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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 that depends on four fundamental economic factors: real potential GDP, the equilibrium real interest rate, the population share of the middle-aged cohort, and institutional quality. 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 35 years yield long credit cycles that last between 15 and 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, especially because they allow for economic interpretation of observed credit developments.

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

JEL classification: E32, E51, E21, G01, D15

Non-Technical Summary

This paper proposes a theory-based approach to identifying excessive household credit developments. In a first step, we derive an equilibrium relationship for the trend level of real household credit using a structural economic model that takes into account household heterogeneity and borrowing constraints. The structural model implies that the equilibrium real household credit stock is driven by the following four fundamental economic factors: real potential GDP, the equilibrium real interest rate, the population share of the middle-aged cohort, and the level of institutional quality. In a second step, the theory-based household credit gaps are derived as deviations of the observed household credit stock from the credit trend.

We estimate the theory-based household credit gaps in a model that is similar to an unobserved components framework 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, we also contribute to a better understanding of the interaction between financial cycles and business cycles.

Without imposing a priori information on the cycle length, the estimated credit gaps display long cycles that last between 15 to 25 years. In addition, the estimated credit cycles display substantial amplitudes at the country level, suggesting that the observed household credit stock can deviate 20% from the level that would be justified by fundamental economic factors. The estimated theory-based household credit gaps tend to increase many years ahead of systemic financial crises and they possess superior early warning properties compared 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.

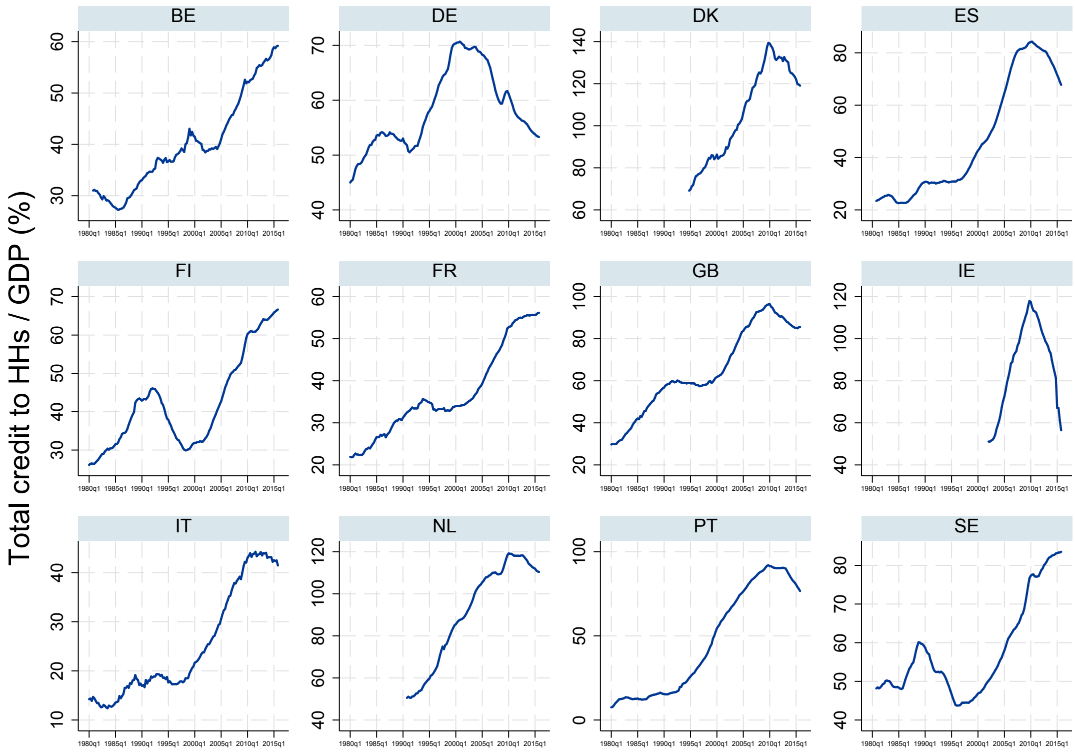
The empirical properties of the estimated credit gaps are appealing. The gaps do not display excessively long periods of high positive values, which can be the case with purely statistical credit gaps especially during periods of economic transition. In addition, they do not tend to fall to as large negative values in the aftermath of financial booms and/or crises as 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.

The estimated credit gaps based on theory are useful for countercyclical macroprudential policy for the following reasons: first, the trend component has a normative economic interpretation as it is determined by fundamental economic factors. This is a clear advantage relative to a purely statistical trend, which can only be a heuristic interpretation of a normative concept. Second, understanding the driving factors of credit gaps, e.g. via the decomposition technique proposed in the paper helps informing policy makers in the selection of the most appropriate mix of macroprudential instruments.

1 Introduction

Excessive credit growth and leverage have been 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, as leverage and credit growth can vary substantially across countries and time. This can be illustrated through developments in the household credit-to-GDP ratio, a commonly used measure of leverage, as shown in Figure 1 for 12 EU countries over the last 35 years.

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



Sources: Bank for International Settlement, ECB, Eurostat, see also Table B1 in Appendix B.

Oftentimes household credit-to-GDP ratios have trended upwards for a long time after which they turned down 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 institutional reforms. For example, it could be argued

[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.

that the long phases of credit growth rates exceeding GDP growth rates in Ireland and Spain were in part justified by the economic development in these countries, but at some point credit developments became unsustainable.

This paper attempts to address such questions through a theory-based approach to identifying excessive household credit developments. In a first step, we derive a model-based equilibrium-relationship for the level of household credit that depends on economic fundamentals. In particular, an adjusted version of the overlapping generations model by Eggertsson et al. (2017) is used to derive an equation for the trend of the household credit stock that depends on real potential GDP, the equilibrium real interest rate, the population share of the middle-aged cohort, and the level of institutional quality. In a second step, semi-structural household credit gaps are derived as deviations of the observed household credit stock from the credit trend that is determined by these fundamental economic factors.

The resulting semi-structural household credit gap model is estimated in the spirit of an unobserved components system for the 12 EU countries shown in Figure 1 for the period 1980 - 2015. Our estimation strategy that incorporates information from economic theory builds on existing empirical frameworks for estimating potential GDP and the equilibrium real interest rate and the respective gaps (Blagrave et al., 2015; Clark, 1987; Holston et al., 2016; Laubach and Williams, 2003; Mésonnier and Renne, 2007). However, our approach differs from these unobserved components models as we use data on economic fundamental factors for estimating the trend component. 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 (Glick and Lansing, 2010; International Monetary Fund, 2012; Mian and Sufi, 2014; Mian et al., 2015).

We estimate long cycles for household credit that last between 15 and 25 years without imposing any ex-ante restrictions on the frequency of the cyclical component as is often done in statistical approaches.[3] In addition, the amplitude of the estimated semi-structural household credit 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 slowly afterwards. The estimated credit gaps' early warning signalling power for financial crises is superior to that of the purely statistical Basel total credit-to-GDP gap and a Basel-type household credit-to-GDP gap. Our semi-

[3]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.

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.[4] In addition, our credit gaps have decreased much less than the standardised Basel credit-to-GDP gaps since the onset of the global financial crisis.

Since we spell out the economic driving factors of the household credit trend, the proposed framework allows to attach economic interpretation to the estimated credit gaps. This is a major advantage compared to purely statistical credit gaps like the Basel total credit-to-GDP gap, where the trend is computed based on a statistical smoothing method. Our framework implies that household credit gaps are driven up by real household credit growth and driven down by increases in the factors that push up the real household credit trend, namely the level of institutional quality, real potential GDP, the population share of the middle-aged cohort, and reductions in the equilibrium real interest rate. Such a decomposition of changes in credit gaps can be useful in a policy context as it allows determining at each point in time whether credit growth is higher than justified by changes in underlying economic fundamentals. It also helps telling which particular changes in economic fundamentals justify a given level of credit growth.

Many existing empirical papers rely on purely statistical methods for finding normative benchmarks for credit, e.g. by removing smooth and persistent statistical trends (see e.g. Aikman et al., 2015; Basel Committee on Banking Supervision, 2010; Borio and Lowe, 2002; Drehmann et al., 2011; 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 well 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 the a priori assumed persistent trend will remain at its inflated level for a long time. Indeed, at the end of 2015 large negative credit-to-GDP gaps were 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.[5] The

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

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

statistical methods themselves have also been criticised on methodological grounds e.g. by Hamilton (2017) and van Norden and Wildi (2015).

There are a few papers that try to measure equilibrium credit with a more structural approach, usually in a co-integration framework, but none of the approaches is fully convincing so far.[6] 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 in the long-term co-integration relationship, although these variables themselves should be affected by credit booms. This can be problematic and may lead to underestimation of credit excesses, if the co-integration system does not feature an additional mechanism that pulls all variables back to their long-run equilibrium. For example, given that house prices can be assumed to be endogenous to the excessive credit boom, a co-integration relationship that uses observed house prices as an explanatory variable could underestimate deviations of credit from equilibrium, as inflated house prices would push up the credit trend. To mitigate this potential issue, our proposed framework uses equilibrium concepts of the explanatory variables that are less susceptible to the impact of excessive credit growth.

Our paper connects to various strands of the theoretical and empirical literature. On the theoretical side we relate to the literature on secular stagnation (Eggertsson et al., 2017), exogenous borrowing constraints (Aiyagari, 1994; Kiyotaki and Moore, 1997), endogenous borrowing constraints due to limited commitment and enforcement in debt contracts (Alvarez and Jermann, 2000; Kehoe and Levine, 1993; Kocherlakota, 1996), and the role of institutions for economic and financial development (Acemoglu et al., 2005). On the empirical side we contribute to the literature on equilibrium credit estimation (Albuquerque et al., 2015; Buncic and Melecky, 2014; Cottarelli et al., 2005; Juselius and Drehmann, 2015) and the still nascent literature on financial cycles (Rünstler and Vlekke, 2018; Schüler et al., 2015). We also add 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 the context of early warning models (see 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 (Blagrave et al., 2015; Clark, 1987) and the equilibrium real interest rate (e.g. Hamilton et al., 2015; Holston et al., 2016; Laubach and Williams, 2003) in an unobserved components setting.

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

The remainder of the paper is structured as follows. In Section 2 we use an overlapping generations model to derive a simple structural equation for the trend of household credit. Section 3 introduces our empirical modeling framework. Section 4 describes the dataset, while Section 5 presents the baseline estimation results for the semi-structural household credit gaps. Additional robustness analyses are discussed in Section 6. Finally, 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 et al. (2017)[7] 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 as they affect life cycle borrowing and saving patterns. 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 et al. (2017) consists of an endowment economy with overlapping generations, where households go through three stages of life:[8] 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 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 et al. (2017) also incorporate a simple form of income inequality by assuming that a certain fraction of middle-aged households remain credit constrained because of low income. Therefore they need to borrow.

[7]An earlier version of the paper was circulated as Eggertsson and Mehrotra (2014).

[8]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.

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:[9]

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

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 et al. (2017) 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[10] has shown that limited commitment or limited contract enforcement provide microfoundations 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 rather than the observed asset price. This however, would greatly complicate the endeavour to determine the trend of household credit empirically. For the remainder of the paper we therefore assume a borrowing constraint where the 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

[9] Let the (binding) borrowing constraint be $(1+r_t)B_t^i = D_t$. Aggregate credit demand C_t^d 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.

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

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 deductibility 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.

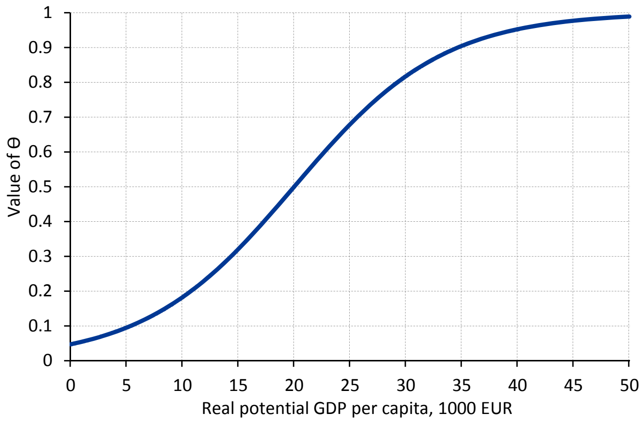
For tractability, we assume that there is a non-linear relationship between institutional quality and the tightness of the borrowing constraint. A non-linear relationship can be motivated by the fact that a household's borrowing capacity in terms of expected future income should be bounded below at zero 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:[11]

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

Figure 2 illustrates an example of this non-linear S-curve mapping from an institutional quality proxy into the tightness of the borrowing constraint. For low levels of institutional quality, maximum borrowing relative to future expected income is close to zero. As the level of institutional quality rises, an increasing share of future expected income can be borrowed by households. Such higher borrowing could for example be justified by better contract enforcement. Once a certain saturation level is reached, further increases in institutional quality do not lead to further increases in households' borrowing capacity relative to future expected income.

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

Figure 2: Mapping from institutional quality proxy into the tightness of the borrowing constraint



Notes: The S-curve is drawn for parameters $\bar{\Theta} = 1$, $x_0 = 20$, and $k = 0.15$. Real potential GDP per capita is used as a proxy for institutional quality in the chart, as this variable is highly correlated with measures of institutional quality both across countries and across time for a given country, as shown in Figure 3 further below in Section 4.

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:

$$\begin{aligned} ln(C_t^{d*}) &= ln\left(1+\frac{\eta}{1+g_t}\right)+ln\left(\frac{1}{1+e^{-k(IQ_t-x_0)}}\right)+ \\ & \quad ln(N_t)+ln(\mathbb{E}_t[Y_{t+1}^{hh}])+ln(\bar{\Theta})-ln(1+r_t^*) \end{aligned} \tag{4}$$

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. $Y_t^{hh} = \lambda_t Y_t / P_t$) and that the logarithm of aggregate GDP follows a local linear trend model with an AR(2) cyclical component.[12] Although the assumption of equally distributed income across households is not fully consistent with the structural model and clearly not realistic, it is a

[12] 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; Laubach and Williams, 2003). The local linear trend AR(2)-model for the natural logarithm of output can be written as:

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

where y_t^* is potential GDP, $\hat{y}_t$ the output gap and d_t the trend growth rate of potential GDP.

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:

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

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^*).[13] 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.

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 modelled explicitly with fundamental economic factors as derived in Section 2 and the real household credit cycle is modelled as a residual statistical process. For this purpose, a simplified version of the theory-based trend equation (5) for real household credit is used.

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 modelled to be driven by four factors: the logarithm of real potential GDP (y_t^*), the equilibrium real interest rate

[13] 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.

(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.[14] 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 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. Second, long time series for household disposable income are not available for all of the EU countries that we study. The intercept term α_0 in the empirical trend equation will therefore capture the effect of four constant terms from the theoretical trend equation: $\frac{\sigma^2_{\epsilon^*}}{2}, \frac{\sigma^2_{\hat{\epsilon}}}{2}, ln(\lambda), ln(\bar{\Theta})$.

The household credit trend equation that we employ in our framework is similar in spirit to the one used by Castro et al. (2016) for total credit. However, our approach differs from their model in important dimensions. First, we model the credit stock instead of the credit-to-GDP ratio. Second, we use an equilibrium real interest rate measure instead of the nominal interest rate. Third,

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

we use a non-linear transformation of potential GDP per capita instead of the simple ratio of GDP per capita. Fourth, we add a population ratio to the list of explanatory variables and we explicitly model the dynamics of the credit cycle instead of assuming i.i.d. errors. Finally, we calibrate some parameter values based on economic theory which eases estimation of country-specific model parameters, whereas Castro et al. (2016) assume constant parameters across countries and estimate a panel model.

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.

4 Data and descriptive statistics

For the estimation of the model in equations (6) to (8) we use quarterly data for 12 EU countries spanning the period from 1980 to 2015. The countries are Belgium, Denmark, Finland, France, Germany, Ireland, Italy, The Netherlands, Portugal, Spain, Sweden, and the UK. The data for estimation 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 across the 12 EU countries 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.[15] 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.[16] 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 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, 2017). For Denmark, Sweden and 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 hold more than 1.5% of total household credit. The population aged 20 and older is taken as the relevant group of people that receive some form of income, i.e. this population group is used as the denominator of the population ratio.

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

[16] 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.

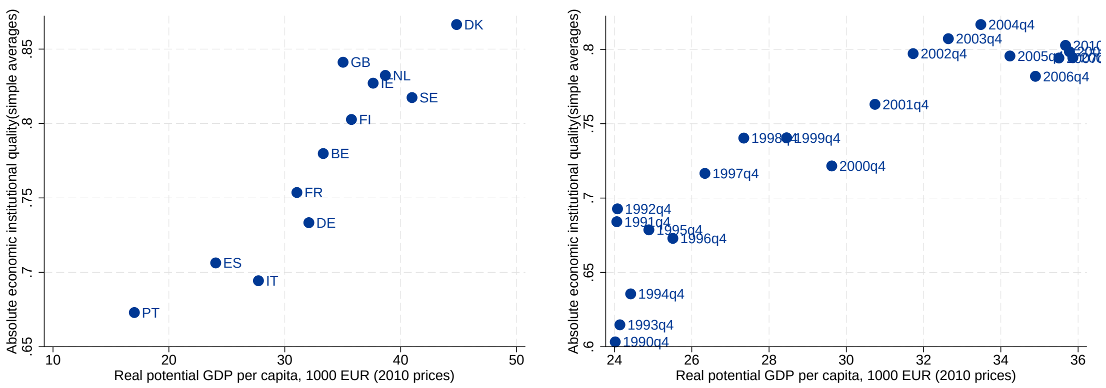
Table 1: Proxy shares of aggregate household debt held across different age cohorts

age cohort	**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 Network (2017); 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 of 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 3: 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.

As it is not possible to obtain long time series for variables that capture the institutional quality of a country[17] we need to resort to a proxy variable. Since good institutions should increase the

[17]Many datasets that provide time series on institutional quality, such as the World Bank's Doing Business database, only start in the 2000s.

productive potential of an economy (see e.g. Acemoglu et al., 2005), we opt for real potential GDP per capita as our proxy variable. For our purposes we only need such a proxy variable as we are not interested in the causal relationship between institutional quality and economic development. Therefore, it is sufficient that real potential GDP per capita exhibits a high positive correlation with measures of institutional quality both across countries and across time, which is shown in Figure 3.

5 Estimates of semi-structural credit gaps

We estimate the semi-structural household credit gap model in a state-space set-up by means of maximum likelihood, where the Kalman filter is used to compute the likelihood function. This flexible estimation approach facilitates the incorporation of insights from economic theory, at least in a semi-structural manner: the approach is adapted from 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 equilibrium real interest rates (Holston et al., 2016; Laubach and Williams, 2003; Mésonnier and Renne, 2007). The novelty of our approach is that we explicitly model the trend component to be driven by fundamental economic factors that embed an interpretation of the long-run equilibrium, such as potential output and the equilibrium real interest rate. In the existing literature trends are usually assumed to follow stochastic trends.

Our estimation strategy proceeds in three steps. First, we calibrate a number of model coefficients based on the parameter values that are implied by the theoretical model derived in Section 2. Second, we use a first-step regression approach to estimate the parameters of the non-linear transformation of institutional quality, as these cannot be estimated in a linear state space set-up. Third, we estimate the remaining parameters of the model in a linear state space set-up with the Kalman filter and classical maximum likelihood.

Regarding the group of calibrated parameters, we make explicit use of some parameter restrictions that are implied by the structural economic model derived in Section 2. In particular, 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, as implied by theory. The unit coefficient for real potential GDP is intuitive: if two economies are equal in every aspect, except that one is a clone of the other at twice the size, the equilibrium credit-to-potential GDP ratio should be the same, i.e. the coefficient should be one. The unit coefficient for the non-linear transformation of institutional quality can also be justified by logical reasoning: given that the fraction of future expected income that can be borrowed (Θ) enters the household credit trend equation in logs, the scaling parameter ($\bar{\theta}$) and the S-curve transformation of institutional quality (γ_t) show up as separate terms with unit coefficients. As the scaling parameter $\bar{\theta}$ is time-invariant, it will be captured by the estimated constant term in the trend equation α_0. 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, as implied by the structural model. This unit coefficient 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 (the young/middle-aged). In Section 6 this assumption is relaxed and the coefficient for the demographic variable is estimated alongside the other remaining coefficients.

The parameters for the transformation of the institutional quality proxy γ_t need to be estimated outside of the linear state space system, due to the modeled non-linearity. We choose the two parameters x_0, a location parameter, and k, a slope parameter, with the following algorithm. 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 described in the previous section. 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).[18] We then select the country-specific model specifications that yield the lowest root mean squared error for each country.[19] Table 2 provides an overview of the relevant population age shares and the estimated parameters for the non-linear transformation of the institutional quality proxy for all twelve EU countries for which the model is implemented. In Section 6 we show that the baseline results are qualitatively robust to using a common age share and non-linear transformation of the institutional quality proxy across all twelve countries.

[18]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.

[19]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.

Table 2: Overview of age shares and pre-estimated parameters

Country	dem	x_0	k
BE	20 - 59	15	0.15
DE	20 - 69	15	0.45
DK	25 - 69	20	0.15
ES	25 - 64	20	0.20
FI	25 - 69	30*	0.20
FR	20 - 64	20	0.15
GB	20 - 64	20	0.30
IE	30 - 59	15	0.15
IT	25 - 69	35*	0.15
NL	25 - 74	20	0.15
PT	25 - 59	35*	0.20
SE	25 - 74	15	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.

The remaining parameters that need to be estimated are the intercept term, the coefficient for the equilibrium real interest rate, the standard deviation of transitory shocks in the credit trend equation (7), as well as the two autoregressive coefficients and the shock standard deviation of the cyclical household credit component in equation (8). These estimates are discussed in more detail in the following paragraphs.

5.1 Baseline estimation results for EU countries

Table 3 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.

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

Table 3: Coefficient estimates for the baseline household credit gap model

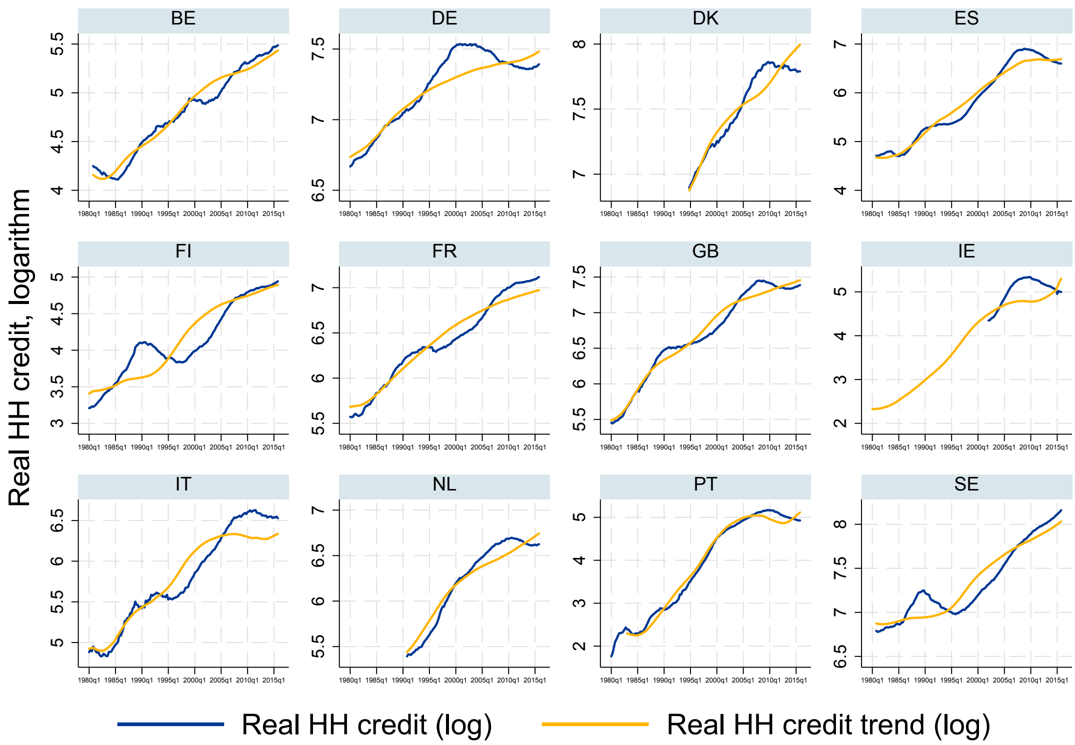
	(1) BE	(2) DE	(3) DK	(4) ES	(5) FI	(6) FR	(7) GB	(8) IE	(9) IT	(10) NL	(11) PT	(12) SE
CREDIT TREND												
Real interest rate	-5.121***	-0.845	-11.786***	-1.436	-2.356	-2.497*	-5.288***	-3.654	-4.987***	-8.828**	-6.310***	-4.874***
	(0.948)	(1.550)	(1.586)	(1.837)	(3.035)	(1.441)	(1.193)	(2.895)	(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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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.

Figure 4 illustrates the evolution of the estimated household credit trends. In all of the countries, both the observed real household credit stock as well as the fundamental household credit trend have increased considerably over the last 35 years. For example, in Portugal and Ireland the fundamentally justified household credit stock has increased by around 300% (increase by 3 on a log scale). In Spain and the UK it has increased by around 200%, while in Belgium, Denmark, Finland, France, Italy, The Netherlands, and Sweden it has increased between 100% and 150%. Figure 4 further shows that in all twelve countries, deviations of the observed real household credit stock from the fundamentally justified trend can be sizeable and that they tend to be highly persistent.

Figure 4: Real HH credit stock and estimated fundamental trend level



Notes: The household credit trend estimate is obtained from the baseline model specification. HH credit data for IE before 2002 is not available from official statistics. The back-casted HH credit series for IE is confidential and cannot be shown here.

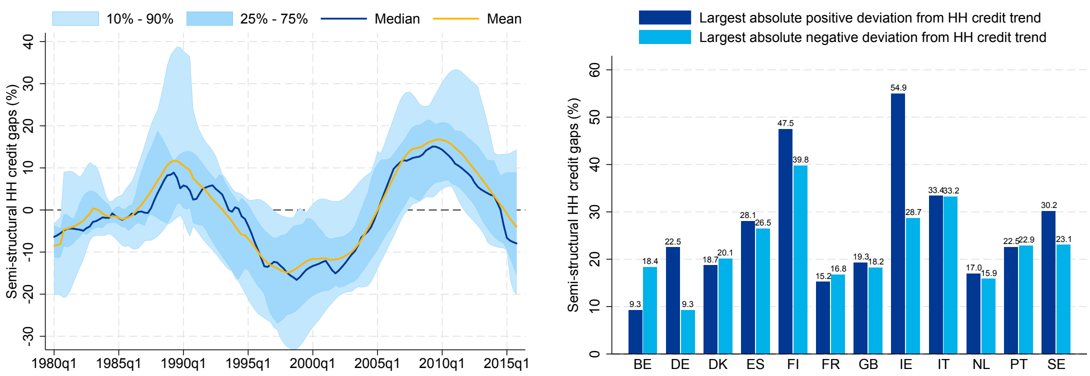
Table 3 shows that the estimated coefficients of the household credit gap equation are all statistically significant at the 1% level and imply stationary processes for the household credit gaps. For all twelve EU countries, the AR(1) coefficients are between 1.71 and 1.96, while the AR(2) coefficients are between -0.72 and -0.97. The two AR coefficients always sum to just below unity, which implies stationary cycles with complex roots that are highly persistent. The standard deviation of shocks to the household credit gaps ranges between 0.4% and 0.8% in most of the countries. 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 the semi-structural household credit model produce fairly long cycles for household credit gaps. This property can be seen from Panel (a) of Figure 5, which plots the cross-country distribution of household credit gaps over the last 35 years. The estimated house-

Figure 5: 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 1981q1 to 2014q4.

hold credit cycles have an average length of around 20 years across the 12 EU countries. At the country level the cycle length 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 Sweden, as shown in Figure 6.

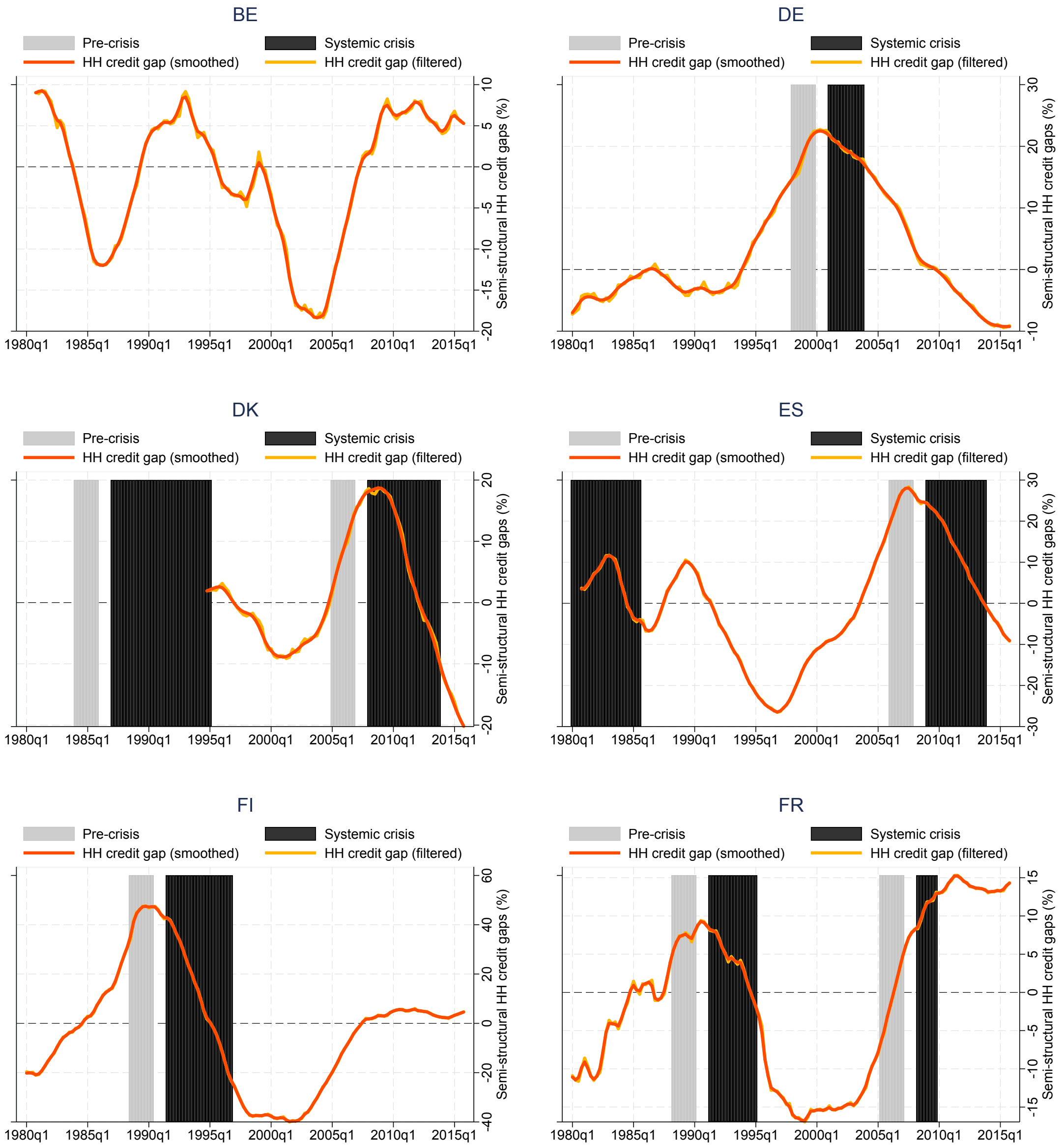
This feature of long cycles for household credit gaps is in line with the literature on financial cycles that has found long cycles for total credit and real estate prices based on statistical filters.[20] In contrast to purely statistical approaches, no ex-ante restrictions are imposed on the properties 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 from the credit trend.

In addition to long cycle lengths, we estimate substantial boom and bust episodes for household credit across the 12 EU countries over the past 35 years. The amplitudes of the semi-structural household credit gaps tend to range between +/- 15% and +/- 30% in most of the countries as shown in Panel (b) of Figure 5. 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.

Figures 6 and 7 further illustrate the properties of the semi-structural household credit gaps at the country level. 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 esti-

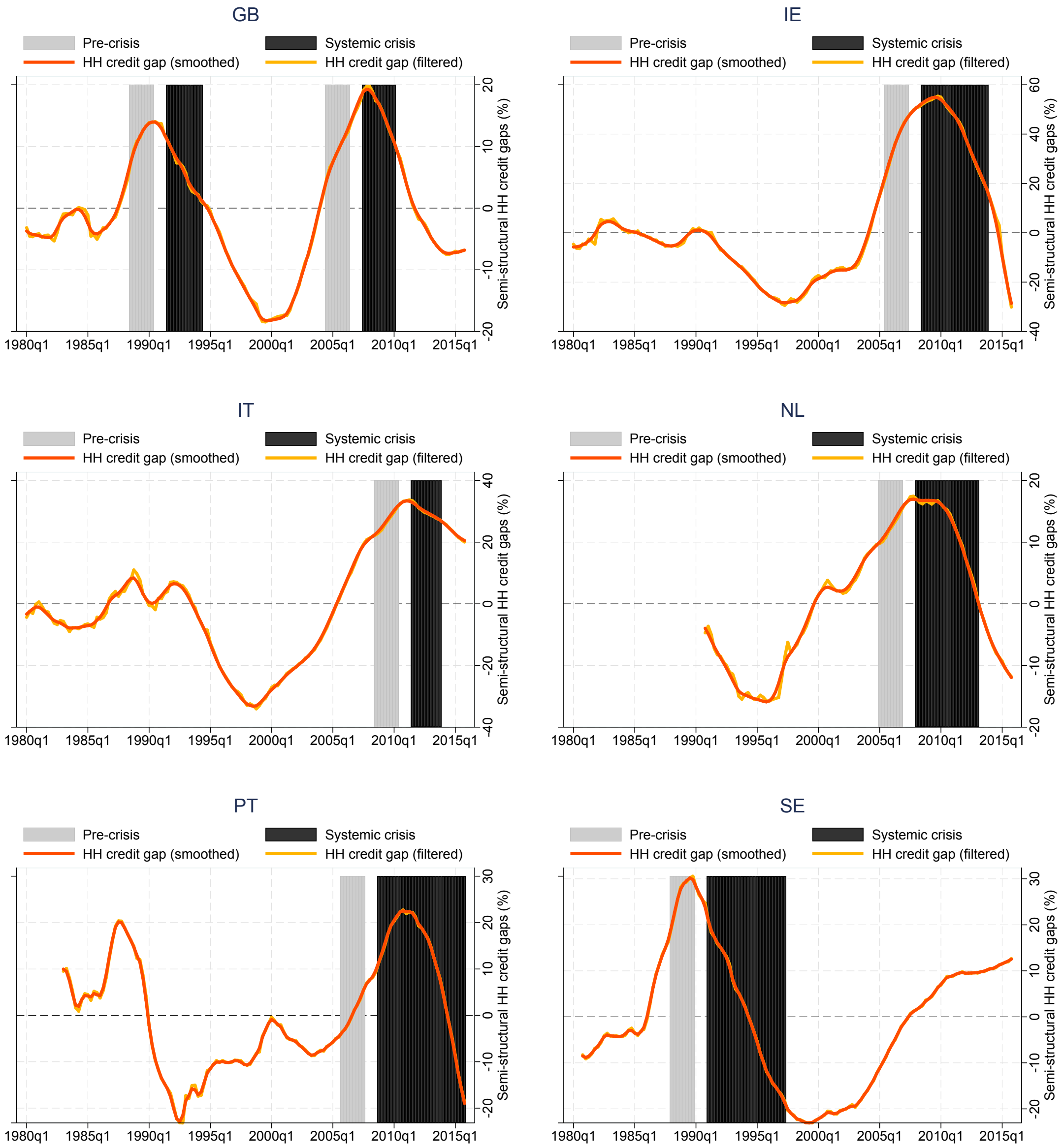
[20]See for example Drehmann et al. (2012) and Schüler et al. (2015).

Figure 6: 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 as in Lo Duca et al. (2017). The pre-crisis horizon is defined as 12 to 5 quarters prior to a systemic financial crisis.

Figure 7: 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 as in Lo Duca et al. (2017). The pre-crisis horizon is defined as 12 to 5 quarters prior to a systemic financial crisis.

mates 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. As 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 model 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. Figures 6 and 7 also show that the semi-structural household credit gaps tend to be positive and reach rather high levels prior to and at the start of systemic financial crises.

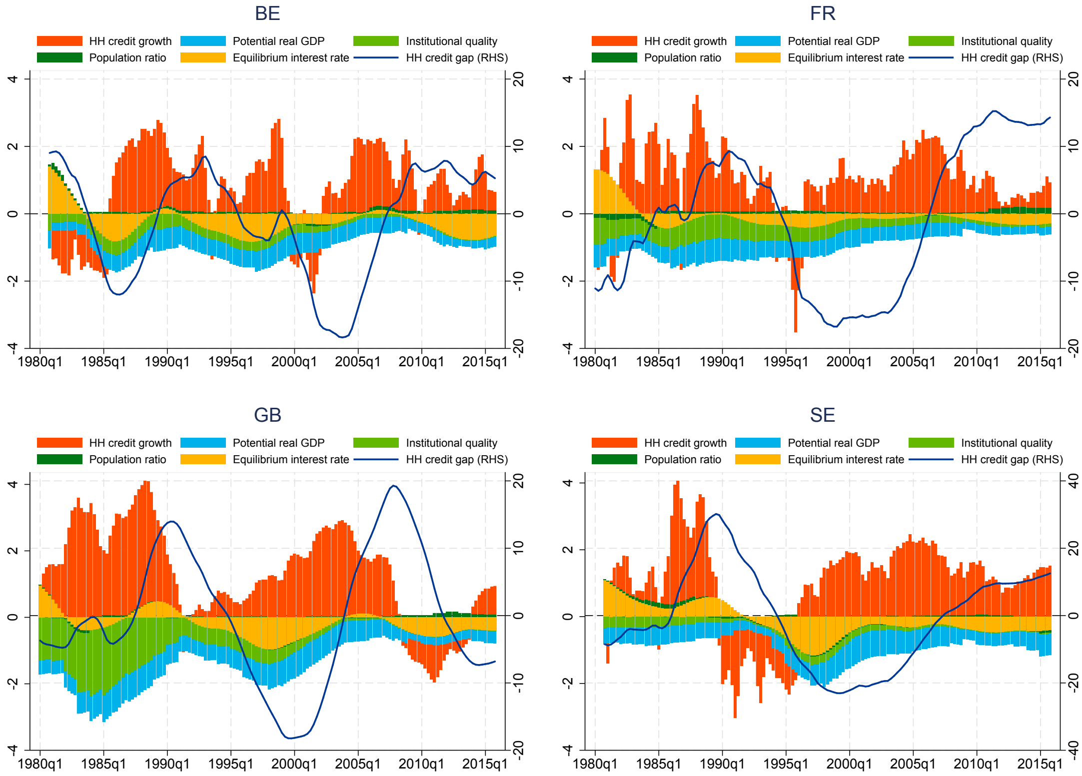
One of the main advantages of the semi-structural household credit gaps compared to gaps based on purely statistical filters is that they allow for economic interpretation. In particular, the trend equation allows to pin down the real household credit stock that is justified by the underlying fundamental economic factors, i.e. the level of institutional quality, real potential GDP, the equilibrium real interest rate and the demographic age structure. While this approach leaves the *level* of the household credit gaps as an unexplained statistical residual, the framework allows to decompose *changes* of the semi-structural household credit gaps into the underlying driving factors according to the following equation:

$$\Delta \hat{c}_t = \Delta c_t - \Delta \epsilon_t^{c^*} - \Delta y_t^* - \Delta \gamma_t - \alpha_1 \Delta r_t^* - \alpha_2 \Delta dem_t \tag{9}$$

In words, changes in the semi-structural household credit gaps are driven up by real household credit growth net of transitory shocks ($\Delta c_t - \Delta \epsilon_t^{c^*}$), and driven down by increases in the factors that push up the real household credit trend. Such decomposition of changes in credit gaps is useful as it allows to determine at each point in time whether credit growth is higher than justified by changes in underlying economic fundamentals, and which particular changes in economic fundamentals justify a given level of credit growth. This can help arriving at an economic narrative of credit developments and possible excesses. Figure 8 shows such a decomposition of the semi-structural household credit gaps for Belgium, France, the UK, and Sweden. Ceteris paribus, higher real household credit growth pushes up the credit gaps. However, the size of the gap can be dampened if the underlying fundamental economic drivers push up the real household credit trend at the same time.

For example, real household credit growth was fairly high in the UK at the beginning of the 1980s, but given that fundamental economic factors pushed the household credit trend strongly upward

Figure 8: Decomposition of changes in credit gaps into fundamental driving factors



Notes: Details on the country-specific model specifications underlying the different household credit gap estimates are contained in Table B2. The bars show the contributions of fundamental driving factors to changes in the semi-structural household credit gaps.

during this period, estimated credit gaps did not rise markedly. In particular, improvements in the institutional quality proxy, increases in real potential GDP, and reductions in the equilibrium real interest rate pushed up the real household credit trend in the UK during the early to mid 1980s, partly justifying high credit growth. Figure 8 also illustrates that very different household credit growth rates can be justified for a given country at different points in time. For example, in France there has been a gradual secular decline in the trend growth rate of real household credit that would be justified by changes in economic fundamentals. The declining negative bars since the mid 1980 illustrate this. In all four countries shown in Figure 8, declining estimates of the equilibrium real interest rate (yellow bars) have lead to increases in the fundamentally justified real household credit stock since the beginning of the 1990s.

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 various statistical transformations (e.g. changes, growth rates, or filtered cycles) of credit aggregates and asset prices have good early warning properties to signal financial crises.[21] We use a univariate signalling approach, which was originally applied by Kaminsky et al. (1998) in the context of currency crises, 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). There are 13 relevant crisis events in the sample across the 12 EU countries. As has become common practice in the early warning literature, we do not try to predict the beginning of a crisis but instead try to predict vulnerability periods prior to a crisis. In total, we test four different pre-crisis horizons: 16-9 quarters, 12 to 5 quarters, 8 to 1 quarters and 4 to 1 quarters prior to a crisis.[22]

Overall, 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 9. On average, the semi-structural household credit gaps turn positive more than four years prior to the start of a systemic financial crisis. Moreover, the credit gaps tend to increase continuously during the pre-crisis periods to reach on average levels of around +20% of the real household credit trend. 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. These dynamics indicate that the baseline semi-structural household credit gaps could be useful for identifying periods of excessive leverage building up in the household sector.

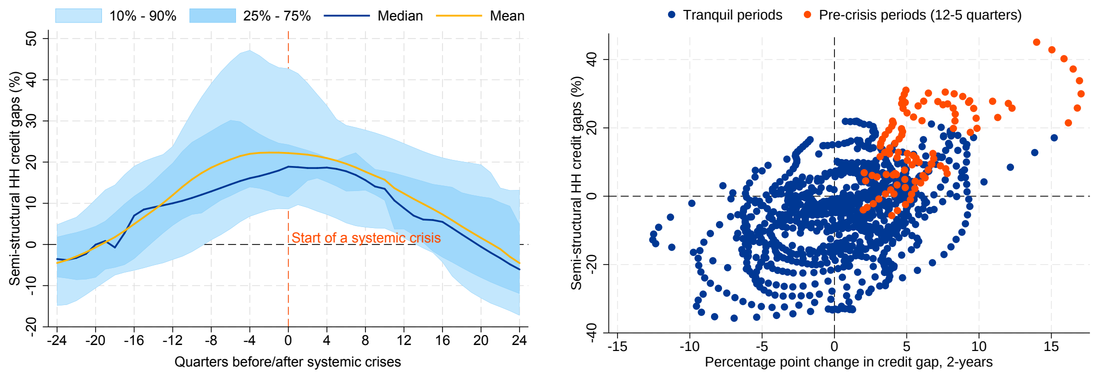
Panel (b) of Figure 9 demonstrates further that there seems to be information content in both the level and the change of the credit gaps. In the vast majority of cases, both the level and the 2-year change of the credit gaps display high positive values during the 12 to 5 quarters prior to systemic 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 not a vulnerable pre-crisis period, i.e. not likely to lead up to a systemic financial crisis over the next 12 to 5 quarters.

[21] 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).

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

Figure 9: 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.

Table 4 shows more formally that the semi-structural household credit gaps have very good early warning properties for systemic financial crises. The Area Under the Receiver Operating Characteristics Curve (AUROC),[23] which is a global measure of the early warning quality of an indicator, is 0.90 for pre-crisis prediction horizons of 12 to 5, 8 to 1, and 4 to 1 quarters. For a prediction horizon of 16 to 9 quarters the AUROC is 0.80. To put these numbers into perspective, the AUROC values for the Basel total credit-to-GDP gap,[24] which is usually considered as one of the best univariate signalling indicators for systemic financial crises,[25] are in the range of 0.72 to 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-

[23]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.

[24]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).

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

Table 4: 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-change 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 as 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.

to-GDP gap, the Basel bank 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 4). At the country-level the semi-structural household credit gaps also possess very good signalling properties. For a prediction horizon of 12 to 5 quarters eight of the countries attain an AUROC of 0.99 or 1.00. Only two countries have an AUROC of less than 0.8.

6 Robustness of semi-structural credit gaps

In this section we show robustness exercises with respect to some of the parameter calibrations, real vs. full sample estimation and a comparison to purely statistical filters and an unobserved components model where the trend follows a stochastic process.

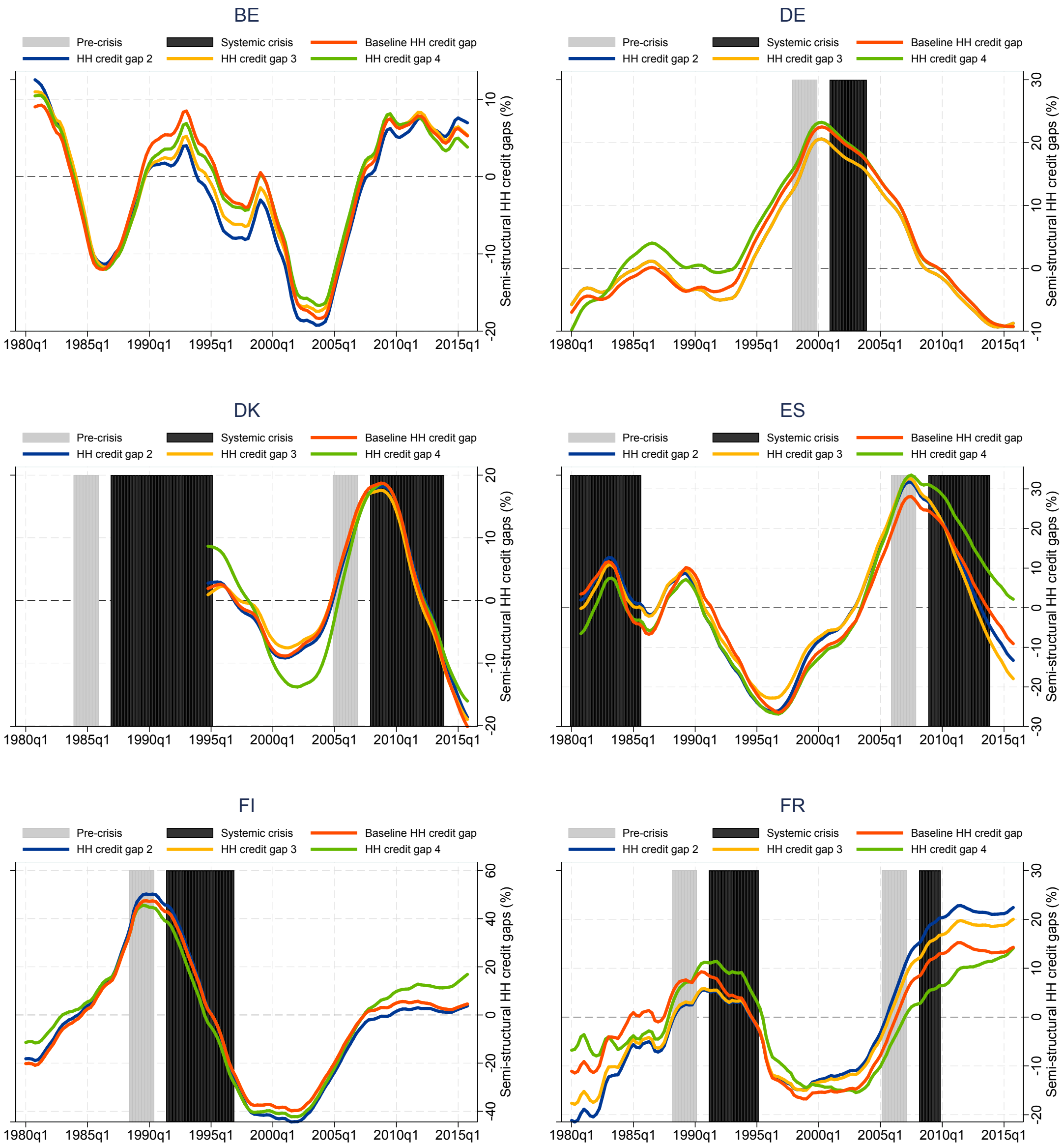
6.1 Robustness to model specification

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 10 and 11 show that the dynamics of the estimated household credit gaps are qualitatively robust to these 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.

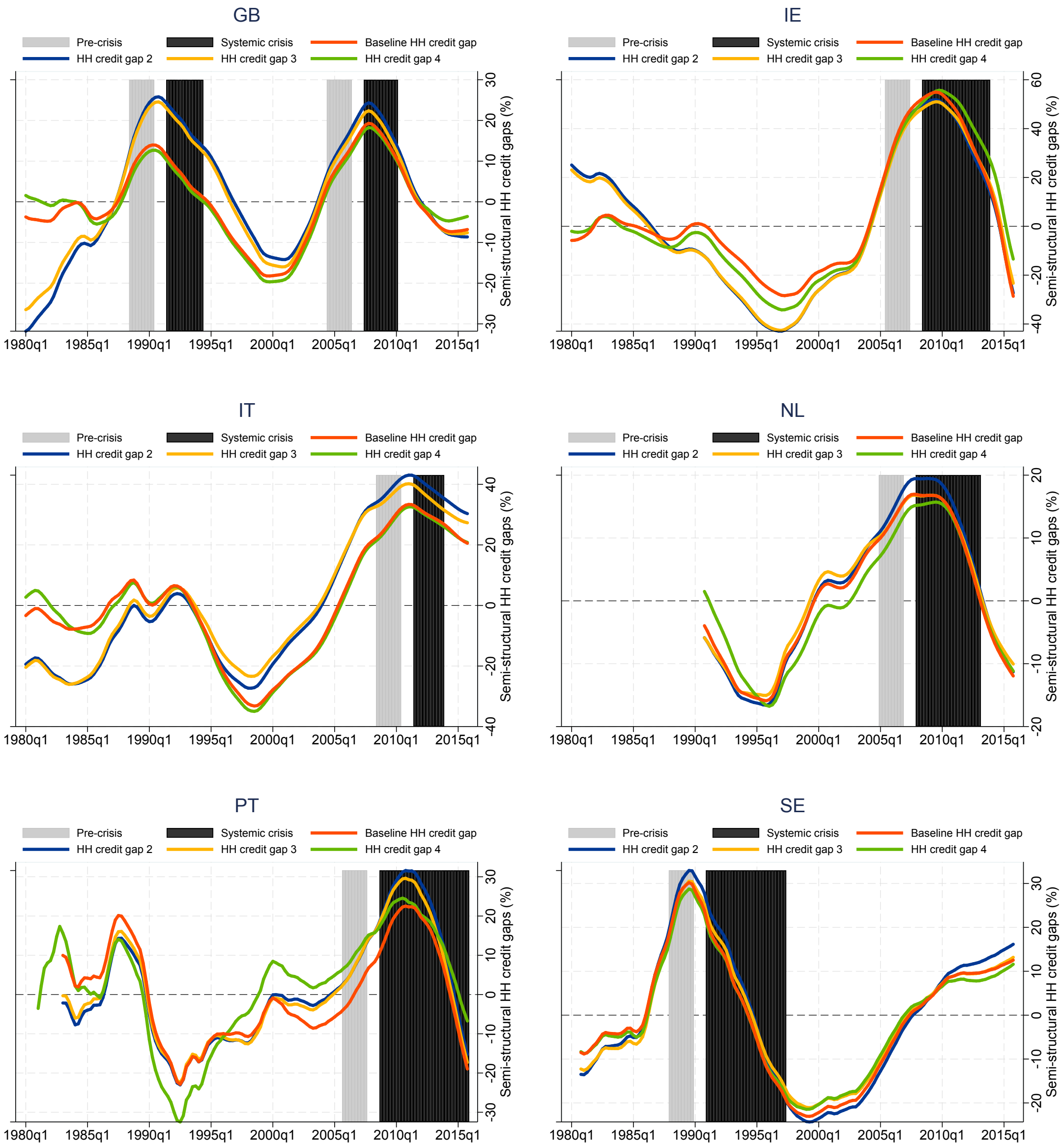
Table 5 further shows that the estimated coefficients for the equilibrium real interest rate are negative in all cases and rather stable across the different model specifications. The AR(2) coefficients of the credit gap equation are also fairly stable across the different model specifications and imply stationary statistical processes in all cases. Finally, for Model 4 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

Figure 10: 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 as in Lo Duca et al. (2017). The pre-crisis horizon is defined as 12 to 5 quarters prior to a systemic financial crisis.

Figure 11: 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 as in Lo Duca et al. (2017). The pre-crisis horizon is defined as 12 to 5 quarters prior to a systemic financial crisis.

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.

Table 5: Robustness of coefficient estimates for the household credit gap model

	(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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.2 Robustness to real-time estimation

To test the robustness of the model results to real-time estimation, we implement two adjustments to the baseline model estimation. First, we restrict the sample for estimation of coefficients to the period 1980 - 2004, so as to test the model performance ahead of the global financial crisis. Second, we use one-sided recursive HP-filtered trend estimates of the real interest rate and real GDP in order to mimic the real-time estimates of the equilibrium real interest rate and real potential GDP.[26] We keep the coefficients in the institutional quality transformation unchanged. Figures A6 and A7 in Appendix A show these quasi real-time estimates of the equilibrium real interest rate and real potential GDP in comparison to the full-sample estimates used for the baseline model estimation.

As shown in Figures 12 and 13 the dynamics of the semi-structural household credit gaps are qualitatively robust to real-time estimation. Hence, the model estimated in real-time would have indicated positive and increasing household credit gaps for most of the twelve EU countries ahead of the global financial crisis, similar to the gaps based on full sample information. However, for the majority of countries the real-time gap estimates are around 10 percentage points higher than the baseline full-sample gap estimates. The higher gap estimates based on the real-time model seem to be mainly related to the fact that the estimated interest rate semi-elasticities (see Table B4 in Appendix B) are lower than for the baseline model. Hence, for the benchmark pre-crisis horizon of 12-5 quarters false positive signals would have been somewhat higher for the real-time gaps and the AUROC somewhat lower at 0.86 compared to 0.90 for the baseline full-sample gaps. For a longer pre-crisis horizon of 16-5 quarters, the AUROC of the real-time gaps of 0.87 is only marginally lower compared to the AUROC of 0.88 for the baseline full-sample gaps.

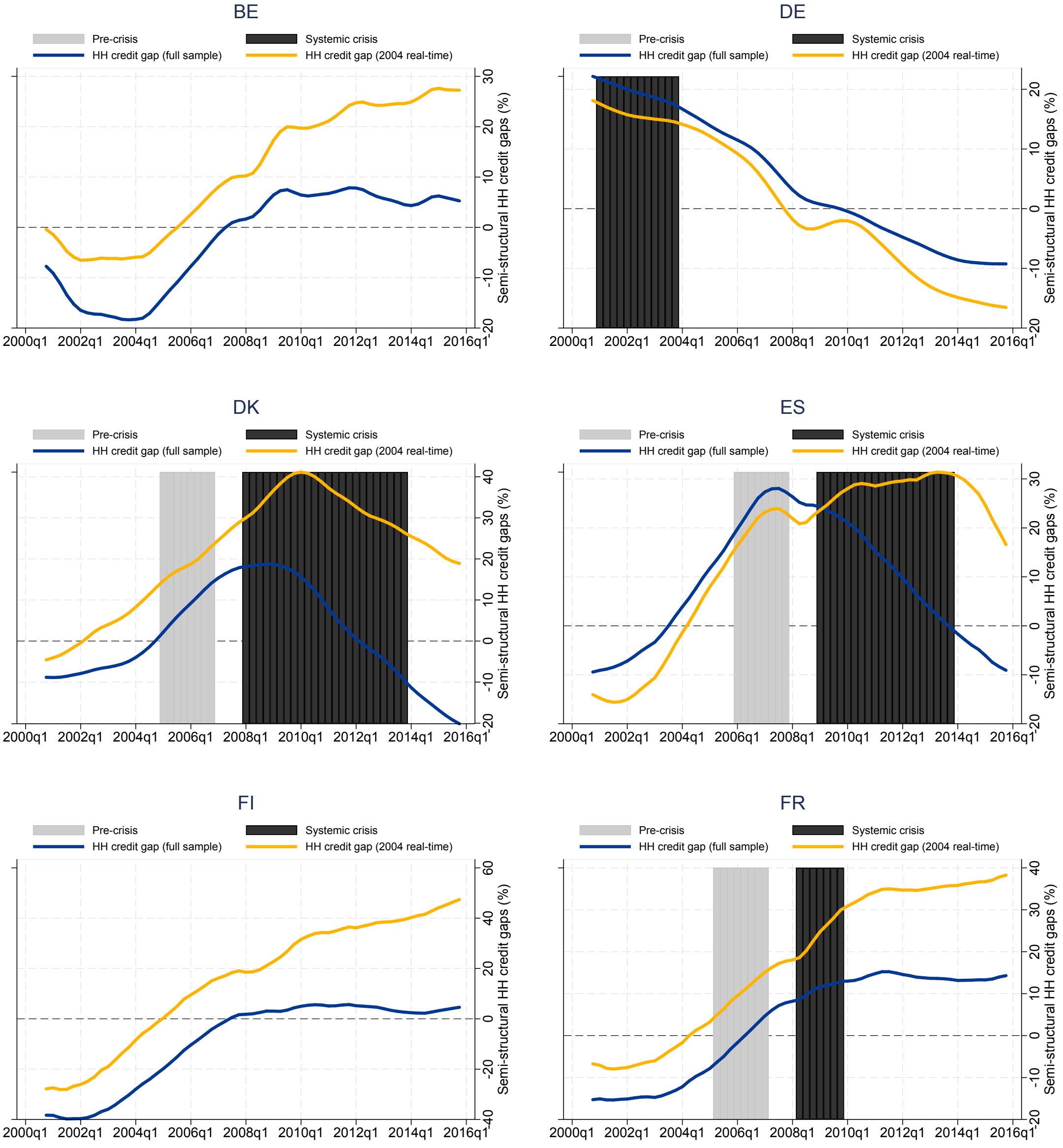
6.3 Comparison to statistical filters and an unobserved components model

We also compare the estimated baseline credit gaps to results from standard statistical filters and an unobserved components model.[27] First, we compute household credit gaps applying an HP-filter with smoothing parameter 400,000 as e.g. in the BCBS and ESRB guidance for the credit-to-GDP ratio. Applying such a smoothing parameter assumes a priori that credit cycles are about four times longer than business cycles, i.e. in the range of 25-30 years. Second, we implement the band-pass filter by Christiano and Fitzgerald (2003), which is another prominent statistical filtering method used e.g. in Aikman et al. (2015). These authors filter credit-to-GDP cycles between 8 and 30 years.

[26] A smoothing parameter of 1,600 is used.

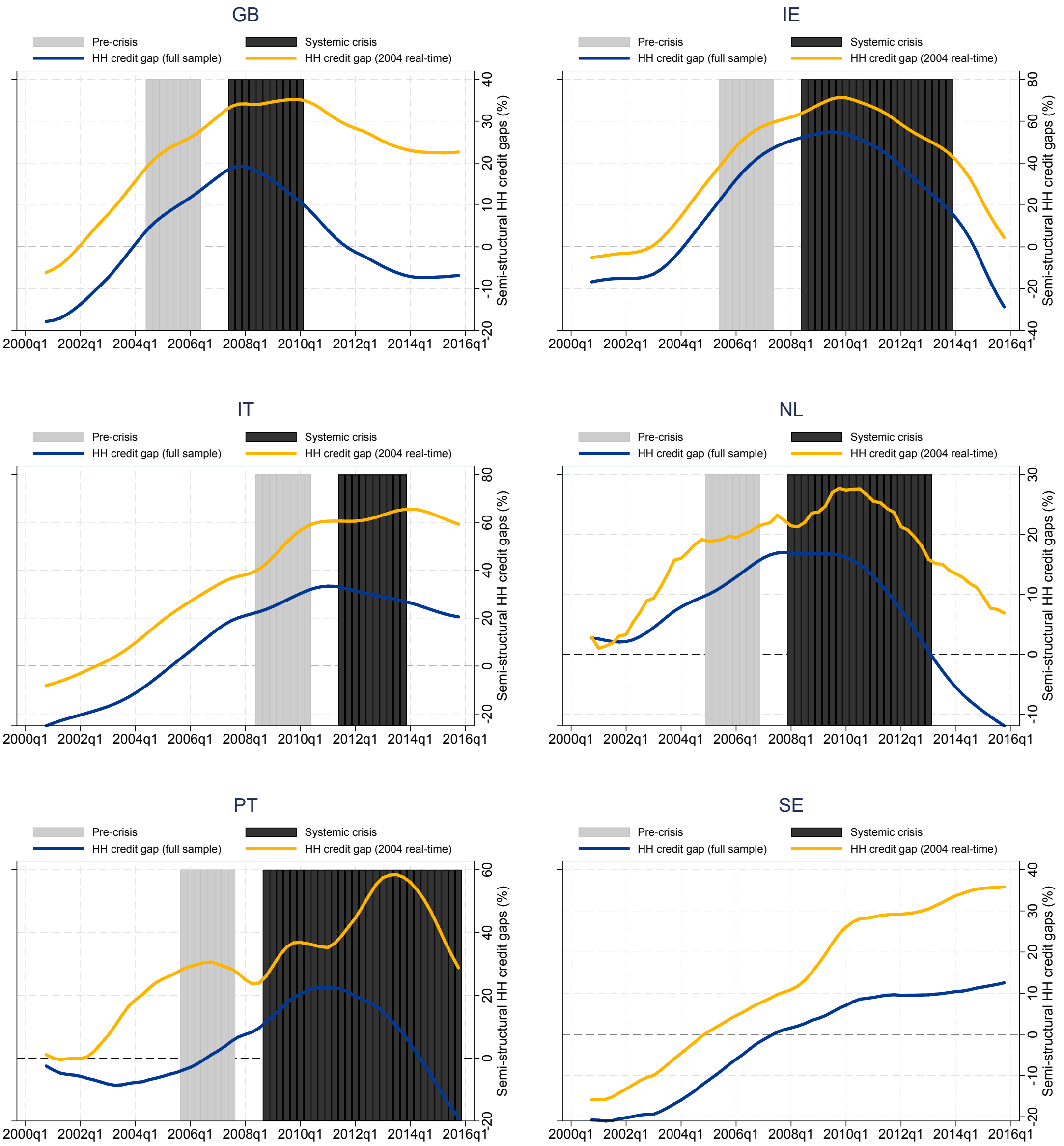
[27] For a comprehensive overview of these methods and their application to euro area countries see Rünstler et al. (2018).

Figure 12: Comparison of real-time and full-sample credit gap estimates 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 13: Comparison of real-time and full-sample credit gap estimates 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.

Third, we compare our baseline credit gaps to those estimated from the unobserved components model used by Grant and Chan (2017) who postulate a standard trend-cycle decomposition, where the trend is a non-stationary second-order Markov process and the cycle follows a stationary AR(2)-process.[28]

Effectively this unobserved components model implies that the trend growth rate of household credit follows a random walk and that all permanent shocks are classified as shocks to the trend-growth rate. By contrast, in the standard local-linear trend model with time-varying drift permanent shocks can affect the trend level and the trend growth rate (see e.g. Clark, 1987). However, the variances of these shocks are usually difficult to identify in the estimation. Moreover, Grant and Chan (2017) show that the HP-filter can be recovered as a special case of their model. The state-space model is estimated by Bayesian methods using a Gibbs-Sampler following the methods outlined in Chan and Jeliazkov (2009). The resulting gaps of all three methods together with the baseline semi-structural credit gaps are shown in Figures 14 and 15.

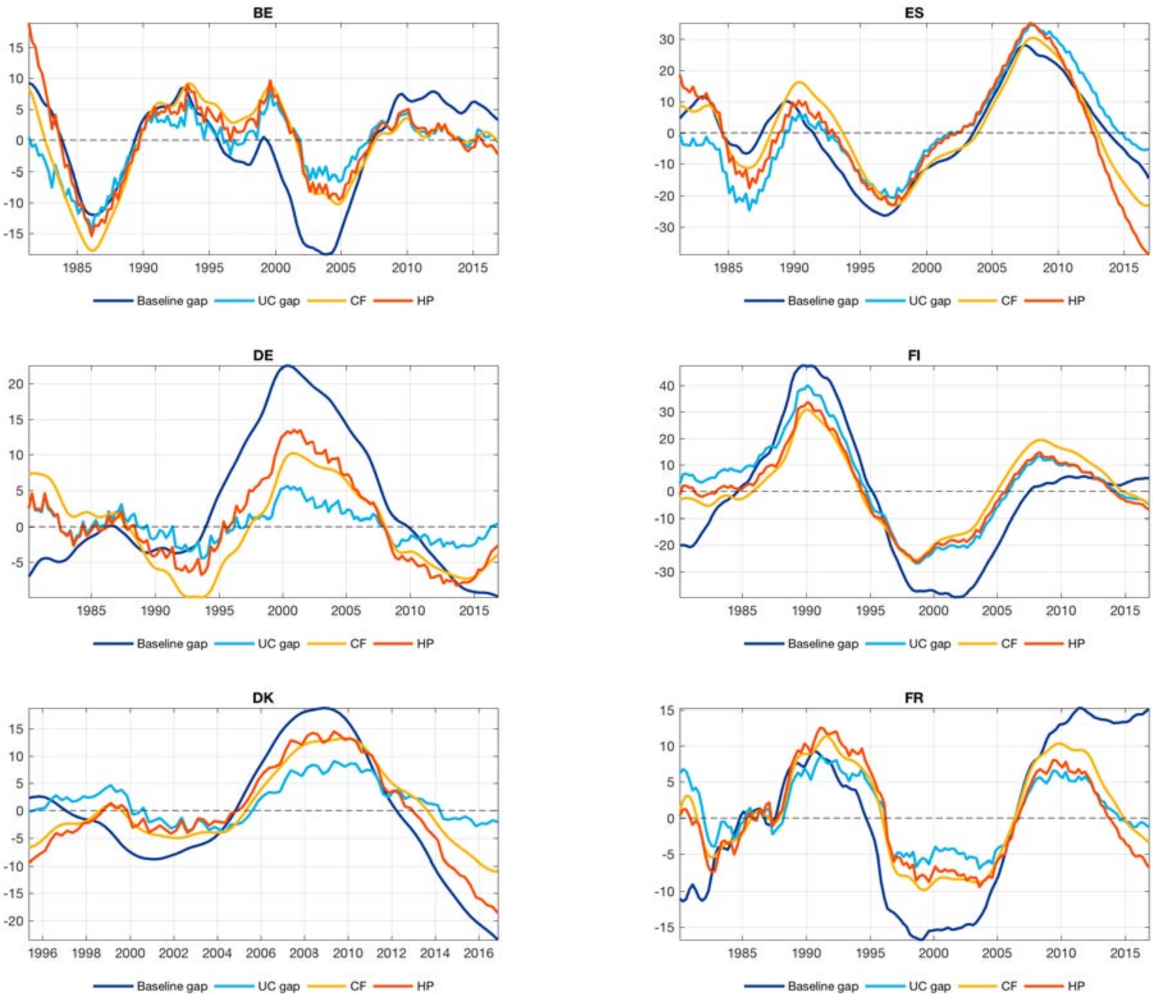
Overall the credit gap dynamics are comparable across the different filtering methods. However, there are some noticeable differences as well. First, in some countries the statistical methods tend to estimate somewhat smaller amplitudes. This could mean that there is some leakage of excessive credit developments into the statistical trend. Second, in the cases of Belgium, Finland, France and Sweden the semi-structural credit gaps tend to be considerably higher than the statistical credit gaps at the end of the sample, which appears more in line with recent credit developments in these countries. Somewhat larger differences can be observed in the case of Italy, where our semi-structural credit gap is positive at the sample end while all other methods yield negative gaps. The positive semi-structural gap is partly explained by the low level of Italian potential output, information that is not available to the other methods which only use the time series of the credit stock. Alessandri et al. (2015) present alternative Basel gap measures for Italy that are also positive around 2014. While these gaps are not directly comparable to our concept, this shows that estimated credit gaps in Italy are surrounded by considerable uncertainty.

[28] The model specification is

$$\begin{aligned} c_t &= \hat{c}_t + \tau_t \\ \Delta\tau_t &= \Delta\tau_{t-1} + v_t^{\tau} \\ \hat{c}_t &= \phi_1 \hat{c}_{t-1} + \phi_2 \hat{c}_{t-2} + v_t^{c} \end{aligned} \tag{10}$$

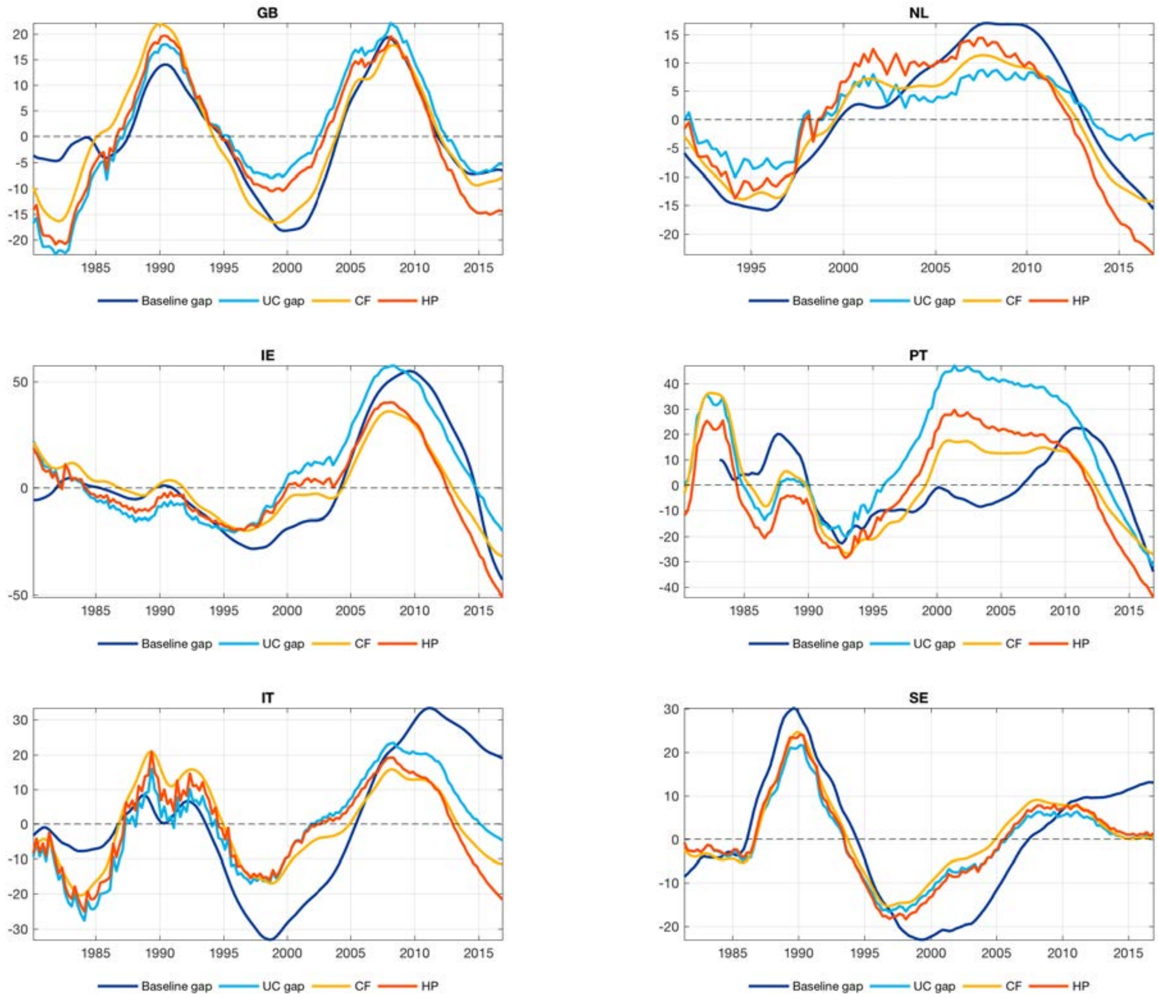
where τ_t is the credit trend and $\hat{c}_t$ the credit gap and the shocks v_t^{τ} and v_t^{c} are assumed to be uncorrelated.

Figure 14: Comparison to statistical filters and standard unobserved components model I



Notes: Full sample estimations. Baseline gap refers to the benchmark semi-structural credit gap, UC refers to the unobserved components model by Grant and Chan (2017), CF denotes the Christiano-Fitzgerald filer for cycles between 8 and 30 years and HP denotes the HP-filter with smoothing parameter 400,000.

Figure 15: Comparison to statistical filters and standard unobserved components model II



Notes: Full sample estimations. Baseline gap refers to the benchmark semi-structural credit gap, UC refers to the unobserved components model by Grant and Chan (2017), CF denotes the Christiano-Fitzgerald filer for cycles between 8 and 30 years and HP denotes the HP-filter with smoothing parameter 400,000.

7 Conclusion

This paper proposes a theory-based approach to identifying excessive household credit developments. In a first step, we derive an equilibrium relationship for the trend level of real household credit using a structural economic model that takes into account household heterogeneity and borrowing constraints. The structural model implies that the equilibrium real household credit stock is driven by the following four fundamental economic factors: real potential GDP, the equilibrium real interest rate, the population share of the young/middle-aged cohort, and the level of institutional quality. In a second step, the theory-based household credit gaps are derived as deviations of the observed household credit stock from the credit trend.

We estimate the theory-based household credit gaps in a model set-up similar to an unobserved components framework for 12 EU countries using quarterly data for the period 1980 - 2015. Focussing our analysis on household credit, which was one of the major drivers sparking the global financial crisis, we also contribute to a better understanding of the interaction between financial cycles and business cycles.

Without imposing a priori information on the cycle length, the estimated credit gaps display long cycles that last between 15 to 25 years. In addition, the estimated credit cycles display substantial amplitudes of around 20% at the country level, which implies that the observed household credit stock can deviate 20% from the fundamental credit stock. The estimated theory-based household credit gaps tend to increase around four years ahead of systemic financial crises and they possess superior early warning properties compared 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 credit gaps do not display excessively long periods of high positive values, which can be the case with purely statistical credit gaps especially during periods of economic transition. In addition, our estimated credit gaps do not tend to fall to as large negative values in the aftermath of financial booms and/or crises as those observed for Basel credit gaps in a number of euro area countries. This property should mitigate the risk of underestimating cyclical systemic risks.

The estimated credit gaps based on theory may be useful for countercyclical macroprudential policy for the following reasons: first, the trend component has a normative economic interpretation as it is determined by fundamental economic factors. This is a clear advantage relative to a purely statistical trend, which can only be a heuristic interpretation of a normative concept. Second, understanding the driving factors of credit gaps, e.g. via the decomposition technique presented in the paper helps informing policy makers in the selection of the most appropriate mix of macroprudential instruments.

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 et al. (2017). We are currently working on that approach. In addition, a (semi-)structural approach to modelling firm credit would be desirable.

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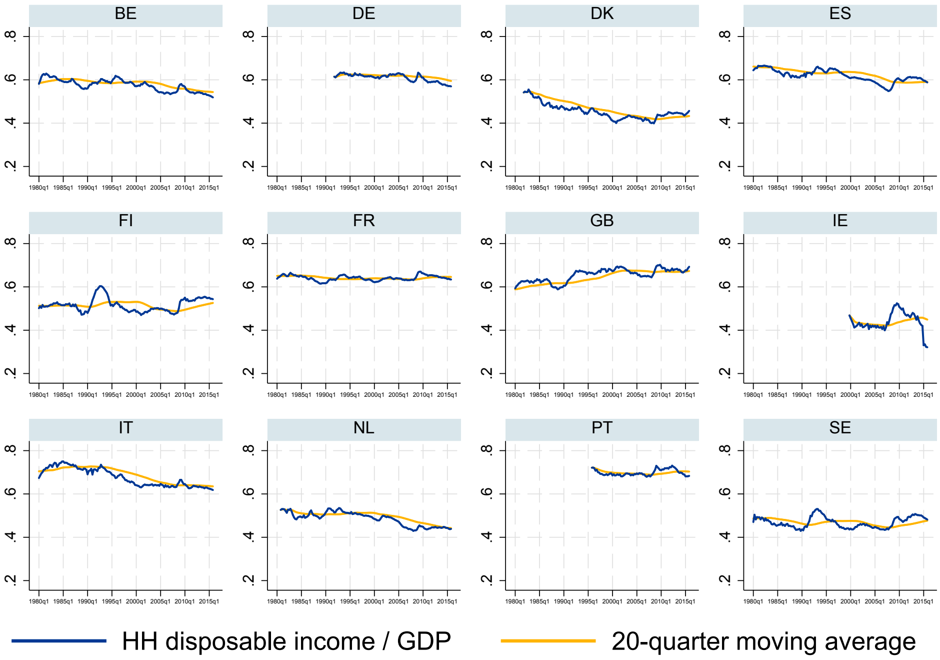
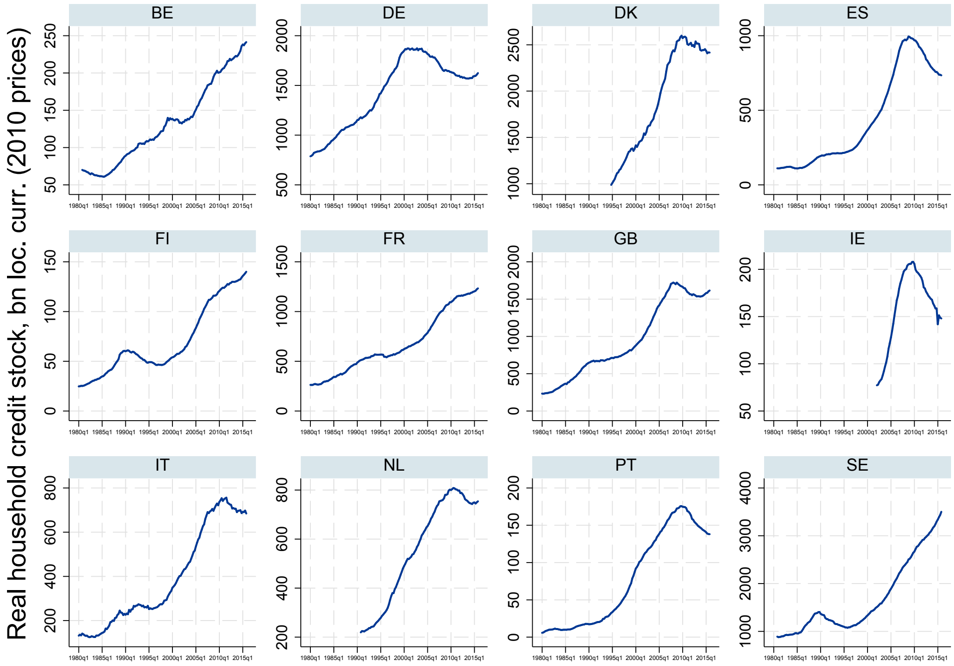
Appendix A: Additional figures

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



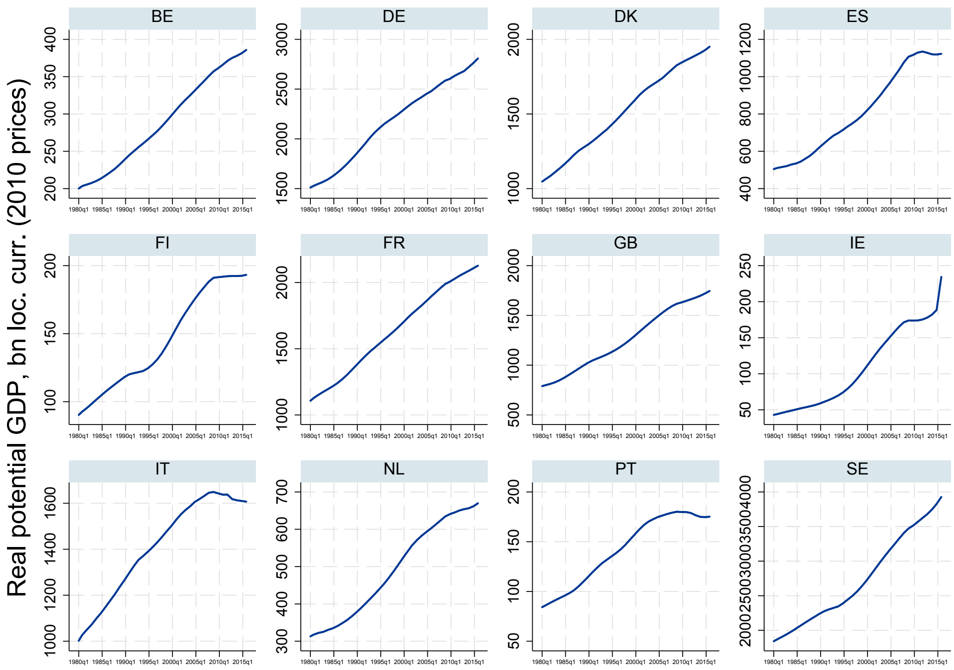
Sources: See Table B1 in Appendix B.

Figure A2: Real household credit across countries



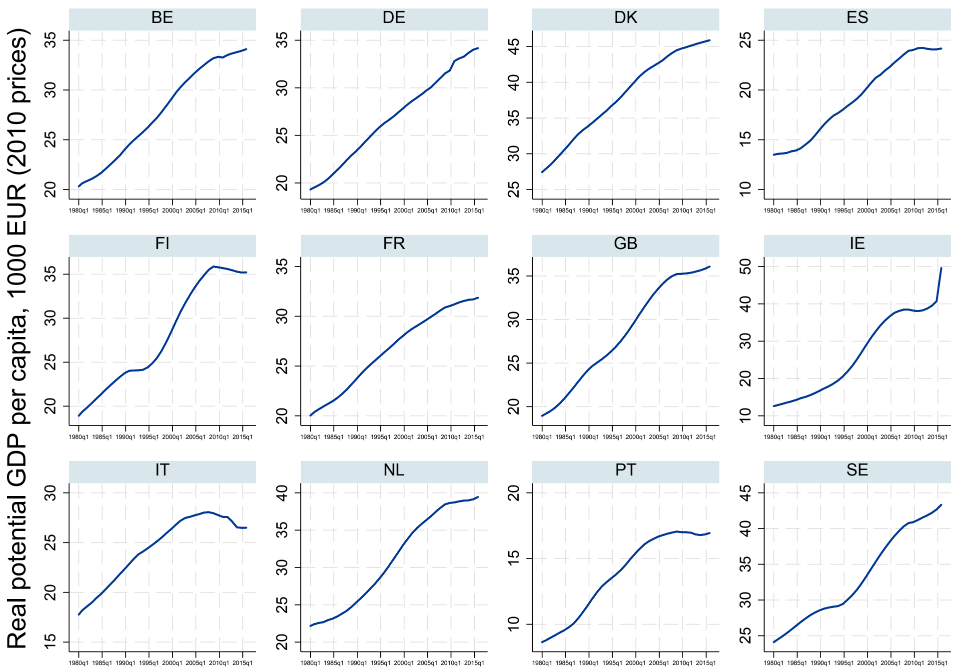
Sources: See Table B1 in Appendix B.

Figure A3: Real potential GDP across countries



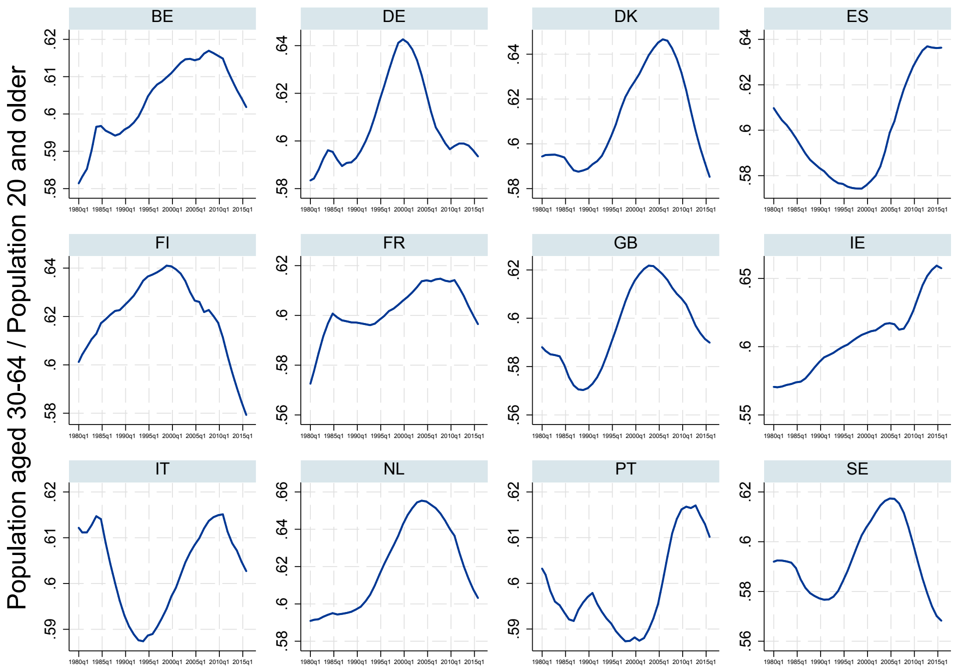
Sources: See Table B1 in Appendix B.

Figure A4: Real potential GDP per capita across countries



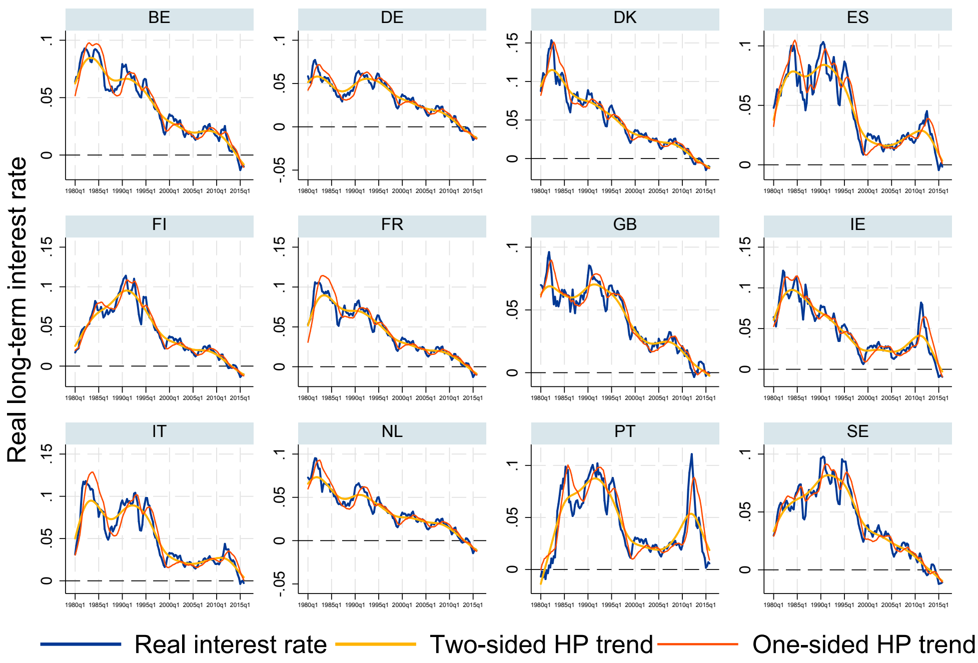
Sources: See Table B1 in Appendix B.

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



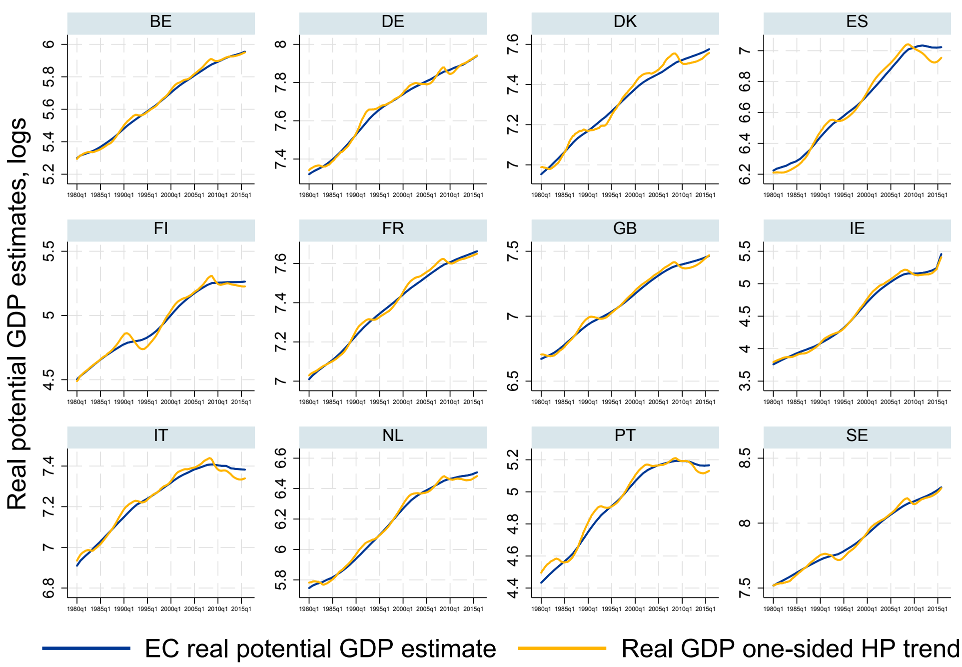
Sources: See Table B1 in Appendix B.

Figure A6: Real long-term interest rates across countries



Sources: See Table B1 in Appendix B.

Figure A7: Comparison of potential GDP estimates 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 4 for details regarding the early warning exercise.

Table B4: Coefficient estimates for the real-time model specification up to 2004 Q1

	(1) BE	(2) FI	(3) FR	(4) DE	(5) IE	(6) IT	(7) NL	(8) PT	(9) ES	(10) DK	(11) SE	(12) GB
CREDIT TREND												
Real interest rate	-2.216***	-0.879	-0.613	-1.954***	-0.299	-1.744***	-4.494***	-1.738	-0.405	-4.632***	-1.626**	-0.941
	(0.599)	(1.013)	(0.554)	(0.603)	(0.715)	(0.674)	(1.727)	(1.359)	(0.591)	(1.589)	(0.656)	(0.741)
Intercept	-0.330***	-0.477***	-0.471***	-0.199***	0.080	-0.815***	0.279**	1.756***	0.300***	0.300***	-0.251***	-0.034
	(0.038)	(0.078)	(0.046)	(0.066)	(0.055)	(0.052)	(0.130)	(0.099)	(0.073)	(0.058)	(0.062)	(0.046)
Shock SD	0.007***	0.004***	0.004***	0.007***	0.014***	0.015***	-0.000	0.009***	0.004***	0.007***	0.004***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.021)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CREDIT GAP												
AR(1) coefficient	1.659***	1.773***	1.566***	1.929***	1.769***	1.805***	1.137***	1.883***	1.825***	1.840***	1.815***	1.924***
	(0.131)	(0.080)	(0.135)	(0.045)	(0.143)	(0.080)	(0.137)	(0.045)	(0.070)	(0.113)	(0.100)	(0.070)
AR(2) coefficient	-0.689***	-0.791***	-0.584***	-0.933***	-0.791***	-0.833***	-0.147	-0.904***	-0.835***	-0.884***	-0.825***	-0.948***
	(0.131)	(0.079)	(0.135)	(0.045)	(0.140)	(0.079)	(0.138)	(0.044)	(0.071)	(0.114)	(0.099)	(0.069)
Shock SD	0.006***	0.013***	0.008***	0.003***	0.007***	0.007***	0.017***	0.014***	0.007***	0.005**	0.006***	0.005**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Observations	94	117	97	97	97	97	54	85	94	38	94	97
log likelihood	278.565	322.623	297.608	297.652	232.704	224.013	140.891	202.377	292.638	111.160	300.190	288.470

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

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