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CREDIT-TO-GDP GAP CALCULATION USING MULTIVARIATE HP FILTER

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Credit-to-GDP gap calculation using multivariate HP filter*

(Hitel/GDP rés számítása többváltozós HP szűrő segítségével)

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Abstract

Periods of excessive credit growth can imply emergence of systemic financial stress which may result in financial crisis causing severe losses in the real economy. The base indicators of overheatedness in the credit markets are the expansion of the credit-to-GDP ratio and its deviation from its long-term trend, the credit-to-GDP gap. When calculating the latter, the major methodological challenge is to develop a model capable of executing the most reliable trend-cycle decomposition. This study presents a multivariate Hodrick-Prescott approach for the decomposition process, which defines the cycle with the inclusion of explanatory variables chosen by considering both statistical and economic selection criteria, successfully solving the problems raised by previous Hungarian research. The model also plays a role in the Hungarian macroprudential policy as in the future it will serve a basis for the calculation of the country specific, additional credit-to-GDP gap: one of the main quantitative factors influencing decisions regarding the countercyclical capital buffer (CCyB).

Összefoglaló

A túlzott hitelezés számottevő rendszerszintű pénzügyi kockázatot jelent, ami nagymértékű reálgazdasági veszteséggel járó pénzügyi válság kialakulásával fenyeget. A hitelpiac túlfűtöttségének alapmutatója a GDP-arányos hitelaggregátum alakulása, illetve annak saját hosszú távú trendjétől való eltérése, a hitel/GDP-rés. Ez utóbbi mutató meghatározásának kiemelt módszertani problémája, hogy a trend-ciklus felbontást minél megbízhatóbb modell segítségével tudjuk elvégezni. A tanulmány egy olyan többváltozós Hodrick-Prescott szűrőt mutat be, mely a ciklust közgazdasági és statisztikai szempontok alapján megválasztott magyarázó változók bevonásával határozza meg, sikeresen adva választ az eddigi tematikus MNB kutatások által felvetett problémákra. A modell a magyar makroprudenciális szabályozásban is szerepet kap: az irányadó anticiklikus tőkepufferrátát meghatározó kvantitatív elemek közül az országspecifikus tényezőket tükröző addicionális hitel/GDP-rést a jövőben ez alapján állapítja meg a Magyar Nemzeti Bank.

1 Introduction

Among systemic financial risks excessive credit growth is one of the most severe, as recessions following it tend to have the greatest effect on the real economy (Jordà et al. 2015). During the expansion stage of the credit cycle, lending is driven by fierce competition that invokes reduced risk awareness and places emphasis on excessive credit growth that often results in a level of indebtedness that may exceed the equilibrium defined by underlying macroeconomic fundamentals. This leads to a build-up of systemic financial risks that are likely to cause severe crisis upon realisation. Thus, it is vital for macroprudential authorities to identify the risks in time and take pre-emptive measures to counteract them, avoiding or at least reasonably reducing the real economic effects of the potentially forthcoming crisis.

There is consensus in the relevant literature that the development of the credit-to-GDP ratio is a good base indicator of the sustainable level of lending activity (BCBS, 2010; Drehmann et al., 2010).[1] Country level indebtedness plays an important role in the growth potential of GDP, as a lower than equilibrium level credit-to-GDP might reduce the growth rate of the economy, while a too high level increases the probability of a financial crisis.

In order to define what level is too low or too high, the equilibrium time-path of the credit-to-GDP ratio must be identified. The primary indicator of financial systemic risk, the credit-to-GDP gap is then defined as the deviation from said equilibrium level. Positive gap values accentuate potential hazards, while negative values indicate slack in the credit markets. However, the clarity of this information relies on the chosen methodology for the trend-cycle decomposition (Drehmann and Tsatsaronis, 2014).

This paper provides brief discussion on the distinction between univariate and multivariate methods. The univariate approach analyses solely the time series of the target variable, thus complete the trend-cycle decomposition disregarding any possible exogenous effects, while multivariate methodologies involve explanatory variables selected by criteria based on economic theory.

The primary focus of this paper is the introduction of a model developed on Hungarian data. Hungarian lending data reflects the typical issues of a transition economy such as short time series, limited number of available explanatory variables, possible structural breaks. The modelling framework presented can be particularly interesting for researchers studying the challenges due to the trend-cycle decomposition in transition economies.

Deciding which filtering approach is optimal for the trend-cycle decomposition is far from trivial. There are multiple methods each relying on different assumptions therefore leading to different decompositions. The performance of the selected method is highly dependent on the characteristics of the target variable. Moreover, the definition of performance itself is dependent on the incentives behind the development of the filters in question as application of different filters outline differing aspects of the financial cycle. With this in mind, the aim of the authors is to develop a multivariate filter that is best suited to support macroprudential policy instruments such as the countercyclical capital buffer.

Hosszú et al. (2015)[2] gives a detailed overview of the most relevant approaches for the Hungarian credit-to-GDP trend-cycle decomposition (the Christiano-Fitzgerald filter, the Beveridge-Nelson filter and the univariate and multivariate Hodrick-Prescott filter methods). Their comparative study on the different filtering methods arrives at the conclusion that the most efficient approach for Hungarian data is a multivariate Hodrick-Prescott filter (hereinafter multivariate HP filter), which considers the country level specifics of both the dependent variable and the economic environment.

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[1] Tough most researchers agree with this, there are also critical voices. Buncic and Melecky (2014) assert that the credit-to-GDP is not an appropriate quantity to assess the equilibrium level of indebtedness as their empirical analysis rejects the unit income elasticity of credit restriction implicitly imposed by the credit-to-GDP ratio.

[2] The study of Hosszú et al. (2015) plays a special role in our paper as it serves as a reference point to the authors in many aspects being also developed by the colleagues of the Hungarian Central Bank. Therefore, the relationship between the two approaches is discussed more in detail at 2.2.5 in the methodology section.

There is an existing debate in the wider literature whether the HP filter is the best for the calculation of the credit-to-GDP gap. While most of the authors agree that the most suitable filtering method for the credit gap calculation is a univariate HP approach[3], there are also critical voices[4] (Hamilton, 2016; Giordiani et al., 2017). The critiques mainly focus on two topics: the value of the smoothing parameter and the robustness of the model. This paper addresses both problems: the first will be discussed in section 2.2.3, while the latter in 2.2.4.

The comparison of different filtering methods however is not the focus of the paper. In this aspect, the authors rely on the findings of the existing literature. As both the international research (BCBS, 2010; Drehmann et al., 2010) and the Hungarian study (Hosszú et al., 2015) agree that the HP filter is the most feasible approach, this study focuses on the optimal application of the multivariate HP method.

The authors conclude that inclusion of explanatory variables in the standard HP method improves real-time performance, in accordance with the findings of the relevant literature (see Hosszú et al., 2015 and/or Borio et al., 2014). The improvements over the univariate HP filter include reducing both endpoint bias and phase shift, as well as trend values that follow the actual data less closely, hence reflect more stable structural fundamentals. Thus, the authors believe the proposed model provides a more realistic picture of the credit cycle and can be particularly useful in assisting regulatory activity.

The remainder of paper is structured as follows: section 2 describes the underlying data set and introduces the theoretical background of the applied methodology. Section 3 presents the development procedure, describing both the key challenges of the development process and the proposed solutions thereof. Section 4 discusses the resulting filter design, while section 5 concludes. Further technical details are presented in the appendix.

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[3] Drehmann and Tsatsaronis (2014) argues that the univariate HP filter is the most suitable method for the trend-cycle decomposition, while Alessi and Detken (2009) recommends the univariate HP credit-to-GDP gap as the best early warning indicator.

[4] Amongst these it is worth to emphasize the recent study of the Swedish National Bank (Giordiani et al., 2017) where a simple alternate filtering approach is presented, which eliminates the model's sensitivity on the length of the time window.

2 Data and methodology

2.1 DATA

As the results are highly dependent on the definition of the underlying data, especially the primary target variable components, the following section discusses data such as the credit aggregate, GDP and the explanatory variables. Dilemmas arising with regards to the optimal segmentation of the credit aggregate are also discussed.

2.1.1 Credit aggregate

Among the underlying data, the credit aggregate has the most significant effect, as the systemic risk the model is supposed to measure originates from the credit cycle. For the same modelling purpose, the BIS and ESRB recommendations (BIS, 2010; ESRB, 2014a) take the most extensive definition comprising of all loans taken by domestic households or non-financial companies. The definition used for the model presented in this paper differs from this recommendation in two points. First, it focuses on the part of the credit aggregate where excessive credit growth can be both assessed and restrained by policy. Second, it uses exchange rate adjustment in order to filter distorting effects caused by FX-denominated loans.

The country specific credit definition contains only loans disbursed by domestic private financial institutions. This would exclude three credit segments:

• The exclusion of the loans granted by foreign non-financial companies is motivated by the fact that this aggregate tends to move independently from the domestic credit cycle. These are typically transfers from parent companies to subsidiaries, and as such they do not necessarily constitute loans in the traditional sense.

• The decision to exclude credit granted by domestic non-financial companies is driven by a regulatory point of view as this segment is not subject to macroprudential regulation.

• The loans granted by foreign financial companies are excluded due to difficulties regarding data accessibility.

The exchange rate adjustment is necessary, as the Hungarian banking sector had huge outstanding FX-denominated loan portfolio, which was partly[5] converted to Hungarian Forints in 2015 as part of a policy measure to reduce the country's vulnerability. Without applying exchange rate adjustment, the time series would be exposed to the additional cyclicality of the exchange rates and there would be an obvious structural break in 2015 when the conversion took place. For these reasons, all FX-denominated loans were converted to Hungarian Forints in the time series with a fix conversion rate. The conversion rate used to change the time series was the rate used in the 2015 policy action so as to not introduce a structural break in 2015 Q3.

2.1.2 GDP

The GDP data used follows the BIS and ESRB recommendations (BIS, 2010; ESRB, 2014a). According, the GDP series should be taken as the sum of the nominal GDP in the past four quarters. This recommendation does not mention whether seasonal adjustment is advised. Taking four consecutive quarters should eliminate the problem of seasonality, but still does not cover possible changes of in-year seasonality across years. For this reason, seasonal adjustment is applied to clear the time series from such effects.

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[5] The policy measure behind this only affected the households.

2.1.3 Segmentation

One of the key data related challenges of the model development was to define the optimal segmentation structure of the target variable, the credit-to-GDP ratio. The task at hand was to find the segmentation level with enough granularity to incorporate unique characteristics of the given subsystem of the economy. The basic expectation for a segment level model is that the explanatory variables of the given subsystem should provide both economically and statistically meaningful results, yielding a standalone segment level model.

This was achieved with the division of the credit aggregate to the most meaningful segments possible. The most granular segmentation level given the data constraint of the available variables uses two segments, splitting the credit aggregate to I. Household lending and II. Corporate lending[6]. In the modelling process this split is performed in a way that it remains additive, so the separation of household and corporate loans results in two submodels with two segment-level multivariate HP trends. This way the segment level credit-to-GDP ratios add up to the whole credit aggregate, thus the calculated trends for the corporate and household segments are also additive.

2.1.4 Explanatory variables

Explanatory variables involved in our filter design consist of various financial and real economic indicators as well as business and consumer survey data. Finance related variables reflect the behaviour of financial institutions, thus supply-side symptoms of emerging systemic risk can be tracked through them. Real economic variables capture effects related to the business cycle. Coupled with business and consumer surveys, these indicators excel at depicting economic effects linked to risk-taking behaviour on the demand side, hence may prove to be good proxies while modelling the cyclical properties of corporate lending. Indicators included in the exercise enter the equations with contemporary and lagged values (lagged by one period primarily, though in some cases more lags were tested). Inclusion of lags incorporates the role expectations into the model.

All the time series have been tested for stationarity: KPSS and ADF unit root tests have been run on the series. However, due to anomalies such as scarce observation numbers, noisy data, structural breaks, the implications of these tests should be given further thought. In a somewhat similar[7] filter design, Borio et al., (2014) concludes that stability of means of the explanatory variables is of vital importance. Thus, oftentimes differences were used instead of level values as they are prone to possess more stable means.[8]

Every variable has been demeaned for the practical reason that this way it is easier to calculate the regression function defining the cycle component as the constant element falls out (see section 2.2.2 for further details).

The set of explanatory variables consist of 47 variables, including financial and real economic time series as well as consumer and business surveys and confidence indicators. The list of these variables as well as the applied transformations is summarized in table 3 in the annex.

2.2 METHODOLOGY

2.2.1 Univariate Hodrick-Prescott filter

The research paper published by the Basel Committee on Banking Supervision recommends the univariate HP filter method as the most appropriate for the credit-to-GDP trend decomposition. This view is widely shared by the related literature. The main advantage of the approach is the relatively low data requirement as it is dependent only on the time series of the credit-to-GDP ratio. The trend is given by the solution of the following optimisation problem (1):

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[6] This makes the model to be in line with the results of Hosszú et al. (2015), where the authors used a similar data on Hungarian lending and ended up using the same segmentation structure.

[7] Borio et al. proposes a methodologically similar filter design though their study assesses the business, rather than financial cycle. Methodological conclusions provided in their study are still valid here.

[8] This was mostly done in cases the authors could not decide on the order of integration of the variable in question.

$$\min_{\{\tau_t\}} = \left(\sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=3}^{T} [(\tau_t - \tau_{t-1}) - (\tau_{t-1} - \tau_{t-2})]^2 \right) \tag{1}$$

where y_t stands for the value of the credit-to-GDP at time t, while τ_t is its trend and λ is the trend smoothing parameter chosen accordingly to the relative cycle length[9].

The approach aims to determine a trend series, which balances the dual requirements represented by the two sum expressions: the first stands for minimizing the distance between the trend and the observed values, while the second sets a limit to the time variance of the trend series. The role of the smoothing parameter in the function is to weight the second expression. Thus, a smaller value for the λ parameter returns a more time variant trend curve. As the λ nears zero, the trend fits the observed values more and more tightly, while the trend series becomes linear as the smoothing parameter approaches infinity. The optimal value of λ is therefore a crucial question. This topic shall be covered in detail in section 2.2.3.

Application of the univariate HP filter is possible using either a one-sided or a two-sided variant. The one-sided approach gives a trend-cycle decomposition for a given point of time using only the information available until that point. The two-sided approach on the other hand uses the whole available sample for the trend estimates.

There are two critical features of the method from an applicational point of view that must be assessed: the accuracy of the estimation at the endpoint of the series and the robustness of the model. Considering these, the two-sided variant is not the ideal choice for an application that requires regular model updates, as it is exposed to the so-called endpoint bias: a phenomenon generated by the fact that at the end of the time series one is not able to consider unobservable future values. Thus, if the time series is extended with additional observations in the future these will affect the estimated trend significantly. Hence the credit-to-GDP gap will also be modified. This problem has to be addressed if the model is applied in a regulatory practice, where model updates are necessary. Moreover, stable endpoint values are critical as they may trigger actions from macroprudential authorities.

It is also worth discussing the factors influencing the starting values of the trend estimation. In the case of the one-sided filter there is a burn-in period of 6-8 quarters during which the trend values are almost equivalent to the observed values, thus lack any additional information. The reason for this lies within the core logic of the one-sided approach as described above as it takes only the observed values before time point i into account. In the beginning of the time series, when there are only a few observations available, the results fit very tightly to the observed factual data. Because of this, the estimated gap series is characterised by a slow ramp up (boom) period and a swift adjustment after the crises (bust): a scenario the authors deem very unlikely.

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[9] For finding the optimal value of the trend smoothing parameter we need to know the length of the cycle for the related time series. The length of the observed time window is of crucial importance in this matter as if one lacks the necessary amount of observations to obtain an overview of multiple cycle lengths only assumptions remain to rely on.

1. Figure
The credit-to-GDP ratio and its univariate, one-sided trend
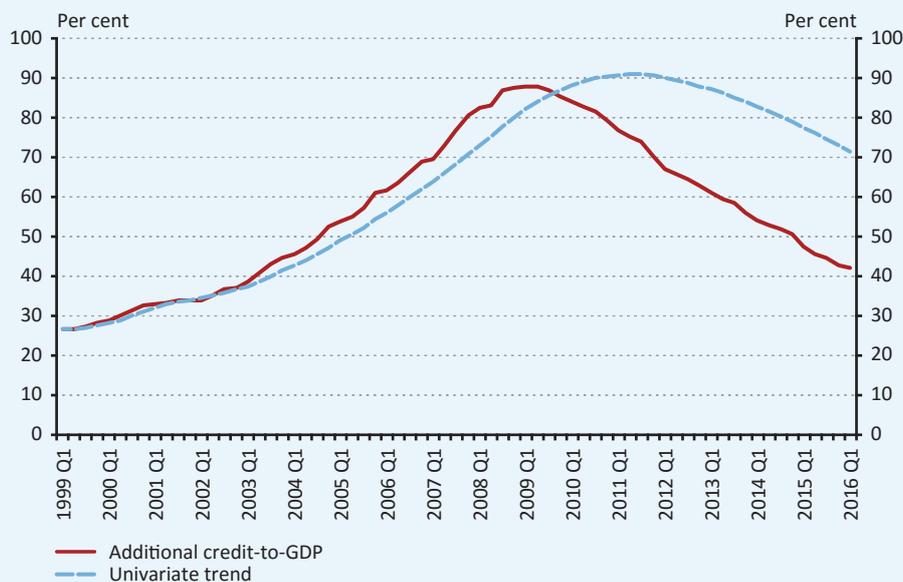
Note: For the calculation, the exchange rate adjusted credit stock disbursed by the Hungarian financial institutions and the cumulated four quarter moving value of the GDP were used. This is equivalent with the additional credit-to-GDP definition used by the local macroprudential regulation. For the filtering, we applied the smoothing parameter of 400,000, the value most widely accepted in the related literature for the relative cycle lengths of the credit and the business cycles.

Figure 1 shows the trend-cycle decomposition of the Hungarian credit-to-GDP with a univariate HP filter. The above-mentioned burn-in period can be observed on the figure even though the first four quarters of the series are omitted. There is one additional feature of the approach however, that is clearly shown: the phase shift of the trend compared to the observed data. The most obvious point to look at is the peak of the additional credit-to-GDP ratio versus the peak of its univariate trend: the trend is 8 quarters late compared to the fact values with the peak. Overall, the whole trend series looks as if it followed the time path of the actual data with a notable delay. This phase shift is a well-known attribute of the HP trend (Gyomai and Nilsson, 2011), and is worth counterweighting if one looks for means of enhancing the model efficiency.

2.2.2 The multivariate Hodrick-Prescott filter

Multivariate filtering approaches consider not only the target time series but also explanatory variables. This results in a trend that explains the development of the credit-to-GDP gap with involvement of macroeconomic fundamentals, as it does not reduce the trend-cycle decomposition to the analysis of the credit-to-GDP series, but also takes the changes in the economic environment into account. The multivariate approach is also able to significantly reduce the phase shift effect which is discussed in section 2.2.1.

The major methodological innovation of the model presented in this paper compared to other published credit-to-GDP trend-cycle decompositions is that the model is cast into state-space form.[10] This enables evaluation of the fitted models namely the inclusion of statistical criteria to test the connection between the dependent variable and the explanatory variables. In other words, this methodology allows one to ensure having only statistically significant variables in the model, which the authors consider to be an important step towards an unbiased filter. The statistical filtering of candidate models leads to a more stable methodological foundation of the model.

The employed approach is based on the Local Linear Trend (LLT) or „Smooth Trend" method. The name is related to the fact that among state-space models these result in a smooth trend shape, which makes a trend-cycle decomposition possible

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[10] As mentioned before a very similar approach for the output gap may be found in Borio et al., 2014.

where the cycle is not considered to be only noise. It is important to note however that the methodology presented in this paper differs from the common LLT framework in two points (following the approach described in Borio et al., 2014). First, the trend is not modelled as a random walk, instead the trend smoothing component is taken from the HP filter function. This comes with the advantage that knowledge about the cycle length, either as an observed factor or as an expert opinion, can be accounted for with the smoothing parameter. Second, unlike the regular LLT practice, here it is not directly the credit aggregate that is explained by the regressors, but the cycle component, because from a regulatory point of view there is much more information in understanding and modelling the cycle.

In the observation equation, the dependent variable is split into latent components. In our case this means splitting the credit-to-GDP series into unobservable trend (τ_t) and cycle (μ_t) components:

$$\left(\frac{Credit}{GDP}\right)_t = \tau_t + \mu_t \tag{2}$$

The state equation represents the assumed dynamics of these latent components (state variables). Thus, two[11] equations are needed, one for the trend and one for the cycle:

$$\tau_t = 2 \times \tau_{t-1} - \tau_{t-2} + \varepsilon_{1,t}$$
$$\mu_t = \varepsilon_{2,t} \tag{3}$$

$$\frac{Var(\varepsilon_{1,t})}{Var(\varepsilon_{2,t})} = \frac{1}{\lambda} \tag{4}^{[12]}$$

The cycle component in the case of the univariate HP filter is represented by solely the error term $\varepsilon_{2,t}$, but for the multivariate case the regression function[13] (5) takes its place:

$$\mu_t = \varepsilon_{2,t} + \sum_{i=1}^{N} \beta_i x_{it} \tag{5}$$

where x_{it} is the value of the variable explaining the cycle component at time t, while β_i is its ceteris paribus effect on μ_i due to a unit change.

Thus, in the case of the presented variant of the multivariate HP filter the explanatory variables enter the state equation of the cycle component. The trend and cycle dynamics affect each other (through the observation equation and the link between residual variances), so the explanatory variables of the cycle are implicitly affecting the trend as well.

2.2.3 Determining the value of the trend smoothing parameter

In the case of the univariate HP filter, the optimal value of the trend smoothing parameter (λ) can be determined with the help of the „signal-to-noise" ratio (Laxton and Tetlow., 1992; Schlicht, E., 2004). The recommended value for filtering the credit-to-GDP ratio is 400,000 according to the related literature (European Systemic Risk Board, 2014a). This is

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[11] In conventional state-space formulation the state equations would comprise 3 equations, as latent dynamics of state space models possess Markov property by definition (state dynamics must be formulated in a way that $x_t = Ax_{(t-1)} + \varepsilon_t$, with x_t being the vector of state variables while ε_t is the vector of innovations). With that said, the authors believe it is unnecessary to postulate the precise formulation, since the above representation makes interpreting dynamics of the system much less cumbersome.

[12] Notice that the state equation of the trend is the trend-smoothing component of the Hodrick-Prescott filter from equation (1), while equation (4) sets the relative importance between fitting to the data and limiting the time variability of the trend series.

[13] The constant parameter is missing from the function as all used variables are demeaned.

equivalent to assuming a credit cycle about four times longer than the business cycle (Ravn and Uhlig, 2002; Drehmann and Tsatsaronis, 2014).

These assumptions play a critical role in the shape of the trend function. As shown on figure 2 the different λ values result in a growing difference in the trend shape over time.

2. Figure
The univariate trend of the credit-to-GDP ratio with different lambda values
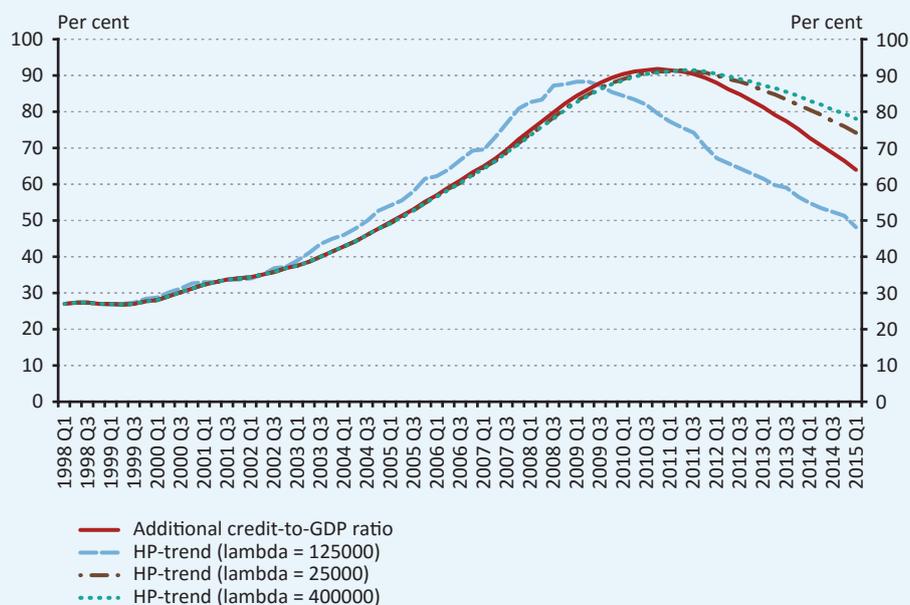
Note: For the calculation, the same credit definition is used as in figure 1.

The selection of the optimal λ value for the multivariate case is identical to that of the univariate one (Dermoune et al., 2008). Thus, the above discussion about the assumption on the relative cycle lengths holds for the presented models as well. In this study, λ is taken as 400,000 as it is suggested by the ESRB.

2.2.4 Robustness

In regulatory applications, it is vital that the applied methodology provides robust trend estimates in a sense that they do not change significantly (or ideally at all) as the model is re-estimated in future periods. As mentioned before, this requirement validates the claim that one-sided filters should be utilised as they lack such distorting effects. The univariate HP filter method recommended by the ESRB certainly does suffice, however it renders the methodology subject to hindrances such as phase shift (discussed in detail in section 2.2.1) – a symptom characteristic of asymmetric[14] filtering methods. Moreover, the one-sided nature of the filter results in clearly biased estimates, especially at the beginning of the available data. Multivariate methodologies can mitigate these effects; however, they break the one-sided logic of the univariate, one-sided HP filter. The reason behind this is that the coefficients depend on the estimation sample, thus future re-estimations affect past values as well. At first glance, this might seem a severe difficulty because this makes retrospective evaluation of the model impossible.[15] However, findings presented in this paper indicate that the magnitude of the endpoint bias declines parallel with the expansion of the estimation sample.

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[14] It can be shown that the univariate one-sided HP filter approximates an ideal asymmetric bandpass filter, for reference see Baxter et al (1999).

[15] That is, the resulting trend series relies on contemporary insight into the credit cycle, thus one is unable to infer how things would have been if the methodology under inspection was introduced before past crises events.

2.2.5 Methodological approach compared to related literature

Among the related literature the study of Hosszú et al. (2015) plays a differentiated role serving as an inspiration and a reference point to this paper. As there are many similarities in the two approaches, a comparison of the papers will not only help to better accentuate the research interests that motivated the authors in this study, but also to point out the methodological innovation this paper can contribute to the existing literature.

The similarities of the two papers can be summarized easily. Both aim to find a satisfactory solution to credit-to-GDP trend-cycle decomposition, develop a multivariate model based on HP methodology, uses Hungarian data series (though different time windows) and end up differentiating between household and corporate segments.

The methodological differences however target key areas of the research this paper is based on and should therefore discussed more in detail. They can be addressed by covering four topics: (i) the structure of the model, (ii) testing the explanatory variables for significance, (iii) defining the smoothing parameter and (iv) aggregation and model averaging.

Model structure. The methodological background of the multivariate approach is discussed above in 2.2.2. Equations (3) and (5) describe the logic of the model that the authors have put into practice. There are two equations, one for the trend and one for the cycle, where the regression function is defined.

Hosszú et al. applies a different logic and defines three equations, introducing two regression functions one for the trend and one for the cycle component.

As the cycle and trend mutually define each other, the authors of this paper argue that it is unnecessary to have an additional equation for the trend, as variables influencing the trend also bear influence on the cycle.
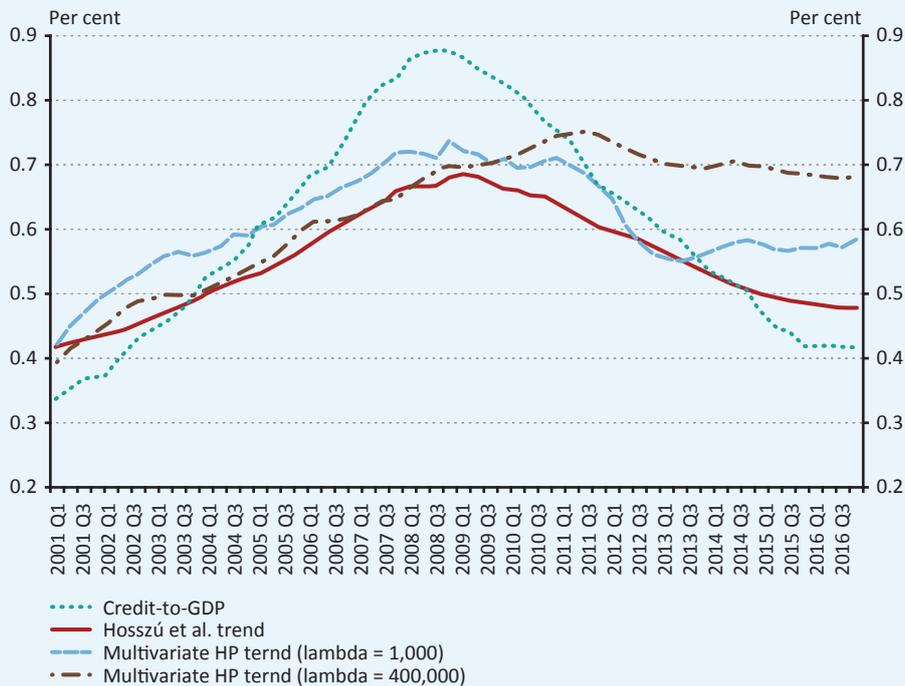
Another model structure related difference is the application of multiple lagged versions of the dependent variable in one model. The Hosszú et al. study applies this approach as it catches the autoregressive nature of the credit cycle. This bears importance for two reasons. One is that with the lagged dependent variables at hand the smoothing parameter is no longer interpretable as the relative cycle lengths of the business and the credit cycle, thus, we have absolutely no guidance about the value for lambda which introduces the problem of having to include different lambda iterations which impacts the estimated cycles far too much (see figure 3 below). Furthermore, it is no longer possible to know whether the chosen variables lead to the difference in the estimated cycle or the lambda.

Testing for significance. One of the main achievements of this paper is casting the multivariate HP in state-space form, allowing the statistical testing of the explanatory variables. This was clearly inspired by Hosszú et al. as they name this as a possible enhancement of their model.

Defining the smoothing parameter. Section 2.2.3 already covered how important the role the smoothing parameter plays in the HP filter is (see figure 2 as well) as it defines how closely the trend follows the development of the actual credit-to-GDP. As pointed out earlier, the model structure Hosszú et al. follows does not allow defining the lambda parameter based on economic intuition as it no longer can be interpreted as the relative cycle lengths of the business and credit cycles. Therefore Hosszú et al. is forced to choose the lambda values upon discretion and when they do so they end up choosing relatively low values. In their final model they average many competing model variants which differ in the applied lambda parameters as well, so they end up taking multiple lambda values with a range of 0.0001; 0.001; 0.01; 0.1; 1; 10; 100 and 1000.

In this paper the authors decide to apply a method within the HP framework what allows to use economic intuition to underpin the definition of the smoothing parameter. With this and the supporting literature at hand the value of 400,000 was taken as discussed in section 2.2.3.

3. Figure
Comparison of different lambda values of the multivariate HP trend with the Hosszú et al. results

Per cent · Per cent

····· Credit-to-GDP
—— Hosszú et al. trend
– – – Multivariate HP ternd (lambda = 1,000)
–·–·– Multivariate HP ternd (lambda = 400,000)

Although there are many differences between the approaches applied in Hosszú et al. and this paper, figure 3 supports the argument that the main component that explains the divergence of the two trend shapes is the lambda value.

Aggregation and model averaging. Though section 3.2 covers this topic in detail it is worth to emphasize the choice of values supporting the modelling structure presented in this paper. The goal is to maximise the number of relevant variables included in the model on one hand while preserving the transparency of the model build-up on the other. This leads to a choice to aggregate a limited number of models with a selected set of explanatory variables.

The modelling process presented in Hosszú et al. follows a different path aggregating a large number of models for both the household and the corporate segments. This approach has its advantages, but these comes at the price of sacrificing transparency.

Of course, transparency itself has its grades ranging from the univariate model to the complex system presented in the Hosszú et al. study. In this paper the authors aim to present an approach what offers a handy solution from the implementation point of view, having a limited number of variables where the constant monitoring of the historical values is still feasible.

3 Model development

3.1 MODEL SELECTION

Due to the vast number of explanatory variables, it is desirable to establish criteria to narrow the scope of models that are considered plausible. The model selection strategy utilises (i) Bayesian Information Criteria as goodness-of-fit measure; (ii) tests on the statistical significance of regressors; as well as (iii) various other „metrics" constructed to set up a hierarchy among specifications (*soft criteria*) or outright reject them (*hard criteria*). In this section, the model selection criteria are discussed in detail.

3.1.1 Rejection criteria and hierarchy

Model candidates undergo systematic evaluation that comprises of the exclusion of certain variables and models, then establishing a hierarchy among specifications that met the criteria.

Rejection criteria are defined as follows:

1. All variables included in the models must have statistically significant effect on the cycle component. This requirement is further strengthened by demanding statistical significance to be robust, that is: significance levels should be largely insensitive to modifications to the estimation sample. This is achieved by only selecting models where variables stay significant in the last six periods.

2. Estimated coefficients must have signs consistent with economic theory. In principle this is straightforward, but transformations such as taking differences might make this criterion more difficult to check.

3. Effects of included variables should be balanced, meaning deviation from the univariate HP trend values must not be dominated by only a select few variables. Principles of quantitative evaluation are described in section A.2 in the annex.

Hard criteria, while successful in thinning the set of variables and models under investigation, do not suffice. This is due to the vast ensemble of specifications passing these criteria (100 for households, 395 for non-financial corporations). As such setting up additional constraints and setting up a ranking hierarchy prove useful. To this end, soft criteria have been applied:

1. A supplementary metric was defined to assess the *robustness* of models. This continuous quantity allows for ranking models with respect to their supposed robustness. (This is elucidated in the annex.)

2. *Goodness-of-fit* measure, namely Bayesian-Schwartz information criteria allow for ranking models in this dimension.

The final ranking of the models has been calculated as a weighted average of their ranks in the above mentioned soft criteria and the balance criterion with emphasis put on the robustness criterion (70% weight was applied for the robustness rank, while 15-15% for the goodness-of-fit and the balance criteria).

3.1.2 Selection process

To identify models that meet the criteria, a three-tier algorithmic procedure was adopted:

Firstly, candidate variables were inspected for data quality[16] and availability. The second tier is based on narrowing the set of relevant variables and selecting specifications that meet the significance criterion.

The second tier is as follows:

1. Given a set of explanatory variables (V_i), with a total number of N_i variables, models with every combination of i explanatory variables are estimated.[17]

2. Every model is checked for significance criterion. Passing specifications are then saved.

3. Variables included in any of the passing[18] specifications yield the initial set of variables (V_{i+1}) for step i+1.

Steps 1-3 are repeated until a maximum cap of variables involved in a model is reached[19]. Not only does this procedure help us reduce calculation times by excluding irrelevant variables early on, but also erodes the possibility of including highly collinear regressors in the same model.

The optimal number for setting the maximum cap of variables proved to be four in our case, as additional variables did not result in significantly improving model performance. Therefore, the models taken into account have 2 to 4 explanatory variables.

4. Figure
Cluster plot of models arranged in BIC and robustness indicator dimensions, NFCs

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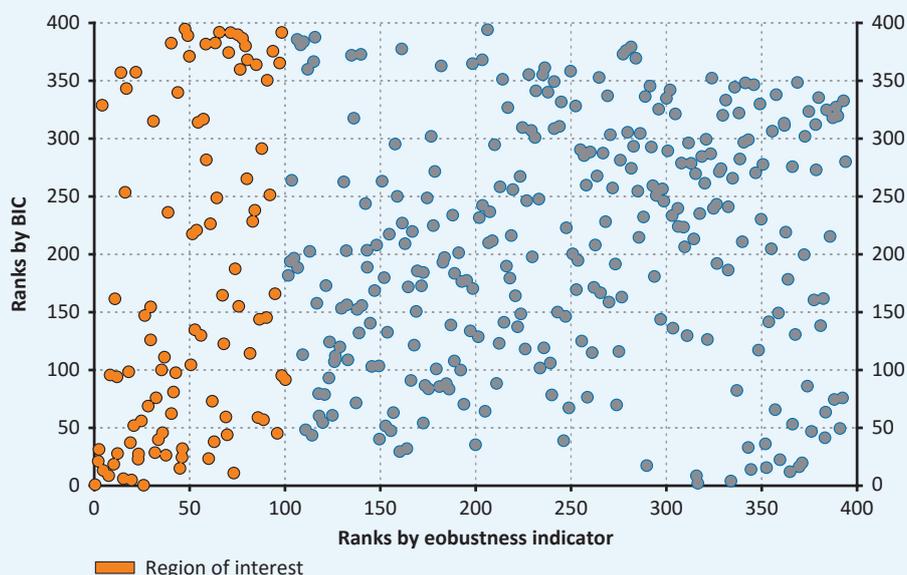
[16] Borio et al., 2014 finds that the applied methodology is sensitive to outliers in the data. Moreover mean-stability of the series also plays an important role here.
[17] That is $M_i = \binom{N_i}{i}$ different specifications.
[18] In practice, very few variables were rejected. This is partly fortunate, because it indicates that the initial selection of variables was adequate. In addition, it suggests that not many variables fell prey needlessly to the utilised step-wise like procedure.
[19] Note how the number of models estimated, M_i increases sharply as $i \rightarrow N_i/2$, even while moderately reducing M_i in the process. Thus, to keep computational times reasonable it is advised to stop at relatively low values of i.

Upon reaching the cap for included variables, models that meet the significance criterion are checked for the remaining criteria. Passing specifications are then ordered in goodness-of-fit and robustness dimensions, yielding a cluster in an X-Y scatter plot (third tier). The primary region of interest is the area around the origin (see figure 4 for an example in the case of NFCs). Models in this region enter the aggregation process in the order of their rank by BIC and robustness.

3.2 AGGREGATION

Once the narrowest set of plausible models is determined, it has to be decided whether to use a single best model, or consider a set of models by applying a selected aggregation method. This section addresses this question and presents the considered alternatives: the single model approach and the static averaging of a selected set of models.

3.2.1 Aggregation ranking criteria

After the third tier of the selection process it has to be decided by which criteria should a set of the selected models be considered better than another. The bases for the ranking are BIC and robustness indicators, but during the aggregation soft criteria are also considered. Those are as follows:

• It is highly desirable to select heterogenous models as averaging heterogenous models can help us mitigate omitted variable bias. To achieve this, only models with less than two shared variables were selected.

• Care should be taken so that models selected contain variables that are easily accessible and are updated frequently. Basically, it is not advised to include variables whose publication dates lag behind those of the underlying primary data.

• Coefficients and/or effects of explanatory variables must be economically plausible.

3.2.2 Single selection approach

Perhaps the most transparent is to carefully select one model for each of the segments. The applied evaluation strategy might serve as a guideline, though manual validation is necessary: while it is tempting to rely solely on statistical criteria, goodness-of-fit measures and supplementary metrics describing other manifesting properties of models cannot possibly cover every aspect of modelling. Moreover, implications of selected models should be in accordance with views of experts on recent crisis events and recovery. Thus, making the right decision is extremely difficult, giving rise to uncertainty regarding the correctness of one's judgement. Even if one could find the "best" model available they would still risk choosing a miss-specified model as no benchmark nor diagnostic tools are available to check for either omitted variables nor overfitting. In addition, higher diversity of the explanatory variables is a desirable feature of the model both for sake of robustness and for covering a wider range of the macroeconomic fundamentals. Selecting a sole model would decrease this diversity.

However, this method certainly has its advantages. The ease of identifying the effects of explanatory variables makes selecting a single model more a transparent solution than utilising aggregated models. In addition, applicability of this approach is less constrained by data availability. Overall the authors believe selection of a single model per segment has weak guarantees against the above-mentioned potential pitfalls, hence this method is deemed less preferable.

3.2.3 Static averaging

The second approach discussed comprises of identifying a desired set of models for each segment, then compressing the output into a single series by taking their average (this might be done with equal or different weights[20]). This method still suffers from the caveats of the single choice approach, though these difficulties are less pronounced. One could still choose a wrong set of models, however the likelihood of such a scenario decreases as more models enter the averaging process. This involves a trade-off between reducing the maleficent effects of misspecification, and transparency.

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[20] Weighted averages do not work well here, since it is uncertain how weights should be assigned. Weighing schemes can still be constructed, though the danger emerges that they would reflect subjective views more so than desirable.

It should be emphasised that making use of numerous models might also cause problems with data availability. These difficulties can be accounted for by considering data requirements of models during selection, or by choosing a relatively moderate number of models.

5. Figure
Illustration of various aggregation methods
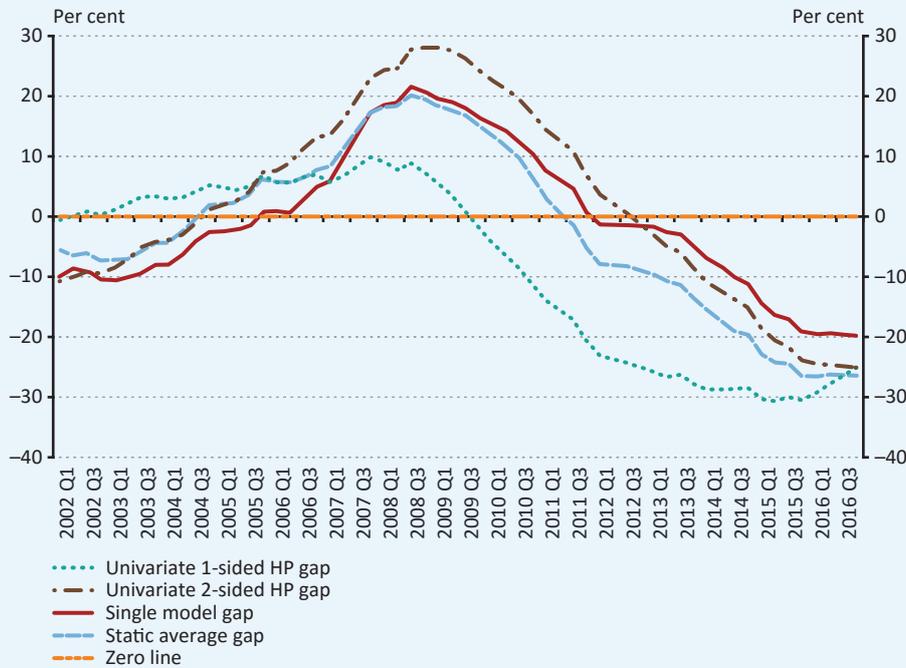
Overall the authors believe it is best to pick a limited set of models for each segment then take their arithmetic average. Pros of this method include more-or-less preserved transparency, low data requirement, and smaller chance of mistaken choice. Additionally, averaging multiple models might also prove to be helpful in reducing omitted variable bias.

In this phase, the priority of the selection process was to gain a heterogenous set of models with regards to the explanatory variables involved. For this reason, 3 models were selected per segment, as this proved to be the maximum number of models where the explanatory variable diversity still could be granted. With this choice of aggregation, the overall transparency of segment level models is preserved. Data requirements are also kept reasonably low, while the heterogenous models incorporated reduce exposure to misspecification.

4 Results

The most efficient approach to capture the macroeconomic drivers of the financial cycle proved to be the segmentation of the credit aggregate. As section 2.1.3 describes, the target series, namely the credit-to-GDP ratio was divided into households and non-financial corporations segments. The authors deem these segments granular enough for individual models to be able to capture sector specific effects, thus provide a more realistic picture on systemic risk related to over-heatedness in these segments. An additional advantage of the approach is that this way the segment-level trends are also available and interpretable, resulting in a more accurate assessment of systemic risk. The overall credit-to-GDP gap is then the sum of the household and the corporate gaps.

This section presents the segment level models and provides an overview on aggregate results.

4.1 CORPORATE LENDING

The corporate credit-to-GDP ratio shows smaller cyclical movements compared to the overall credit aggregate. The main reason for this phenomenon is that short term working capital loans tend to follow the economic cycle, resulting in a stable credit-to-GDP ratio. The cyclical movements are present, however, for long term corporate loans, so in this segment it is possible to reveal macroeconomic connections, which can help explain the cyclicality.

As described in section 3, the final segment-level model is the simple arithmetic average of three selected models, chosen out of 719 specifications by predefined selection criteria. Table 1 presents the coefficients and statistics of these three models, while the selected models are presented in the appendix. The exact description of the explanatory variables, as well as the whole list of variables analysed is given in table 3 in the appendix.

Each model uses four variables with as few overlapping variables between models as possible.

There are two points worth highlighting about the above table:

1. The coefficients of explanatory variables[21] as they define the effect of given variables on the cycle development.

2. The results of the significance tests reflecting the explanatory power and the relevance of variables. It is notable how most variables are significant at the 1% level.
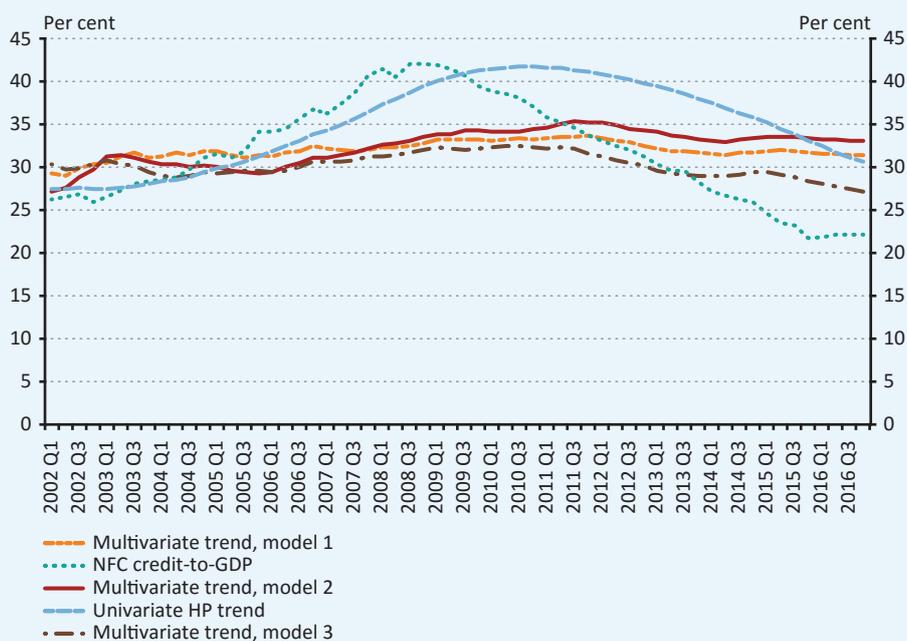
It can be observed in figure 6 that the three trends follow a similar path, but with the help of the different explanatory variables each of them reflects a different aspect of the macroeconomic environment defining the financial cycle.

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[21] Every value is to be taken as percentages. Comparing these with the results show on figure 6 it is important to note that the relative importance of these variables is not directly related with the relative magnitude of the coefficients, as these are highly dependent from the given variables scale and in connection with this the variables range.

1. Table
**Selected models for the corporate segment**

Explanatory variables	Model 1	Model 2	Model 3
5-year government bond yield (%-change)	0.1050*** (4.0873)		
German GDP (-1) (year-on-year %-change)	0.0956*** (5.357)		
Retail trade (-1) (%-change)	−2.0412*** (−6.4662)		
Retail confidence indicator (-1)	−0.3802*** (−8.4453)	−0.3484*** (−5.1493)	
Debt-to-deposit ratio (-1) (%-change)		0.4267*** (2.6360)	
Economic sentiment indicator		−0.4202*** (−5.4296)	
Industrial production trends		0.2250*** (5.0571)	0.2012*** (3.3737)
Industrial confidence indicator (-1)			−0.4426*** (−4.6090)
Capacity utilisation (-1)			0.7406*** (4.8118)
Construction industry confidence indicator			−0.3640*** (−10.6168)
Supplementary indicators	**Model 1**	**Model 2**	**Model 3**
BIC	−3.2448	−2.8179	−2.9021
Robustness indicator	0.0569	0.1194	0.1832
Rank	1	62	260

Note: Coefficients of the cycle equation are presented. *** - significant on the 1% level, **-significant on the 5% level. Z-stats in parentheses. Critical (absolute) values are 2.96 and 1.96 accordingly. All variables were demeaned. This is done so that estimating one additional coefficient (the intercept) is avoided. Percent changes were calculated as logarithmic differences. Negative integers in parentheses indicate lagged variables.

6. Figure
Comparison of different corporate trend curves

Multivariate trend, model 1
NFC credit-to-GDP
Multivariate trend, model 2
Univariate HP trend
Multivariate trend, model 3

The overall corporate model is given by taking the simple arithmetic average of these three models. As described in section 3.2, this is the most efficient way to increase the robustness of the final model. The result of the static averaging procedure is shown below in figure 7.

7. Figure
Corporate credit-to-GDP with its univariate and multivariate HP trend
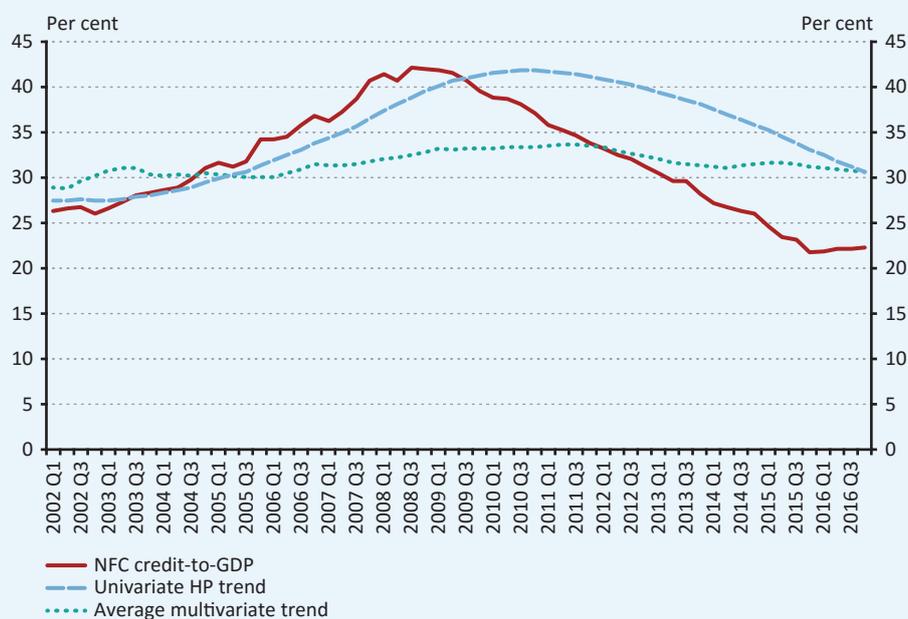
The inclusion of macroeconomic explanatory variables results in a more stable trend compared to the univariate model. The multivariate approach shows a stable growth period until the crisis; however, this growth is slower than the growth dynamics of the factual credit-to-GDP, thus the multivariate model shows signs of excessive credit growth from the first quarter of 2006. Note how the slope of the univariate trend exceeds the multivariate trends exactly in this excessive credit growth period, and that the univariate model shows the most intensive growth during the year preceding the crisis. The multivariate corporate credit-to-GDP ratio also shows lower volatility then the univariate approach.

8. Figure
Average corporate credit-to-GDP gap
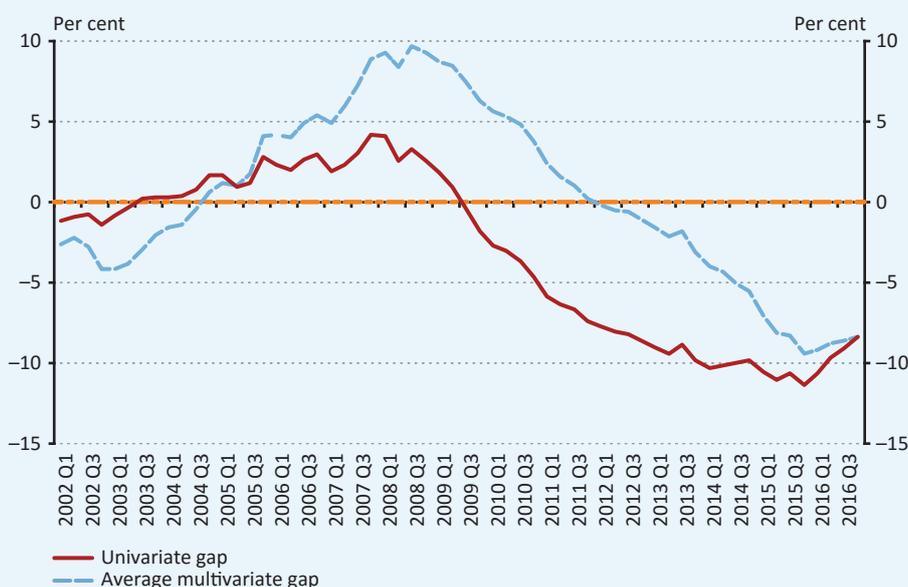
The average multivariate credit-to-GDP gap (see figure 8) shows a more rapid increase in the overheatedness before the crisis than the univariate gap. The closing of the negative gap according to the most recent observations is slower in the case of the multivariate approach simply due to the fact that the multivariate trend is more stable and less exposed to the movements and level of the credit-to-GDP itself. In other words, the effect of the explanatory variables enables the multivariate trend to calibrate the signal of an overheated credit cycle to the macroeconomic environment.

4.2 HOUSEHOLDS LENDING

The historical development of the segments' credit-to-GDP ratio is deeply impacted by the post-transition macroeconomic environment. As the 90s were characterised by high inflation and high nominal interest rates, household lending started to build up only by the end of the decade. As a result, the observed credit-to-GDP ratio starts from a low level, with its course being defined by financial deepening and unbroken growth until the crisis in 2008. One of the biggest challenges in evaluating a trend-cycle decomposition model is to decide from which point of time should the credit growth be identified as excessive.

The low starting level of the household lending also raises the question whether it is possible to apply a starting point of 1998 or should a later point be chosen. Further analysis reveals that if the household-corporate split is applied with a univariate HP filter method and the 1998 starting point is used, then the starting momentum of the credit growth causes a bias in the trend (see figure 6).

The multivariate approach has the advantage to filter this effect out as the included explanatory variables provide stability to the model in times of economic recovery. The mechanism behind this is that during the recovery the credit aggregate is still declining but this effect is counteracted by the improving macroeconomic environment depicted by the explanatory variables. For this reason, keeping the 1998 starting point for the household segment did not prove to have any major negative effects on the multivariate approach, while the longer time window increases the robustness of the model as the coefficients become more stable over time.

Just like the corporate model, the final household multivariate trend is taken as the average of the three best selected models. Table 2 gives an overview on the three selected models.

2. Table Selected models for the households' segment			
Explanatory variable	**Model 1**	**Model 2**	**Model 3**
Disposable income(-1) (%-change)	−5.567*** (−5.325)		
Unemployment rate(-1) (%-change)	0.891*** (5.187)	0.953*** (5.801)	0.805*** (5.145)
Financial system leverage (%-change)	0.309** (2.518)		
RoE (quarter-to-quarter change)		−1.115*** (−3.505)	−1.405*** (−4.037)
Interest rates, housing loans (%-change)		0.197*** (2.693)	
Households' financial situation, next 12 months(-1)		−0.327*** (−6.315)	
Debt service ratio (%-change)			0.507*** (2.154)
General economic situation next 12 months (survey)			−0.333*** (−7.518)
Supplementary indicators	**Model 1**	**Model 2**	**Model 3**
BIC	−1,5350	−1,4968	−1,4824
Robustness indicator	0,2707	0,2709	0,2138
Total rank	31	42	45

Note: All variables were demeaned. This is done so that estimating one additional coefficient (the intercept) is avoided. Percent changes were calculated as logarithmic differences. Negative integers in parentheses indicate lagged values.

*Coefficients for the cycle component are presented. *** - significant on the 1% level, **-significant on the 5% level. Z-stats in parentheses. Critical values are 1.96 and 2.96 accordingly.*

The three chosen models follow a similar path, with small deviations experienced in the case of model 1. The household trends converge to a stable value of 38% fairly early in the post-crisis period. The effect of the explanatory variables enables the trend to eliminate the momentum originating from the intense build-up phase before the crisis.

9. Figure
Comparison of different trend curves for households
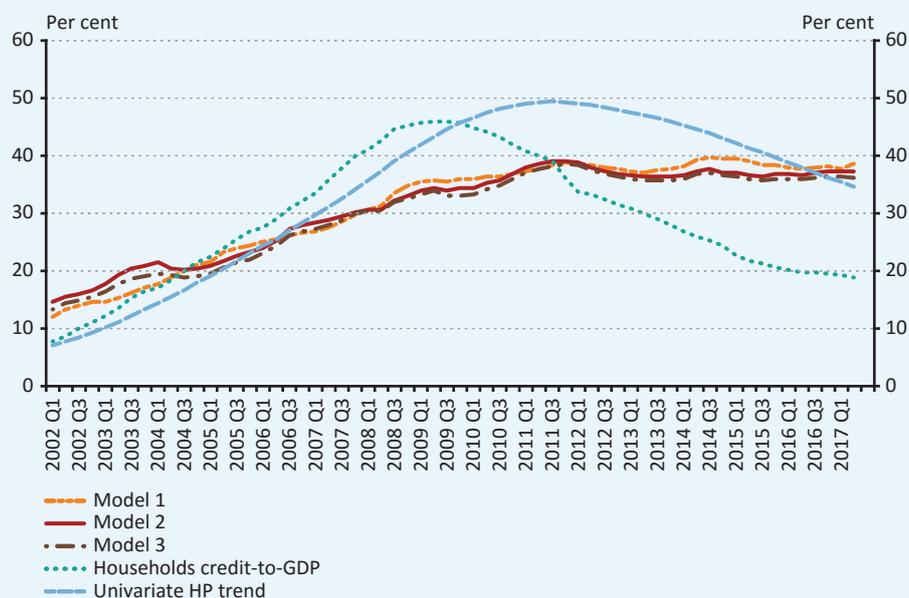
The average household model is given by taking the simple arithmetic average of the three chosen household trends, following the same logic as described in section 4.1 for the corporate sector.

10. Figure
Household credit-to-GDP with its univariate and multivariate HP trend
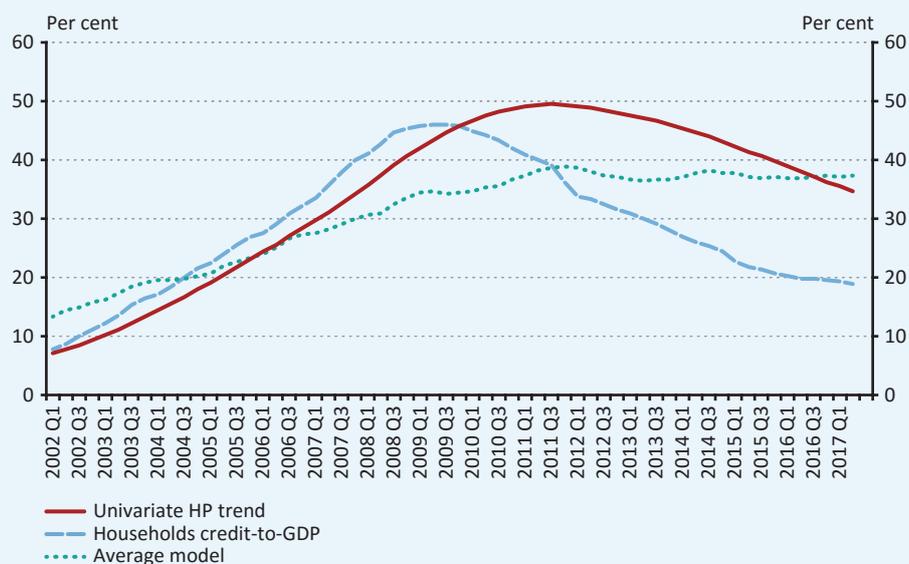
As the three chosen models gave similar trend shapes, the average model is not much different from the above discussed results. The two-fold advantage of the multivariate methodology can be pointed out here as well. On the one hand, the trend does not simply follow the momentum of the factual data with the phase shift error of the univariate approach,

but incorporates the development of the involved macroeconomic fundamentals. On the other, in the long run this trend seems to converge to a stable long-term value, defined by the explanatory variables. This latter feature of the model makes strategic policy planning easier, as the optimal level of indebtedness can be calculated on segment level.

11. Figure
Average household credit-to-GDP gap
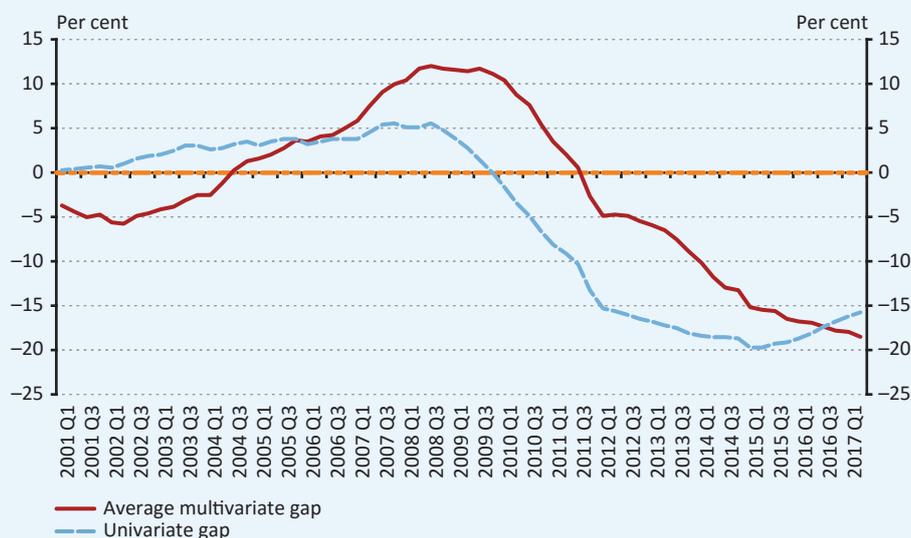
As seen in the corporate results, the multivariate model shows a more rapid growth in the cyclical component during the pre-crisis phase. This means a positive credit gap from 2004, and a quicker build-up phase for a potential countercyclical capital buffer regulation.

4.3 AGGREGATE RESULTS

The aggregate credit-to-GDP trend is given by the simple sum of the two segment level submodels. The aggregated credit-to-GDP trend should be examined in light of its relation to the level of credit-to-GDP and the univariate trend. This is shown in figure 12:

While the univariate trend shows the typical phase shift from 2005 as it follows the factual data, the multivariate approach converges to a stable level in the post-crisis period, and it fluctuates around the 70% value of the credit-to-GDP ratio in the last 8 years.

Whether the model indicates excessive credit growth or a below-optimal lending activity depends on the position of the cyclical component, i.e. on the difference between the factual credit-to-GDP and the trend, presented in figure 13. The fallback in lending activity during the post-crises period lead the credit-to-GDP gap to fall sharply, so during the 2009-2011 period it sank from the excessive credit growth indication area to the negative range. The credit-to-GDP gap is negative ever since showing that the optimal lending activity is well above the current level.

12. Figure
Country specific credit-to-GDP, its univariate and multivariate HP trends

Per cent

Average multivariate HP trend
Additional credit to GDP
Univariate HP trend
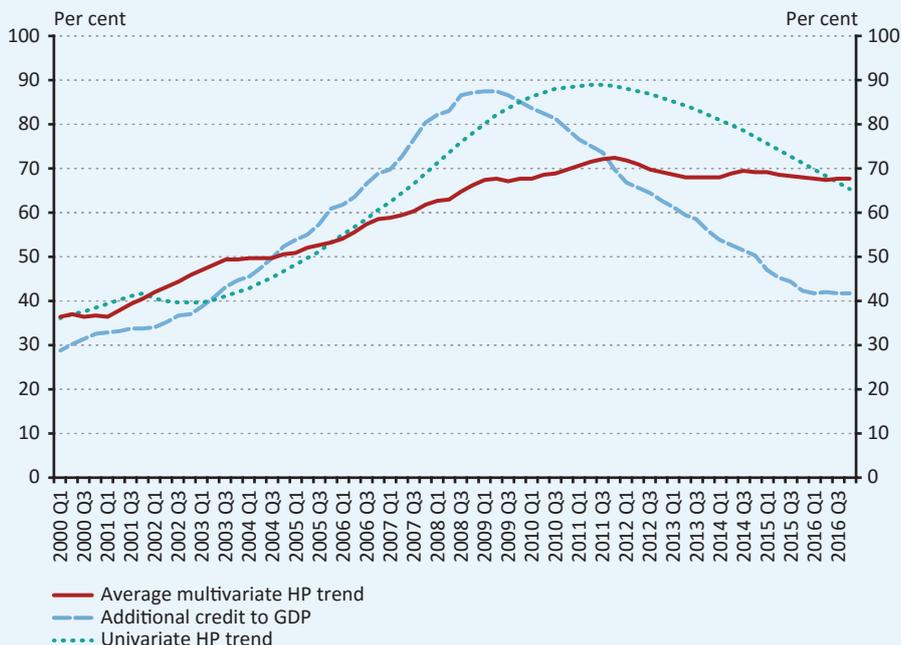
*Note: The univariate trend is calculated with a one-sided HP filter using a lambda value of 400,000.*

13. Figure
Comparison of univariate and multivariate gaps

Per cent

Average multivariate HP gap
Univariate HP gap
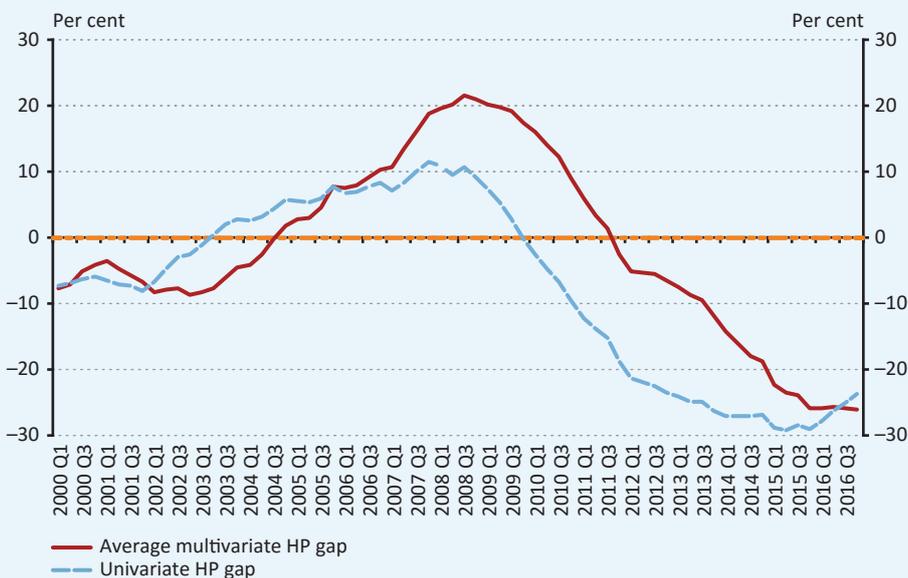
4.4 MODEL ROBUSTNESS

One of the main motivations behind the presented multivariate approach is to ensure the robustness of the model. In other words, this methodology is supposed to reduce the endpoint bias of the filter originated from the recalibration of the explanatory variables whenever new observations are available. This problem has been discussed in section 2.2 and especially in 2.2.4. For this reason, the evaluation of the results should also emphasize this problem.

14. Figure
Robustness of the aggregate multivariate credit-to-GDP gap
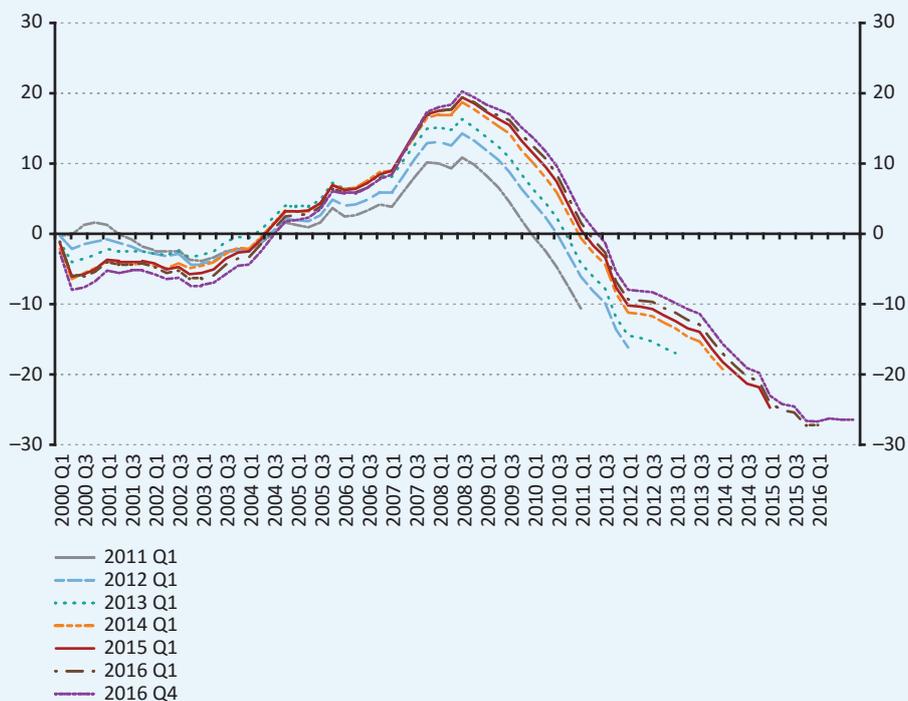
As figure 14 shows the endpoint bias is still present in the model, the effect can be significant, especially in the shorter time window model runs. On the other hand, with the increase of the time window, the bias becomes tendentially smaller, shrinking to a tolerably small magnitude. Annex 5 presents an out-of-sample robustness check, adding four additional observation points. This out-of-sample test confirms that the robustness of the model increases over time up to a point where the bias is eliminated almost completely. This enables the model to be applied for policy use in the current form. Additionally, it is expected that with the expansion of the available time series, the model robustness will increase further.

5 Conclusion

Risks connected to excessive credit growth pose a considerable threat to sustainable economic growth. Amongst the indices providing information of the build-up of such risks the related literature tends to name the development of the credit-to-GDP ratio and the credit-to-GDP gap as the best indicators. Most of the studies also agree that for the definition of the credit-to-GDP gap the most appropriate method is to use a variant of the HP filter.

This paper contributes to the literature by exploring the possibility of a state-space based multivariate HP filter, thus, the inclusion of statistically tested explanatory variables, and by addressing the problem of model robustness.

The presented approach performs the trend-cycle decomposition with the inclusion of both statistically and economically sound explanatory variables. It utilizes a multivariate HP methodology within a state-space modelling framework which enables variable selection to be based on statistical significance. In order to ensure model robustness and goodness of fit, multiple model variants were examined. The selection process resulted in taking the three best models for both the corporate and the households lending segment. The segment level credit-to-GDP gaps are the simple arithmetic average of these, while the overall credit-to-GDP gap is the sum of the segment level models.

This approach enables the model to provide a more exact picture on the economic development and base the calculation of the aggregate credit-to-GDP gap on sound macroeconomic fundamentals. Additionally, the segmentation approach allows the separate analysis of the corporate and households lending, as the credit-to-GDP gap is defined on segment level as well.

The multivariate methodology seems to improve the performance of the univariate filter substantially and in multiple fields. This takes effect on the one hand in the economic interpretation of the results, as the multivariate approach can be interpreted as an equilibrium level of the lending activity. This improvement also appears in objective factors, as the multivariate HP model is able to handle some known flaws of the univariate approach. The most obvious of these is the phase shift problem of the univariate filter: the phenomenon that the univariate trend follows the factual development of the data with a significant time lag poses severe problems for the policy application. This effect is not observable in the case of the multivariate approach. Another addressed problem is the endpoint bias of the filter, which has been reduced to a tolerable magnitude in the presented model.

The authors consider this approach a sound solution for defining the credit-to-GDP gap, which can be recommended for policy application, especially for countries where the length of the available time series proves to be a considerable constraint, like it is the case for most transition countries.

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Annex

A.1 LIST OF EXPLANATORY VARIABLES

3. Table
Explanatory variables, unit root tests and transformations

Variable	KPSS	ADF	Transformation
unemployment rate	NS	NS	logarithmic difference
interest rates, consumption loans	NS	S	logarithmic difference
interest rates, housing loans	S	S	logarithmic difference
PDI	NS	NS	logarithmic difference
major purchases over next 12 months (survey)	NS	NS	–
financial situation over next 12 months (survey)	NS	NS	–
financial situation now (survey)	NS	NS	–
housing purchases next 12 months (survey)	S	S	–
general economic situation next 12 months (survey)	NS	NS	–
MNB housing price gap2	NS	S	–
transactions, residential real estates	NS	S	logarithmic difference
interest rates, sight deposit accounts	NS	S	
debt-service ratio	NS	NS	logarithmic difference
interest rates, savings accounts	NS	S	logarithmic difference
MNB housing price index, real	NS	NS	logarithmic difference
industrial confidence indicator (survey)	S	NS	–
services confidence indicator (survey)	NS	NS	–
retail trade confidence indicator (survey)	NS	NS	–
construction ind. confidence indicator (survey)	NS	S	–
economic sentiment indicator for Hungary (survey)	S	NS	–
industrial production trends, past 3 months	S	NS	–
industrial order-book levels	S	NS	–
industrial export order-book levels	S	NS	–
stock of industrial products	S	NS	–
price expectations, industrial (survey)	NS	S	–
price expectations for exports, industrial (survey)	NS	S	–
employment expectations, industrial (survey)	NS	S	–
industrial production	NS	S	logarithmic difference
production of intermediary goods	NS	S	logarithmic difference
manufacturing production	NS	S	logarithmic difference
purchasing manager index (survey)	S	NS	–
capacity utilization	S	NS	–
german GDP	NS	NS	year on year %-change
retail trade	NS	S	logarithmic difference
total deposits of non-financial corporations	NS	S	logarithmic difference

3. Table			
Explanatory variables, unit root tests and transformations			
Variable	**KPSS**	**ADF**	**Transformation**
interest rates, long-term loans	NS	S	logarithmic difference
debt-to-deposit ratio	NS	NS	logarithmic difference
interest revenue-to-GDP ratio	NS	NS	logarithmic difference
net interest revenue-to-GDP ratio	NS	NS	logarithmic difference
liquid assets-to-total assets ratio	NS	NS	logarithmic difference
leverage	NS	NS	logarithm
RoE (4 quarters moving average)	NS	NS	first difference
RoA (4 quarters moving average)	NS	NS	first difference
3-month interest rate, BUBOR	NS	S	logarithmic difference
10-year government bond yield	NS	S	logarithmic difference
1-year government bond yield	NS	S	logarithmic difference
capital adequacy ratio	NS	S	logarithm

Note: Many of the transformations can be challenged. Variables such as interest rates might be over-differenced for these series do not of necessity have either stochastic or deterministic trends in developed economies. However, these series are prone behave differently in transition economies as financial deepening is clearly reflected through them. Thus, in such cases we chose to differentiate the series because level data produced clearly flawed estimates and data shortage prevents us from discarding observations from the beginning of the series.

NS – non-stationary, S – stationary.

12 variables from the above listed 47 are survey indices. These are taken from a Europe wide survey programme of the European Commission (European Commission, 2017). Hungary has been part of this programme since 2001, so the variables are applicable for the credit-to-GDP model development.

The 18 variables that were selected into the final model set are described more in detail as follows:

The corporate segment model discussed in section 4.1 utilizes the following ten macroeconomic fundamentals:

The *Retail confidence indicator* is a survey index which serves as a good proxy for the economic environment of the SME segment as it reflects the expectations of the actors in the retail trade segment. A negative coefficient is expected from the variable as positive expectations in the retail trade area should have a positive effect on the long-term trend of corporate lending.

The *Change in retail trade* also captures the SME segments economic development as it shows the actual growth tendencies. The coefficient is expected to be negative for the same reason as in the case of the above variable.

The *Change in German GDP growth* captures the tendencies and expectations of the most relevant global factors defining the Hungarian economy on one hand, while directly influences the export possibilities and investment potential in a large proportion of the Hungarian large and medium corporations. A positive coefficient is expected as an increase in the global cycle can increase the Hungarian cyclical component as well.

The *Change of the 5-year Hungarian government bond yields* shows the long run expectations on the Hungarian economy. Increase in the long-term country risk premium boosts investment propensity. A positive coefficient is expected as an increasing country risk factor ceteris paribus poses as a risk on the sustainability of the actual lending activity.

The *Change in debt-to-deposit ratio* reflects the tendencies of the actors' indebtedness. It represents the change in percentages in the segment level debt-to-deposit ratio, so it returns a value of the recent growth pace of indebtedness.

Also, it reflects the risk taking propensity of the banking sector. A positive coefficient is expected as indebtedness is a risk to sustainability of lending, while an increase on the risk taking propensity should increase the cyclical compontent.

The *Economic sentiment indicator* is a survey that captures the current mood of the economy, reflecting the actual stress level, growth expectations and investment notion. A negative coefficient is expected as positive expectations on the economic growth should increase the level of sustainable lending.

The *Construction industry confidence indicator* is a composite survey index reflecting the growth expectations and risk assessment of the actors in the construction industry. As construction investments pay-off in the long run, this indicator channels in assessment of long-term risks. A negative coefficient is expected for similar reasons as in the case of the above sentiment indicator.

The *Industrial confidence indicator* is also a survey composite index with a similar content. This depicts the assessment of the actors in the industry segment. Also here, a negative coefficient is expected.

Capacity utilization is the ratio between the real and the potential production of a given time period, with the latter defined by the available production assets. In the model, it represents the production intensity of the corporations, and so together with the industrial production it covers the sectors credit demand. A positive coefficient is expected as this variable serves as a warning signal of overheatedness in the sector.

Industrial production trends is a good proxy for GDP growth, it reflects the perceived change in industrial production for the past 3 months. As it serves a very similar role as the above indicator, also here a positive coefficient is expected.

The household segment model which is presented in section 4.2 in detail has eight explanatory variables:

Change in disposable income reflect the financial potential of the households, thus, it is a strong indicator of the demand side of the segment. A negative coefficient is expected as increasing household income should increase the sustainable level of lending.

Change in unemployment rate also reflects the demand side, but it is also an indicator of the risk cost development of the household lending. A positive coefficient is expected as increasing unemployment decreases the sustainable level of lending.

The *Change in the average leverage of the financial system* brings the credit supply side into the model reflecting the overall lending behaviour of the banking sector. A positive coefficient is expected as this variable serves as an overheatedness warning indicator.

The *Change of the housing loans' interest rates* and *Households' financial situation for next 12 months* directly follows the credit constrains of the most relevant product in the household lending. In this role a positive coefficient is expected.

Change of the average return on equity of the banking sector is also a supply side indicator, it pictures the profit expectations of the financial institutions and thus also the willingness to lend. A negative coefficient is expected as higher profitability of the banking sector increases the sustainable level of lending.

The survey indicator *Households' financial situation for next 12 months* reflects the financial potential of the sector. A negative coefficient is expected as improving financial situation of the households should increase the sustainable level of the sectors lending.

The *General economic situation next 12 months* is also a survey indicator, it represents the demand side and the financial potential and expectations of the households. Also here, a negative coefficient is expected.

Change in debt service ratio represents both the demand and the supply sides, as it is influenced by both the credit constrains and the disposable income. A positive coefficient is expected as increasing indebtedness should decrease the sustainable level of lending.

A.2 DESCRIPTION OF SUPPLEMENTARY INDICATORS

A.2.1 Robustness

Equation 6. below defines our metric for robustness.

$$\delta_l = \sum_{i=1}^{M} \delta_{l,i} = \frac{\sum_{i=1}^{M} \sum_{t} |\tau_{l,i,t} - \tau_{l,ref,t}|}{\sum_{t} |\tau_{l,ref,t}|} \tag{6}$$

where

• *l* indices the model in question.

• *M* is the number of subsamples on which the model was estimated.

• *ref* indicates the indexed quantity was estimated on the reference sample comprising data from 1998Q1 to 2016Q4.

• The second summation in the numerator as well as the summation in the denominator is defined on a subset of the intersection of samples. In our exercise that is 2002Q1-2014Q1.

Visually speaking $\delta_{l,i}$ relates the area of differences between various trend estimates to the area under the trend estimated on the reference sample (see figure 15).

15. Figure
Visual illustration of the metric assessing robustness of estimated models
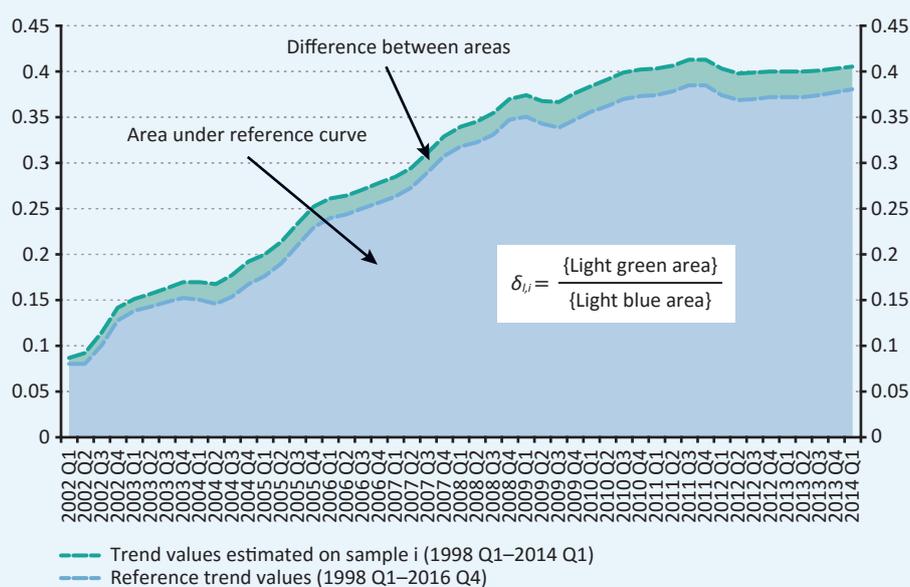
A.2.2 Balance

One way to capture the effect of explanatory variables on the trend-cycle decomposition is to fix estimated coefficients, then perform the decomposition excluding one of the variables. The difference between trend values then measures the effect of said variable. Rotating excluded variables in a cyclical fashion and calculating differences between the "complete" and "truncated" trend values yields the effect decomposition of the model. It is desirable to select models, in which every included variable has significant[22] effect. In other words, no variable dominates the model. To this end we define $\gamma_{l,i}$s. A quantity associated with the ith variable of model l, that relates the deviation from the univariate trend due to variable i to the total deviation.

$$\gamma_{l,i} = \frac{\sum\limits_{t}\left|Eff_{l,i,t}\right|}{\sum\limits_{i=1}^{N_l}\sum\limits_{t}\left|Eff_{l,i,t}\right|} \tag{7}$$

Where $\sum_t\left|Eff_{l,i,t}\right|$ is the effect of variable I, N_l is the number of variables included in the model.

If $\gamma_{(l,i)}>0.6$ for any i, model I is rejected. For visual interpretation see figure 16.

16. Figure
Visual demonstration of our metric for balance
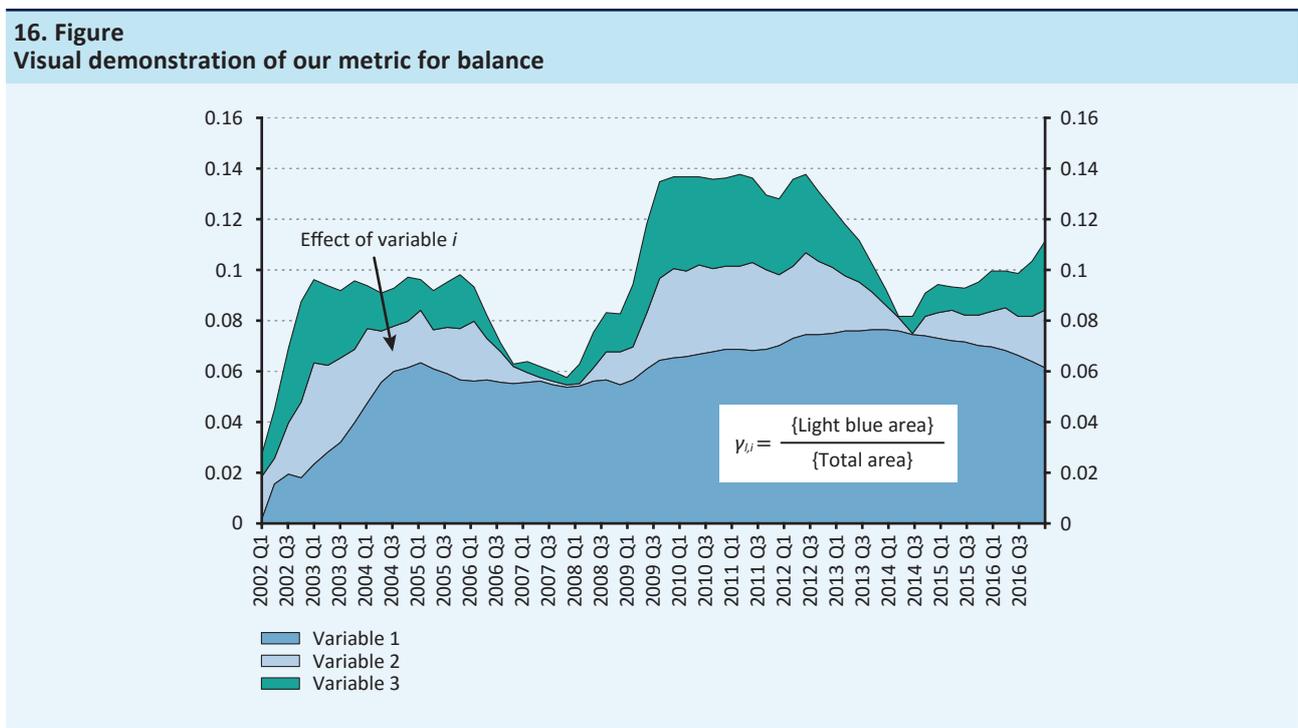
The relative weight of a given variable in a model is calculated by excluding the examined variable from the model and calculating the effect of the variable as the difference between the two trends. The detailed results are presented in section A.4 in the appendix.
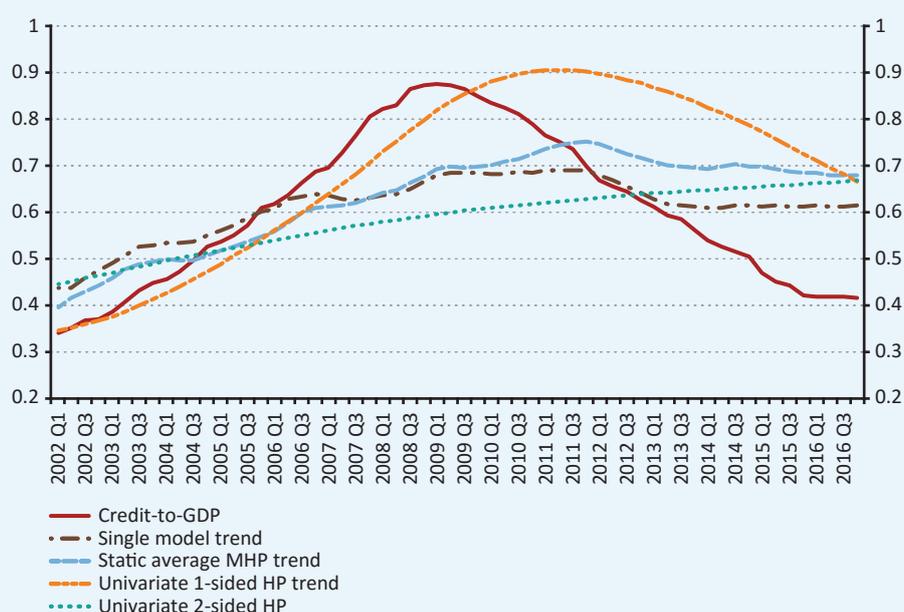
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[22] In a practical sense.

A.3 COMPARISON OF VARIOUS AGGREGATION METHODS

Figure 17 compare several trend estimates. Difference between the single model approach and static averaging is marginal.[23] Also, these gaps are more in line with expert opinions. For demonstrational purpose, two-sided HP gap and trend estimates are also depicted in the figures. The produced multivariate HP trend estimates and those of the two-sided HP filter have a lot in common: they follow the data less closely than one-sided HP, thus reflect more stable fundamentals.

Overall, we believe static averaging is the method of choice here (see table 4 for a summary of pros and cons). It is best seen as an intermediary solution between extremities. It maintains transparency and low data requirement, while also increases the versatility of our model.

17. Figure
Resulting trend values produced by various aggregation methods

4. Table
Pros and cons of various aggregation methods

|	Single model	Static averaging
+	• transparency • low data requirement • easy to track effects of variables	• reduced likelihood of poor selection • transparency can be preserved
–	• risk of poor choice • limited information usage • impossibility of retrospective evaluation	• some transparency is lost • difficulties with data availability might arise • number of models averaged has to be low to prevent difficulties from escalating

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[23] Though the single model shows overheatedness in a more intuitive period, both approaches capture the rapid growth in lending that supposedly occurred few years before the global financial crisis.

A.4 CHARACTERISTICS OF THE SELECTED SEGMENT LEVEL MODELS

A.4.1 First corporate model

The first corporate model, which proved to be the best by the ranking of the selection criteria, uses the explanatory variables *retail confidence indicator* (with one quarter lag), *change in retail trade* (with one quarter lag), *yearly change of German GDP* (with one quarter lag) and *change in 5-year Hungarian government bond yields*.

The corporate trend is fairly stable over time, resulting in an early signal of overheatedness as credit-to-GDP ratio builds up. The involvement of the explanatory variables changes the trend significantly as it can be seen when comparing the univariate and multivariate trends in figure 18.

18. Figure
Trend values produced by corporate model 1
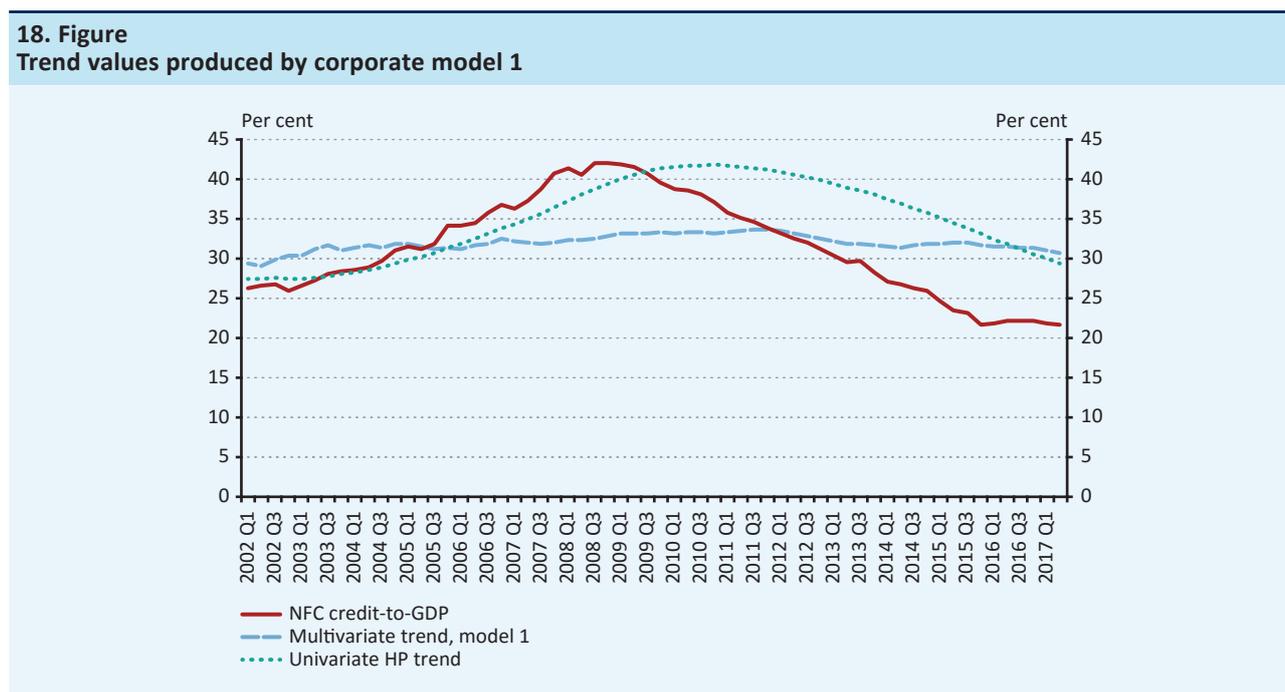
The effect of each distinct explanatory variable is shown in figure 19. Here the individual effects are highlighted, so that the relative importance, the direction and the economic intuition of the distinct effects can be observed, while the whole figure adds up to the difference between the multivariate and the univariate trends (highlighted by the black line in the figure). The effect analysis is performed with excluding the examined variable from the model and calculating the effect of the variable as the difference between the two trends[24].

The interpretation of the coefficients should be performed in light of the fact that the applied methodology explains the cycle with the chosen macroeconomic fundamentals, so the described connections apply to the trend in reverse direction. State-space modelling with the application of the Kalman filter enables the model to estimate both the trend-cycle decomposition and the coefficients of the explanatory variables simultaneously. Another aspect of the interpretation that is worth to be highlighted is that the connection shown in the model results represents correlation and not causality. Thus, the model depicts the strength and direction of the connection between the cyclical component and the explanatory variables, but does not give an answer to whether the variables cause the cycle development or vice versa.

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[24] Meaning the original trend and the one calculated with the exclusion of the examined variable. For the effect analysis, the other variables enter the model with fixed coefficients, so the resulting difference shows only the real effect of the variable, omitted variable bias plays no role here.

19. Figure
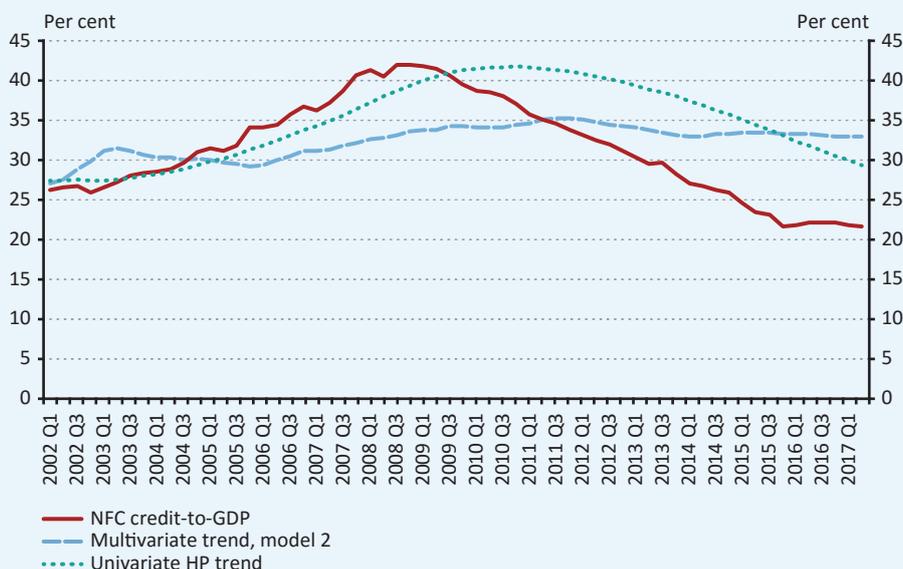**Relative importance of explanatory variables at corporate model 1**
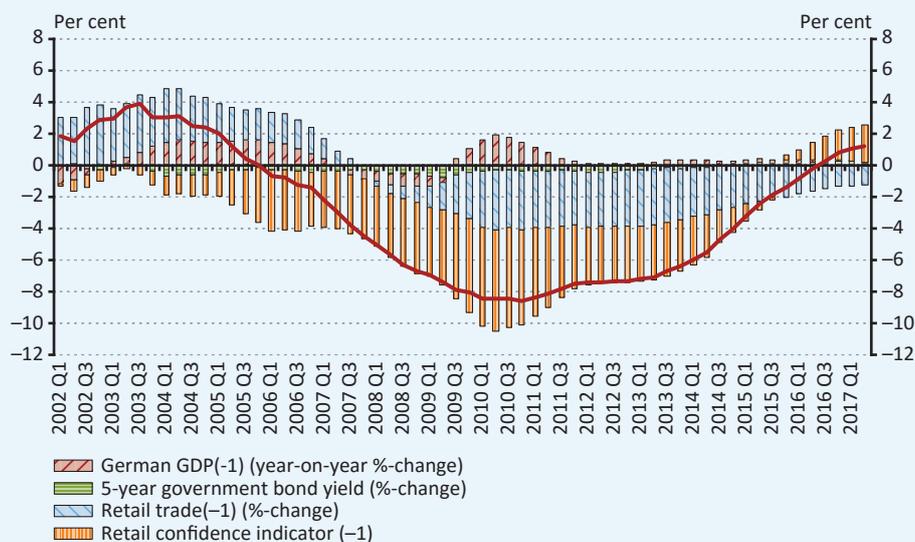
Note: Effects are represented as the deviation from the univariate HP trend due to the variable in question. This is calculated by excluding given variable from the model, and performing the trend-cycle decomposition with fixed coefficients. The difference between the original and the constrained trend values then yields the effect of said variable. Negative integers in parentheses indicated lagged variables.

A.4.2 Second corporate model

The second model uses the explanatory variable set of *retail confidence indicator* (with one quarter lag), the *change in debt-to-deposit ratio* (with one quarter lag), the *economic sentiment indicator* and the *industrial production trends*.

The trend depicted by this model is less stable as it reacts quicker to changes in the macroeconomic fundaments (displayed best in the beginning of the time series, when the positive gap is growing against the credit-to-GDP movements) and the changes of the target variable. Due to this attribute, Model 2 shows positive gap the earliest before the crisis and because of the development of the selected explanatory variables this shows the highest negative gap for the most recent observations.

20. Figure
Trend values produced by corporate model 2

As described above the following figure shows the effect of each distinct explanatory variable so that sum of the values returns the difference between the multivariate and the univariate trends.
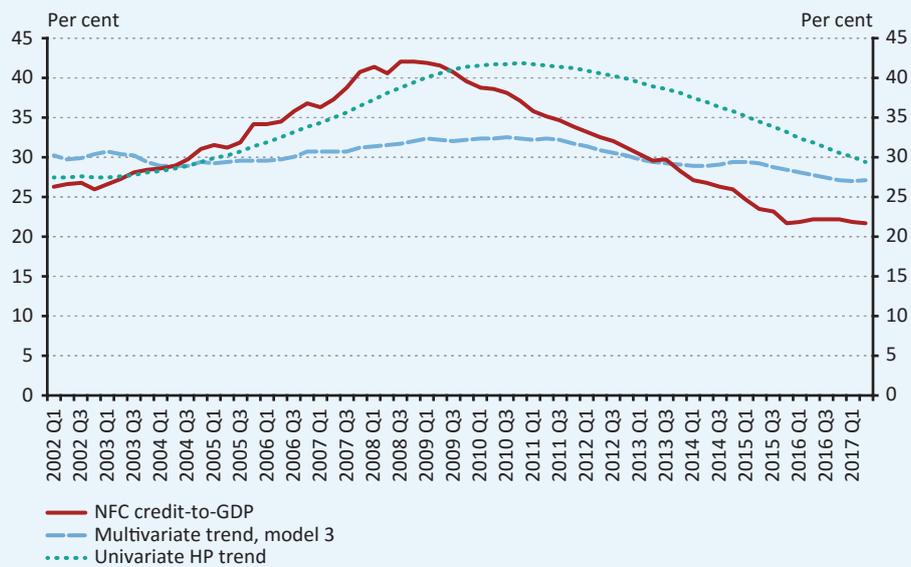
21. Figure
Relative importance of explanatory variables at corporate model 2


A.4.3 Third corporate model

Model 3 places more focus on the production aspect of the corporate segment, gaining additional information with the application of *construction industry confidence indicator, industrial confidence indicator, industrial production trends* and *capacity utilisation* as explanatory variables.

22. Figure
Trend values produced by corporate model 3

The individual effects of the distinct variables over time are shown below on figure 23.

23. Figure
Relative importance of explanatory variables at corporate model 3

Legend:
- Construction industry confidence indicator
- Industrial production trends
- Capacity utilisation(−1)
- Industrial confidence indicator (−1)
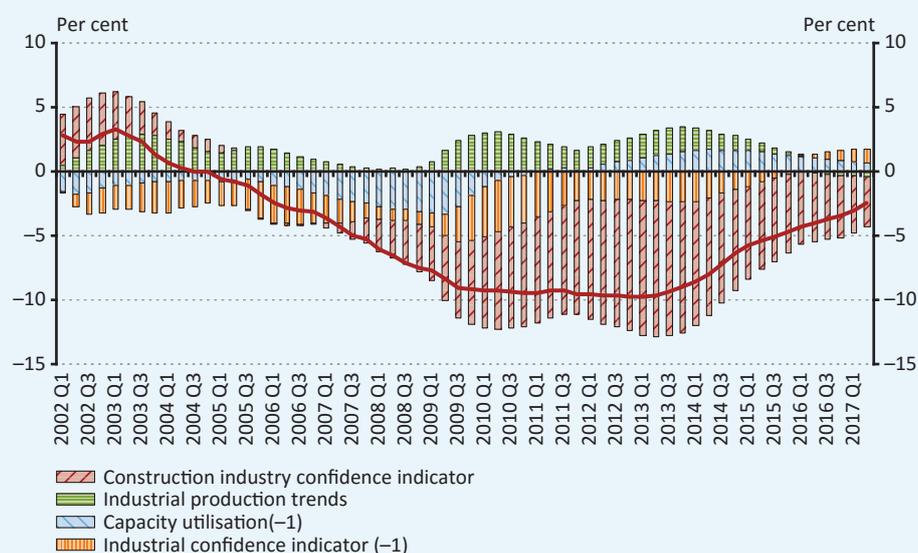
A.4.4 First household model

The first household model is ranked the highest among the selected three by the chosen goodness-to-fit measure (BIC) and robustness. However, unlike the corporate model selection, this was not the highest ranking of all models, it only ranked 31 amongst all models (see table 2). The reason for this is that in case of the households segment providing the highest possible variable heterogeneity within the three selected models proved to be more troublesome, therefore more varieties of selections had to be examined.

The model has three explanatory variables: *change in disposable income* (with one quarter lag)*, change in unemployment rate* (with one quarter lag) and *change in the average leverage of the financial system*.

24. Figure
Trend values produced by household model 1

Legend:
- Households credit-to-GDP
- Multivariate trend, model 1
- Univariate HP trend
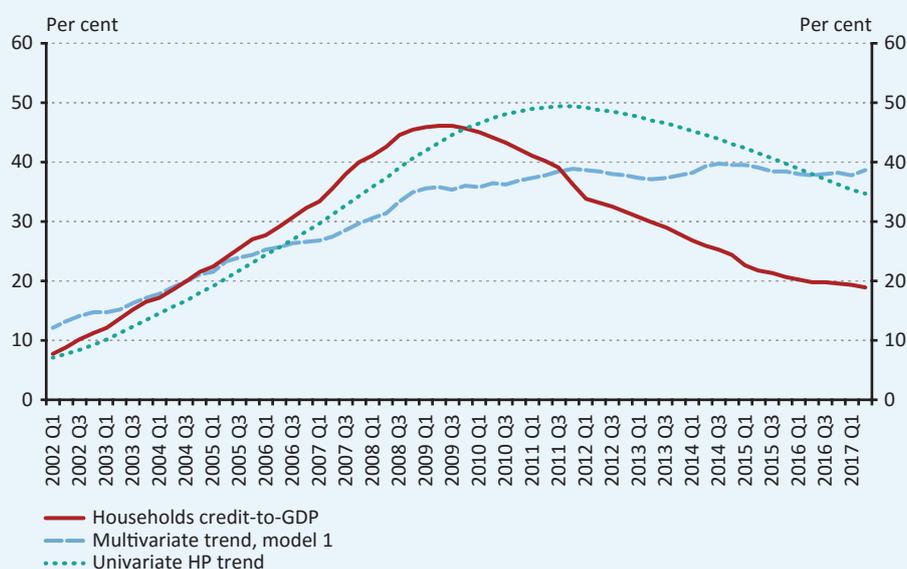
The household trends are fairly similar, though model 1 differs in showing a higher equilibrium path (see figure 24). The individual effects of the explanatory variables are shown on figure 25.
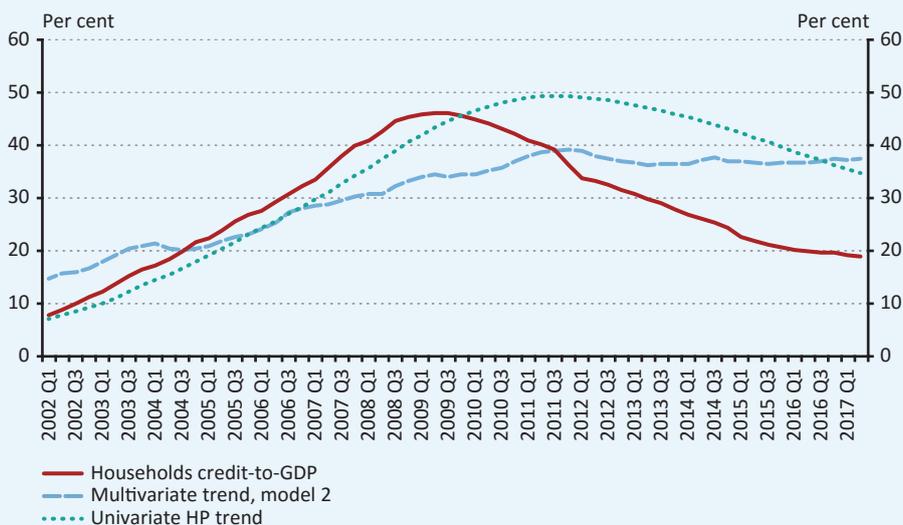
25. Figure
Relative importance of explanatory variables at household model 1

Per cent

Disposable income(−1) (%-change)
Unemploylment rate(−1) (%-change)
Bank leverage (logarithm)
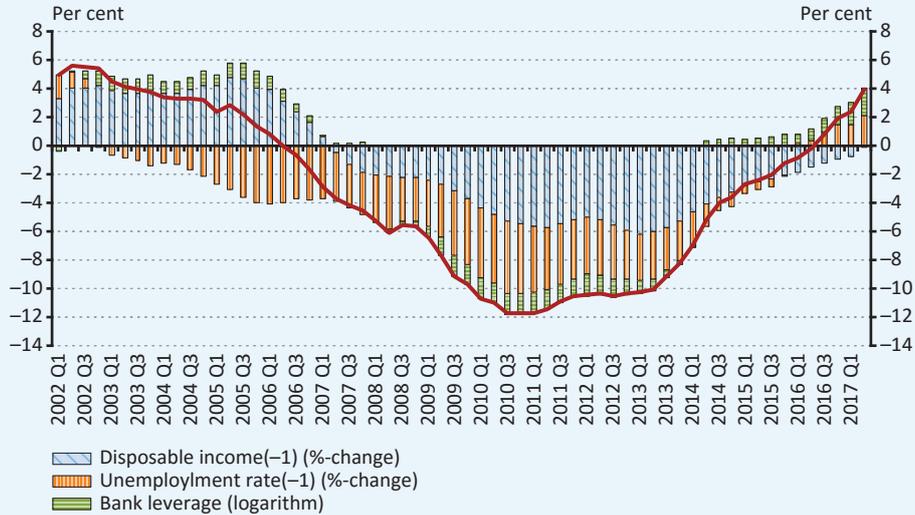
A.4.5 Second household model

The second household model contains four explanatory variables: the *change in unemployment rate* (with one quarter lag), *change of the average return on equity of the banking sector*, *change of the housing loans' interest rates* and *households' financial situation for next 12 months* (with one quarter lag).

26. Figure
Trend values produced by household model 2

Per cent

Households credit-to-GDP
Multivariate trend, model 2
Univariate HP trend

The trend shown on figure 26 shows a bit higher grade of excessive credit growth in the pre-crisis period than model 1, but mostly follows a very similar path. The relative importance of the explanatory variables is presented in figure 27.

27. Figure
Relative importance of explanatory variables at household model 2
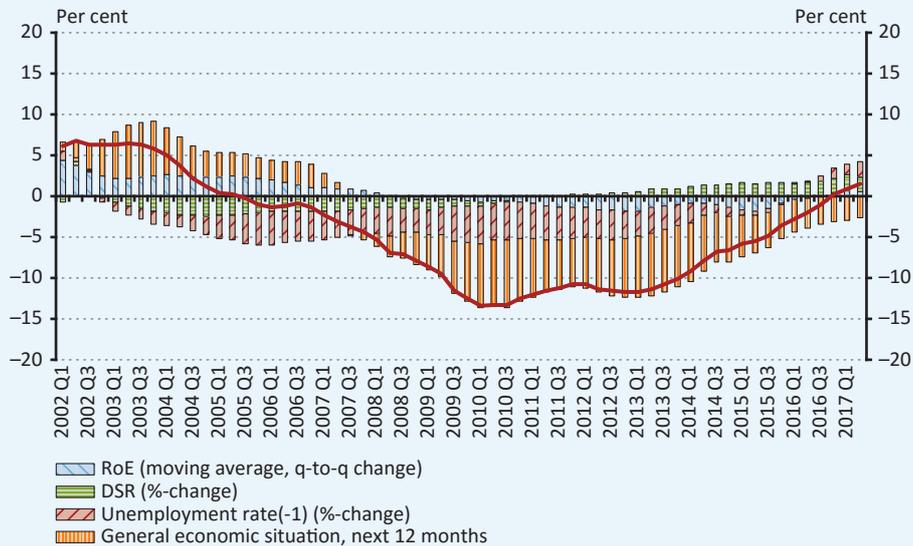

A.4.6 Third household model

The third household model uses *Change in unemployment rate* (with one quarter lag), *Change of the average return on equity of the banking sector*, *Change in debt service ratio* and *General economic situation next 12 months*. As table 2 shows this model has a significant overlap with the previous two, as two of its variables are also present in model 2 and the unemployment indicator is part of all three models. The problem with such overlaps is that the final average model will have the shared variables overrepresented in it, thus, the advantage from having multiply models largely erodes as the resulting trend will be exposed to sudden changes of certain variables. Still, this risk is smaller with having the three models' average at hand than one chosen model.

28. Figure
Trend values produced by household model 3
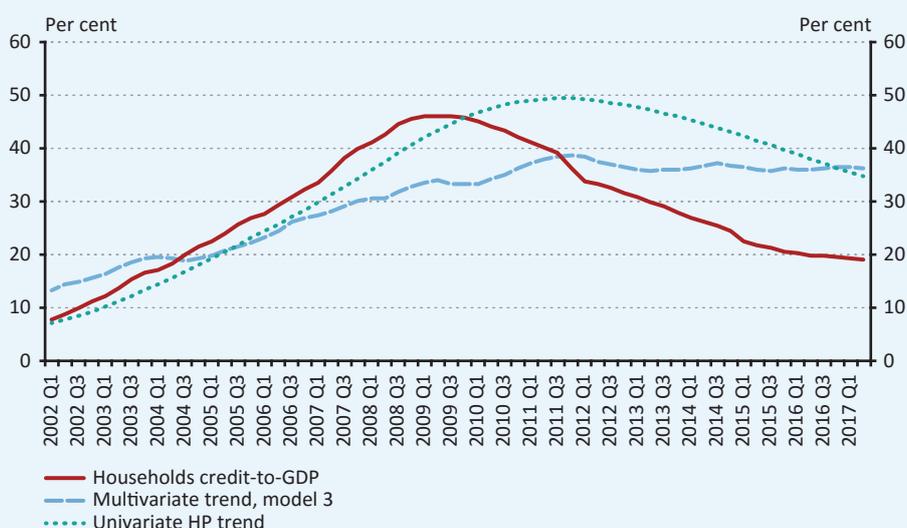
The trend curve defined by model 3 follows the lowest path from the three. As a result, it is the quickest to show excessive credit growth in the pre-crisis period, and it also proved to give the most conservative negative credit gap estimation in the post-crisis phase.
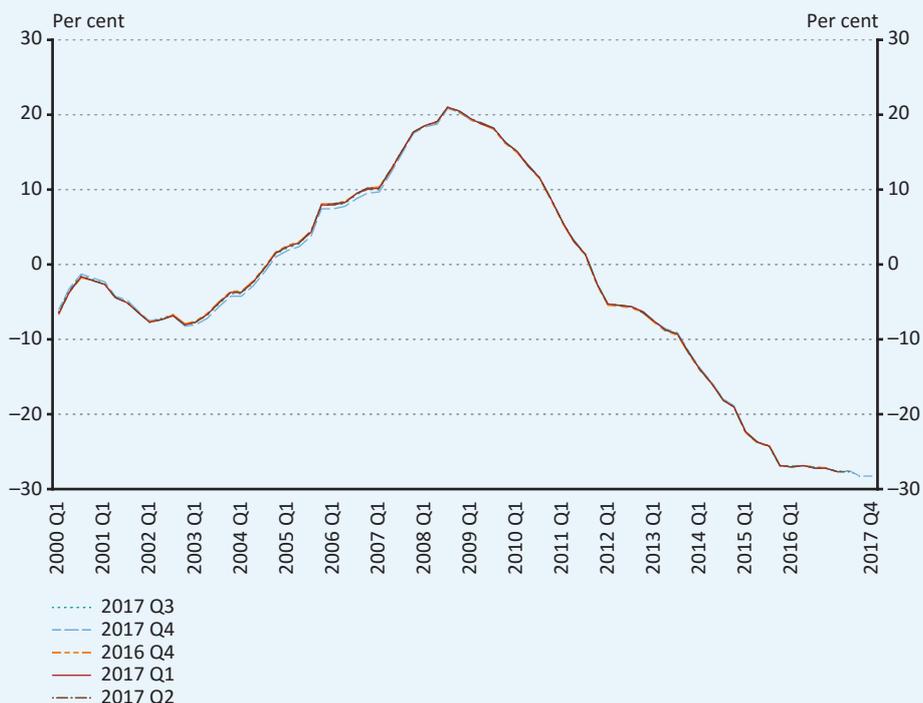
29. Figure
Relative importance of explanatory variables at household model 3

RoE (moving average, q-to-q change)
DSR (%-change)
Unemployment rate(-1) (%-change)
General economic situation, next 12 months
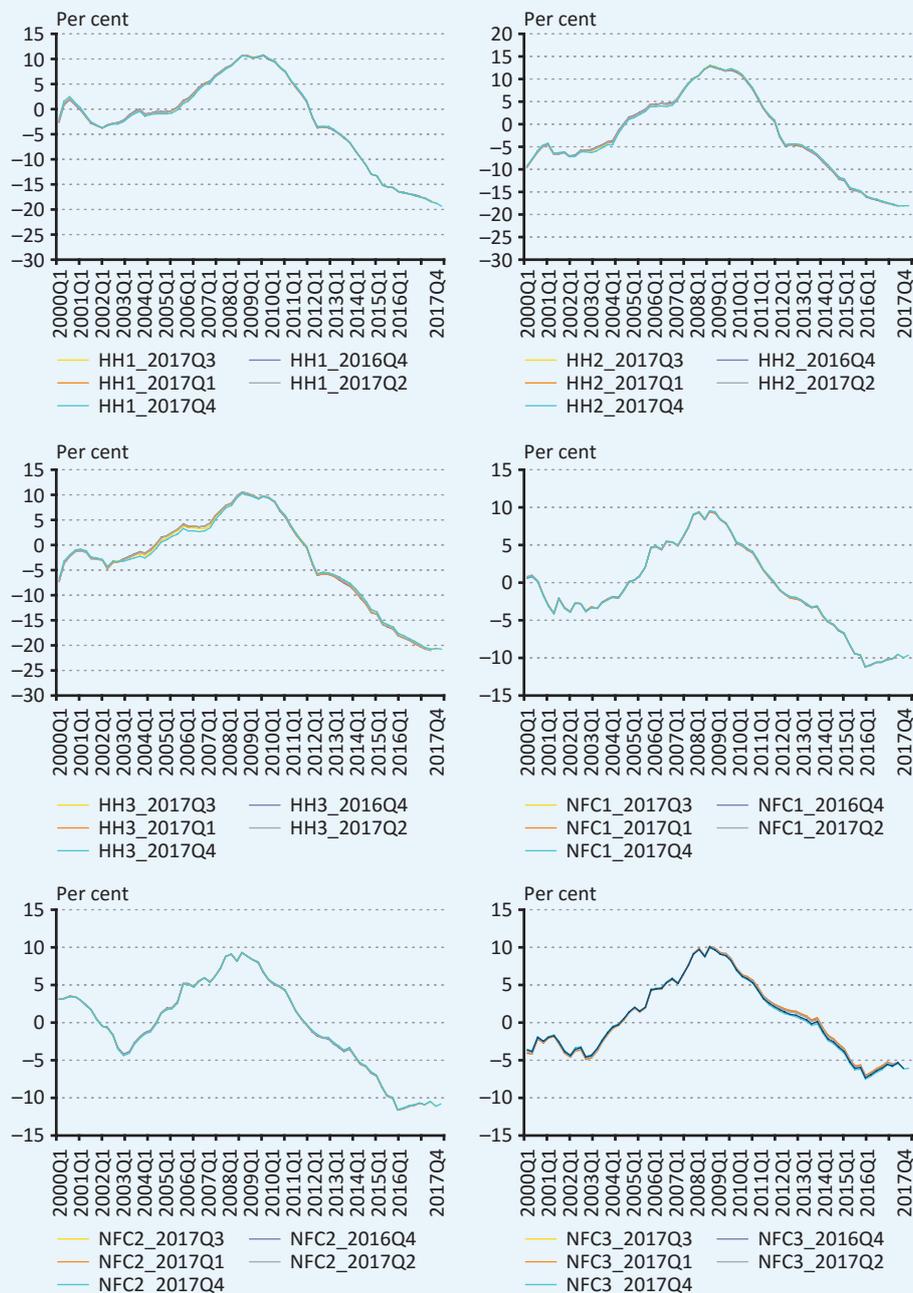
A.5 OUT-OF-SAMPLE ROBUSTNESS

The out-of-sample test is performed by adding four additional observations to the original time series, so that all the sub-models are re-estimated four times as if the given observation point was the last element of the series. As in section 4.4, this is used to measure the effect on the model of adding an additional observation, thus, measuring the end-point bias. As figure 30 shows, the end-point bias is eliminated almost completely on aggregate level.

30. Figure
Out-of-sample robustness of the aggregate model

2017 Q3
2017 Q4
2016 Q4
2017 Q1
2017 Q2

The test was also performed on single model level to monitor the effect of the aggregation as well as the out-of-sample performance of the unique trends. It can be observed on figure 31 that the first two models for both the households and the corporate segments shows almost no end-point bias at all, while the third models in both segments have weak signs of end-point bias. As even the third models' robustness are assessed as strong, the authors consider the results of the out-of-sample test reassuring.

31. Figure
Single model level out-of-sample robustness test

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