-GDP gaps are derived with a recursive HP-filter using a smoothing parameter of 400,000, in line with guidance provided by the BIS and the ESRB. The AUROC cannot be computed for Belgium as there is no relevant systemic financial crisis event in the dataset (The systemic financial crisis that started in 2007 in Belgium is classified as an imported crisis in the dataset).

credit-to-GDP gap, the 3-year change in the household credit-to-GDP ratio, or the 3-year growth rate of real household credit (See Table 3).

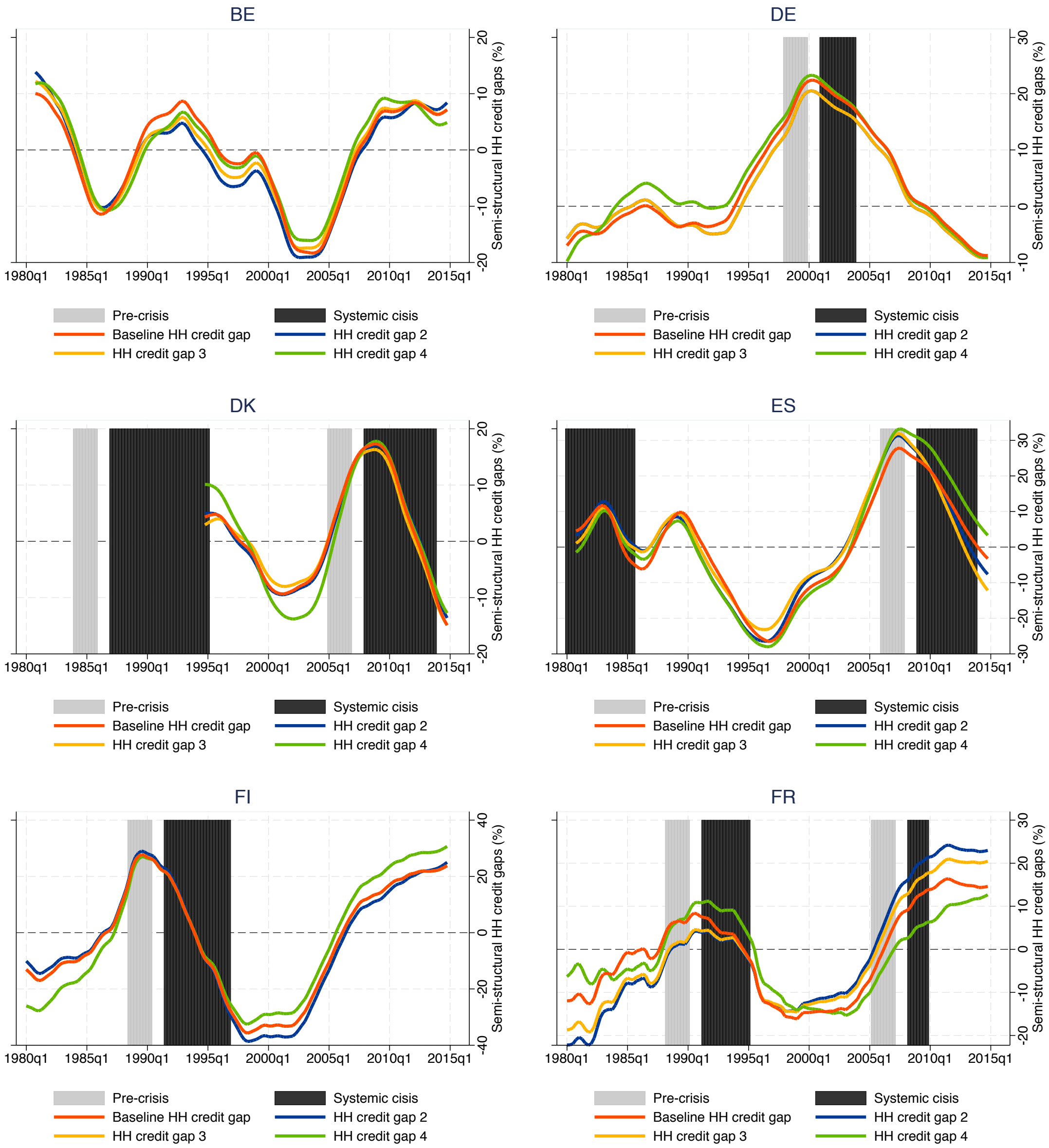
6 Robustness of semi-structural credit gaps

Three robustness exercises are performed for the semi-structural household credit gaps. First, a common age share and non-linear transformation of the institutional quality proxy are used across all countries (Model 2). Second, a common non-linear transformation of the institutional quality proxy is used across countries, but the age share is allowed to be country-specific (Model 3). Third, both measurements are allowed to be country-specific and the coefficient for the age share is estimated alongside the interest rate coefficient (Model 4). Table B2 in Appendix B provides a more detailed overview of all model specifications that are used across the 12 EU countries.

Figures 7 and 8 show that the dynamics of the baseline household credit gaps are qualitatively robust to various changes in the model specification. In particular, peaks and troughs coincide for the different model specifications in most of the countries. For Belgium, Denmark, Finland, Germany, the Netherlands, Spain, and Sweden the differences in the various household credit gap estimates are rather small. For France, Ireland, Italy, Portugal, and the Great Britain some differences in the levels of the different household credit gaps can be observed in particular at the beginning of the the sample period, while the overall dynamics appear to be robust. The differences that are observed in the levels of the credit gaps for these countries seem to be mainly driven by whether country-specific measurements for the age share and non-linear transformation of the institutional quality proxy are used (Baseline and Model 4) or not (Models 2 and 3). Nevertheless, the very good early warning properties of the semi-structural household credit gaps for systemic financial crises are not affected by the different model specifications, as shown in Table B3 in Appendix B.

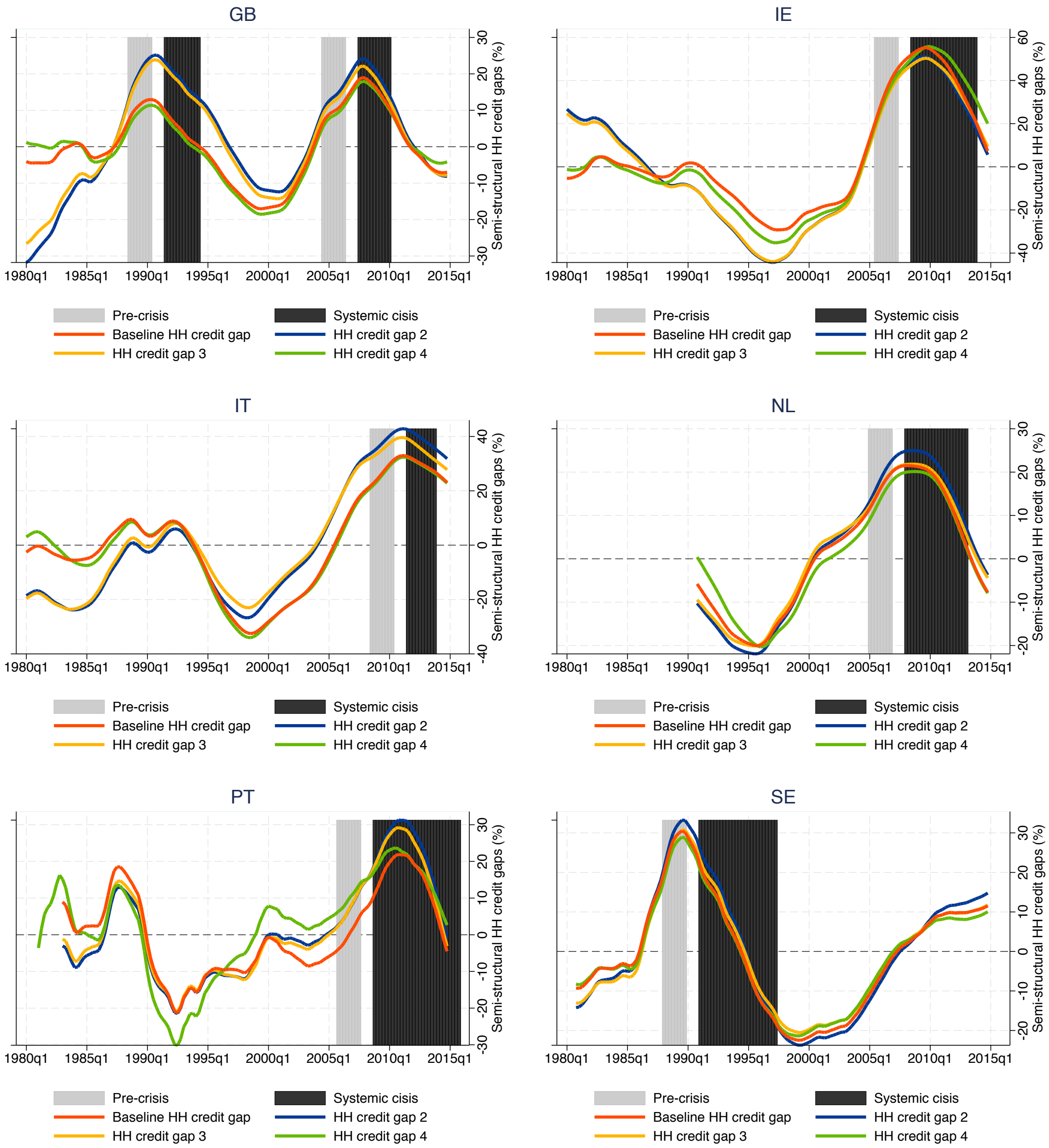
Table 4 further shows that the estimated coefficients for the equilibrium real interest rate are negative in all cases and rather stable across the different model specifications. The AR(2)-coefficients of the credit gap equation are also fairly stable across the different model specifications and imply stationary statistical processes in all cases. Finally, the estimated coefficients for the share of young/middle-aged people relative to all people that receive income imply reasonable responses of the trend level of real household credit to changes in the demographic structure of the population. The estimated age share coefficients are in the range of 0.8 to 3.3, which implies that a 1% increase in the share of young/middle-aged people in the total population leads to an increase in the trend level of household credit of around 0.8% to 3.3%. To put these magnitudes into perspective, the simple structural overlapping generations model that is used to derive the trend equation for household credit implies a unit elasticity for the population ratio: each additional percent of aggregate future expected income that is assigned to people that are most likely to hold debt, should increase the trend level of borrowing by the same amount.

Figure 7: Robustness of household credit gap estimates across EU countries I



Notes: Details on the country-specific model specifications underlying the different household credit gap estimates are contained in Table B2. The systemic crisis events in the figure are based on the definition and dating of systemic financial crises with either a domestic origin or a combination of a domestic and foreign origin contained in Lo Duca et al. (2017). The pre-crisis horizon is defined as 12 to 5 quarters prior to a systemic financial crisis.

Figure 8: Robustness of household credit gap estimates across EU countries II



Notes: Details on the country-specific model specifications underlying the different household credit gap estimates are contained in Table B2. The systemic crisis events in the figure are based on the definition and dating of systemic financial crises with either a domestic origin or a combination of a domestic and foreign origin contained in Lo Duca et al. (2017). The pre-crisis horizon is defined as 12 to 5 quarters prior to a systemic financial crisis.

Table 4: Robustness of coefficient estimates for the household credit gap system

	(1) BE	(2) DE	(3) DK	(4) ES	(5) FI	(6) FR	(7) GB	(8) IE	(9) IT	(10) NL	(11) PT	(12) SE
CREDIT TREND												
Real rate (Baseline)	-5.121***	-0.845	-11.786***	-1.436	-2.356	-2.497*	-5.288***	-3.654	-4.987***	-8.828**	-6.310***	-4.874***
	(0.948)	(1.550)	(1.586)	(1.837)	(3.035)	(1.441)	(1.193)	(2.895)	(1.923)	(4.108)	(1.598)	(1.831)
Real rate (Model 2)	-4.359***	-0.981	-12.636***	-0.785	-2.592	-2.285	-8.357***	-2.940	-4.534**	-10.600**	-7.739***	-6.042***
	(1.171)	(1.478)	(1.575)	(1.912)	(3.021)	(1.617)	(2.284)	(2.656)	(2.233)	(5.116)	(2.211)	(2.014)
Real rate (Model 3)	-5.397***	-0.981	-11.177***	-0.524	-2.356	-2.082	-7.957***	-3.029	-4.343**	-9.754**	-7.356***	-5.678***
	(1.014)	(1.478)	(1.473)	(1.783)	(3.035)	(1.507)	(1.940)	(2.628)	(2.147)	(4.451)	(2.020)	(1.788)
Real rate (Model 4)	-6.100***	-0.724	-13.257***	-1.456	-2.278	-3.441***	-5.893***	-3.436	-5.279***	-9.599**	-3.488*	-5.132***
	(1.981)	(1.927)	(1.406)	(2.537)	(5.949)	(1.220)	(1.407)	(3.032)	(1.938)	(4.399)	(1.864)	(1.770)
Age share (Model 4)	3.057	0.978	2.131**	1.643	1.121	3.117***	2.857	1.535	1.344	3.265	0.774	3.202
	(3.085)	(1.837)	(1.054)	(2.194)	(1.821)	(0.841)	(3.317)	(3.411)	(2.601)	(4.534)	(2.723)	(4.481)
CREDIT GAP												
AR(1) (Baseline)	1.907***	1.912***	1.958***	1.920***	1.906***	1.710***	1.914***	1.957***	1.920***	1.962***	1.799***	1.906***
	(0.041)	(0.041)	(0.028)	(0.032)	(0.048)	(0.087)	(0.035)	(0.026)	(0.041)	(0.029)	(0.068)	(0.037)
AR(1) (Model 2)	1.899***	1.902***	1.959***	1.930***	1.910***	1.743***	1.948***	1.963***	1.917***	1.960***	1.814***	1.921***
	(0.047)	(0.044)	(0.028)	(0.030)	(0.044)	(0.080)	(0.027)	(0.022)	(0.042)	(0.029)	(0.070)	(0.033)
AR(1) (Model 3)	1.900***	1.902***	1.955***	1.934***	1.906***	1.710***	1.943***	1.962***	1.912***	1.957***	1.810***	1.909***
	(0.046)	(0.044)	(0.030)	(0.029)	(0.048)	(0.087)	(0.028)	(0.023)	(0.045)	(0.032)	(0.069)	(0.037)
AR(1) (Model 4)	1.914***	1.920***	1.966***	1.926***	1.916***	1.687***	1.909***	1.954***	1.923***	1.962***	1.773***	1.898***
	(0.042)	(0.044)	(0.020)	(0.033)	(0.060)	(0.089)	(0.037)	(0.028)	(0.039)	(0.028)	(0.073)	(0.040)
AR(2) (Baseline)	-0.919***	-0.916***	-0.971***	-0.929***	-0.912***	-0.716***	-0.926***	-0.963***	-0.925***	-0.967***	-0.819***	-0.913***
	(0.041)	(0.041)	(0.028)	(0.033)	(0.049)	(0.088)	(0.035)	(0.026)	(0.042)	(0.029)	(0.067)	(0.037)
AR(2) (Model 2)	-0.909***	-0.907***	-0.972***	-0.937***	-0.916***	-0.746***	-0.955***	-0.967***	-0.920***	-0.965***	-0.829***	-0.928***
	(0.047)	(0.044)	(0.028)	(0.031)	(0.044)	(0.081)	(0.027)	(0.023)	(0.043)	(0.030)	(0.071)	(0.033)
AR(2) (Model 3)	-0.911***	-0.907***	-0.969***	-0.942***	-0.912***	-0.713***	-0.951***	-0.966***	-0.915***	-0.962***	-0.827***	-0.917***
	(0.046)	(0.044)	(0.030)	(0.030)	(0.049)	(0.088)	(0.028)	(0.023)	(0.046)	(0.033)	(0.070)	(0.037)
AR(2) (Model 4)	-0.927***	-0.923***	-0.980***	-0.933***	-0.921***	-0.696***	-0.921***	-0.959***	-0.929***	-0.968***	-0.791***	-0.905***
	(0.042)	(0.043)	(0.020)	(0.033)	(0.063)	(0.089)	(0.037)	(0.029)	(0.039)	(0.029)	(0.073)	(0.040)
Shock SD (Baseline)	0.004***	0.002***	0.003***	0.005***	0.006***	0.007***	0.004***	0.005***	0.005***	0.002***	0.010***	0.005***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Shock SD (Model 2)	0.004***	0.003***	0.002***	0.004***	0.007***	0.007***	0.004***	0.005***	0.005***	0.003***	0.010***	0.005***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Shock SD (Model 3)	0.004***	0.003***	0.003***	0.004***	0.006***	0.007***	0.004***	0.005***	0.005***	0.003***	0.010***	0.005***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Shock SD (Model 4)	0.003***	0.003***	0.002***	0.005***	0.006***	0.007***	0.004***	0.005***	0.005***	0.002***	0.012***	0.005***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)

Notes: Details on the country-specific model specifications are given in Table B2. Standard errors are in parentheses. Stars indicate significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7 Conclusion

The semi-structural credit gaps that we derive from an overlapping generations model display long credit cycles with substantial amplitudes across time and countries. They possess superior early warning properties relative to a number of established statistical credit gaps, notably the Basel total-credit-to-GDP gap and its household credit-to-GDP gap variant. Our theory-based credit gaps allow for economic interpretation in contrast to these commonly used purely statistical credit gaps. Our estimated semi-structural credit gaps, while increasing well ahead of financial crises, do not tend to increase over excessively long periods of time before such crises. In addition, our estimated gaps do not tend to fall to such large negative values in the aftermath of financial booms as, for example, those observed for Basel credit gaps. This property should mitigate the risk of underestimating cyclical systemic risks. Theory-based credit gaps could therefore provide a useful complement to purely statistical measures of credit excesses, thereby helping to inform the setting of countercyclical macroprudential policy.

Our framework could be extended to allow for endogeneity of potential GDP and the equilibrium real interest rate akin to the set-up used in Laubach and Williams (2003), but augmented with additional exogenous factors that drive the equilibrium real rate as suggested by Eggertsson and Mehrotra (2014) . We are currently working on that approach. In addition, a (semi-)structural approach to modelling firm credit would be desirable.

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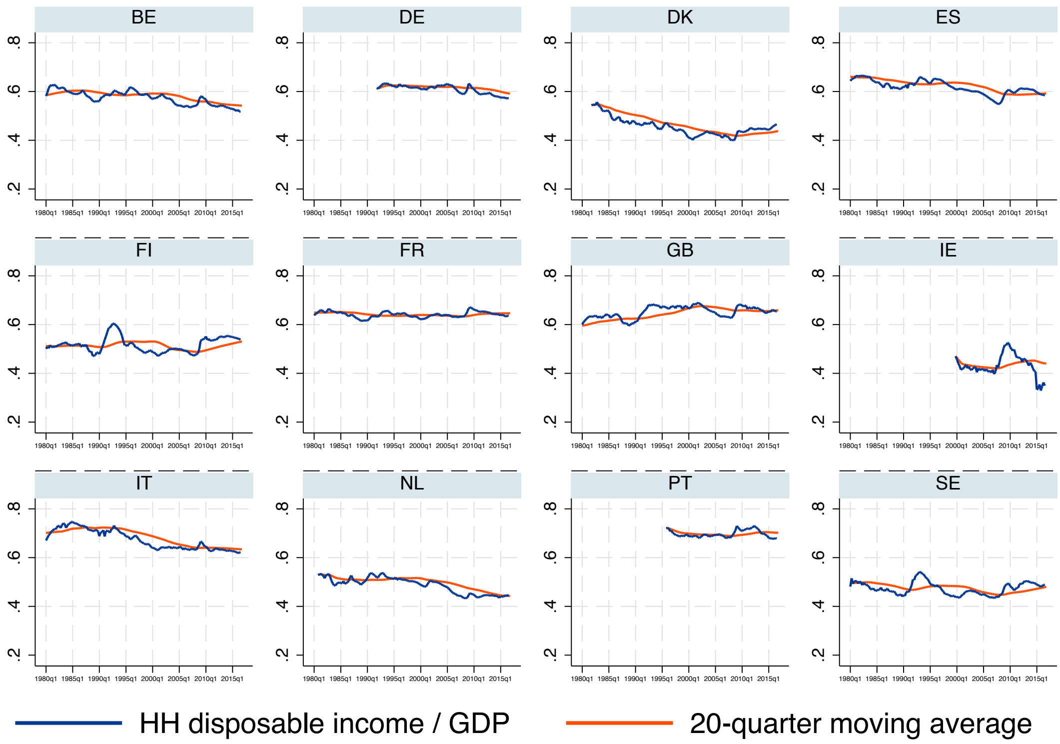
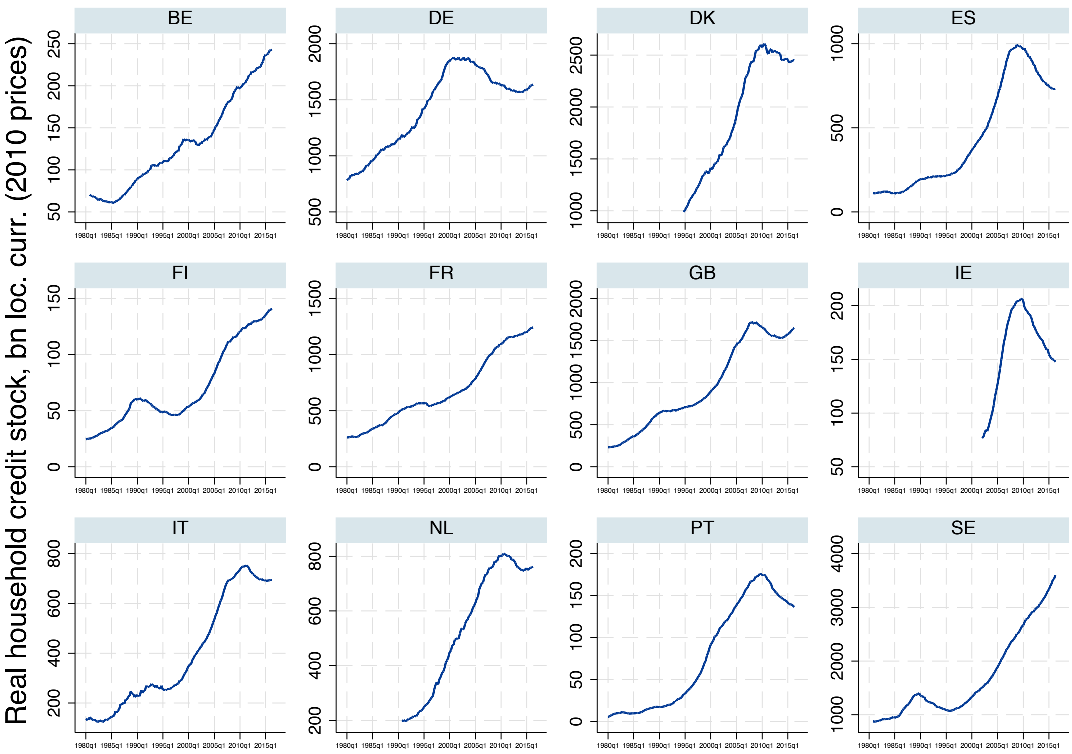
Appendix A: Additional figures

Figure A1: Household disposable income to GDP ratios across EU countries



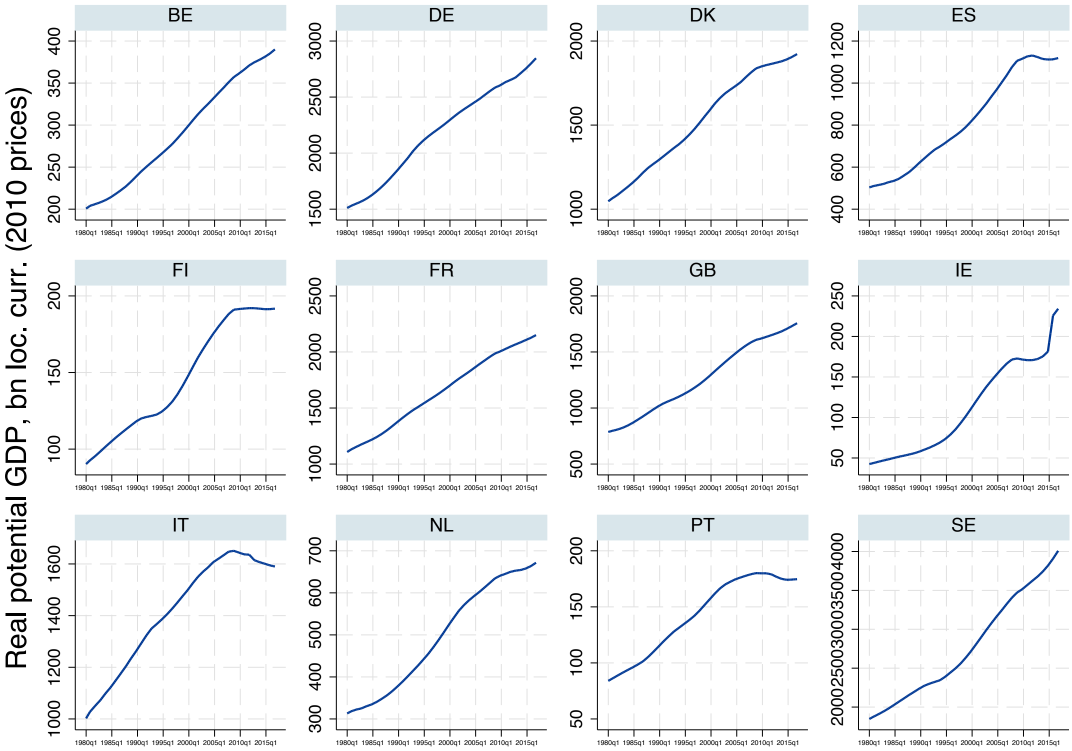
Sources: See Table B1 in Appendix B.

Figure A2: Real household credit across countries



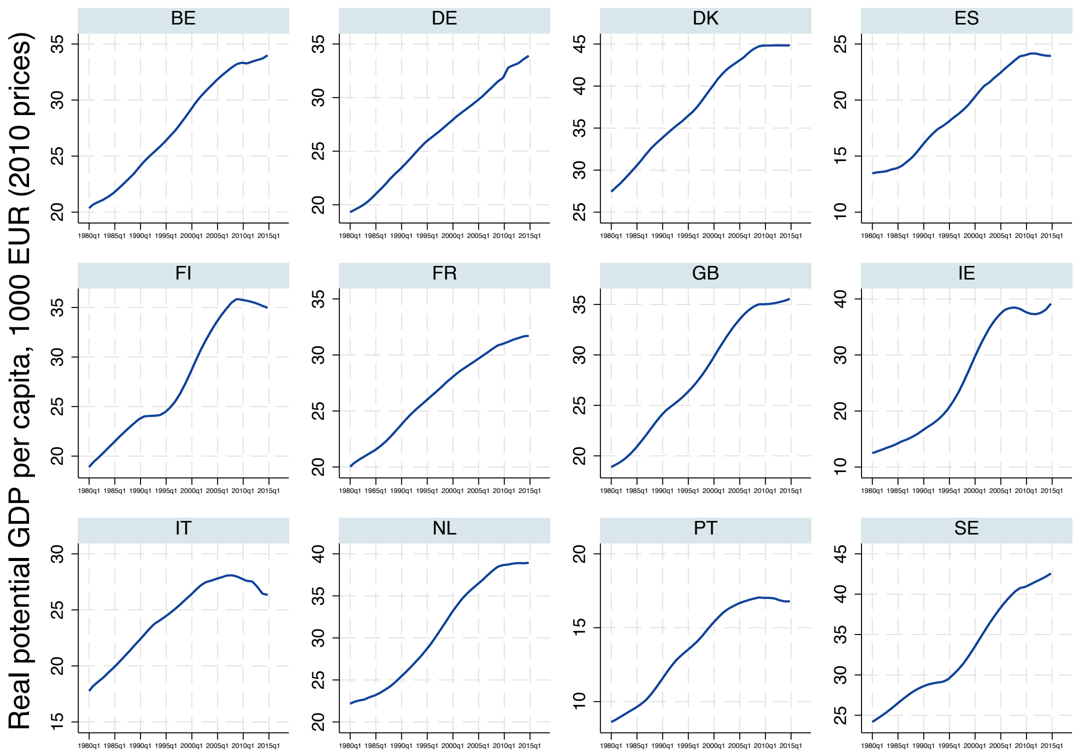
Sources: See Table B1 in Appendix B.

Figure A3: Real potential GDP across countries



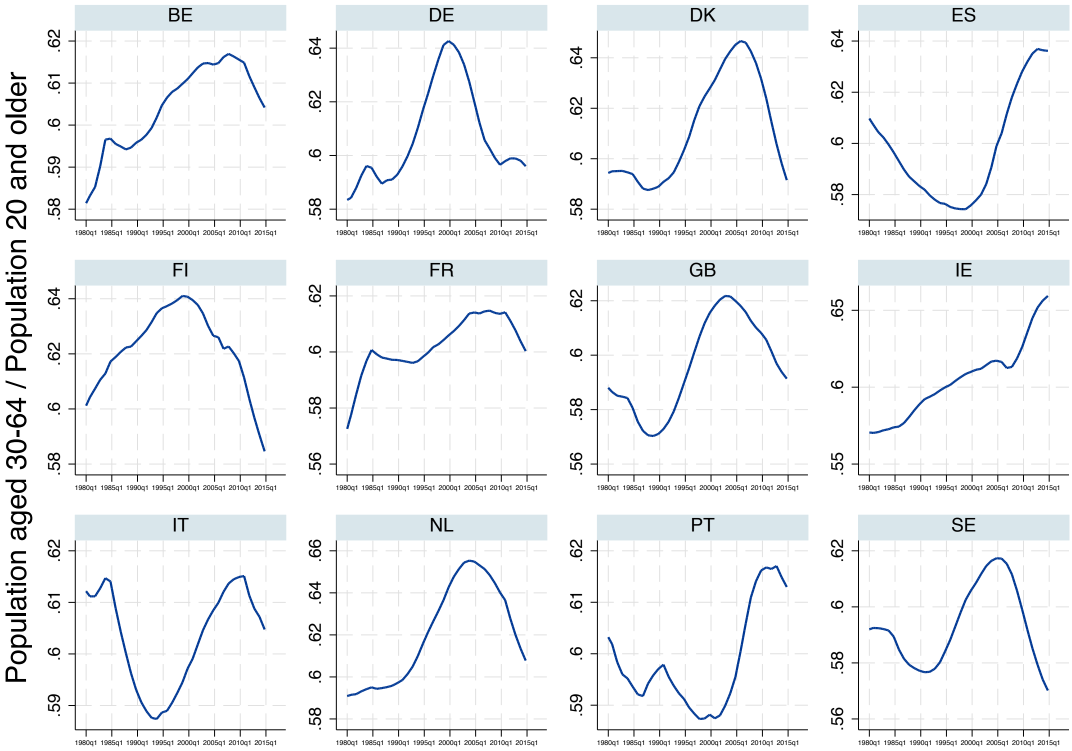
Sources: See Table B1 in Appendix B.

Figure A4: Real potential GDP per capita across countries



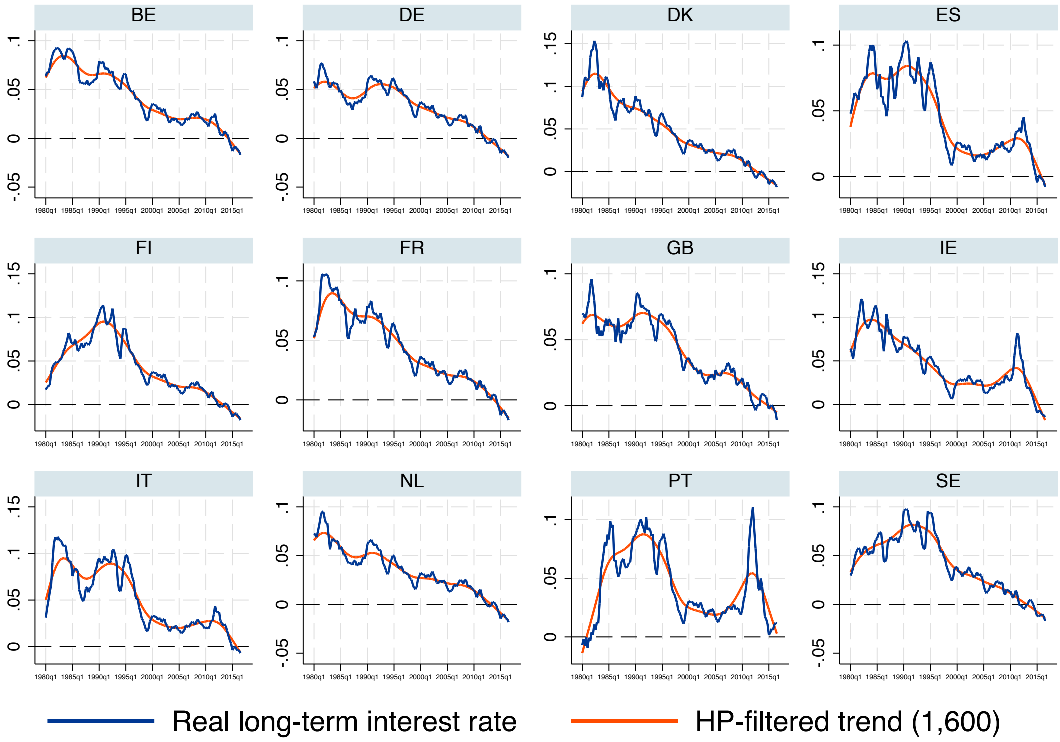
Sources: See Table B1 in Appendix B.

Figure A5: Population ratio (30-64 / 20 and older) across countries



Sources: See Table B1 in Appendix B.

Figure A6: Real long-term interest rates across countries



Sources: See Table B1 in Appendix B.

Appendix B: Additional tables

Table B1: Overview of variables and data sources

Variable	Data source	Backcasting
Household credit	Eurostat Quarterly Sectoral Accounts	BIS long credit series
Consumer price index	OECD Main Economic Indicators	N/A
10-year bond yield	ECB, BIS	N/A
Real potential GDP	European Commission AMECO	N/A
Total population	European Commission AMECO	N/A
Age cohort data	Eurostat	N/A
HH debt micro data	Household Finance and Consumption Survey	N/A

Notes: Annual data is linearly interpolated to arrive at a quarterly frequency.

Table B2: Overview of different model specifications across countries

	Baseline			Model 2			Model 3			Model 4		
	dem	x_0	k	dem	x_0	k	dem	x_0	k	dem	x_0	k
BE	20 - 59	15	0.15	30 - 64	30*	0.20	20 - 64	30*	0.20	20 - 69	15	0.15
DE	20 - 69	15	0.45	25 - 54	15	0.40	25 - 54	15	0.40	20 - 69	20*	0.15
DK	25 - 69	20	0.15	30 - 64	30*	0.20	35 - 69	30*	0.20	35 - 59	15	0.30
ES	25 - 64	20	0.20	30 - 64	30*	0.20	35 - 59	30*	0.20	20 - 59	30*	0.20
FI	25 - 69	30*	0.20	30 - 64	30*	0.20	25 - 69	30*	0.20	35 - 69	15	0.40
FR	20 - 64	20	0.15	30 - 64	30*	0.20	35 - 64	30*	0.20	35 - 64	15	0.40
GB	20 - 64	20	0.30	30 - 64	30*	0.20	35 - 54	30*	0.20	20 - 64	20	0.35
IE	30 - 59	15	0.15	30 - 64	30*	0.20	25 - 64	30*	0.20	20 - 59	15	0.20
IT	25 - 69	35*	0.15	30 - 64	30*	0.20	35 - 54	30*	0.20	30 - 59	20	0.25
NL	25 - 74	20	0.15	30 - 64	30*	0.20	35 - 64	30*	0.20	25 - 74	20	0.15
PT	25 - 59	35*	0.20	30 - 64	30*	0.20	35 - 54	30*	0.20	25 - 59	35*	0.20
SE	25 - 74	15	0.15	30 - 64	30*	0.20	35 - 74	30*	0.20	20 - 74	35*	0.15

Notes: All of the population ratios dem are defined relative to the population aged 20 and older. The parameters x_0 and k for the non-linear transformation are applied to real potential GDP per capita measured in 1000 EUR at 2010 prices. Whenever the parameter x_0 is marked with a * the non-linear transformation is applied to real potential GDP per person aged 20-64 measured in 1000 EUR at 2010 prices.

Table B3: Robustness of early warning properties

	Baseline gaps	Model 2 gaps	Model 3 gaps	Model 4 gaps
Pooled results				
AUROC 16-9q	0.80	0.83	0.83	0.79
AUROC 12-5q	0.90	0.92	0.91	0.90
AUROC 8-1q	0.90	0.90	0.90	0.89
AUROC 4-1q	0.90	0.90	0.90	0.89
Pseudo R2 12-5q	0.39	0.39	0.38	0.35
Observations	1,204	1,204	1,204	1,204
Country results 12-5 quarters				
AUROC BE	-	-	-	-
AUROC DE	0.99	0.99	0.99	1.00
AUROC DK	0.94	0.93	0.95	0.80
AUROC ES	1.00	1.00	1.00	1.00
AUROC FI	0.99	0.99	0.99	0.88
AUROC FR	0.78	0.83	0.83	0.74
AUROC GB	1.00	0.99	0.99	0.99
AUROC IE	1.00	0.98	0.98	1.00
AUROC IT	1.00	1.00	1.00	1.00
AUROC NL	1.00	1.00	1.00	1.00
AUROC PT	0.70	0.90	0.89	0.90
AUROC SE	1.00	1.00	1.00	1.00
Average AUROC	0.95	0.97	0.97	0.94

Notes: Details on the country-specific model specifications are given in Table B2. See notes to Table 3 for details regarding the early warning exercise.