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Contents

Abstract

Within the framework of the Basel III capital regulation, macroprudential authorities may order the accumulation of countercyclical capital buffers in the period when systemic risks are building up. According to recommendations, it is worth setting the size of the capital buffer on the basis of the magnitude of the credit-to-GDP ratio gap. Therefore, the time series of Hungary's credit-to-GDP ratio is decomposed to trend and cyclical components (credit gap) using four trend filtering methods: univariate Hodrick–Prescott filter, univariate Christiano–Fitzgerald filter, univariate Beveridge–Nelson filter and multivariate Hodrick–Prescott filter. The decomposition was carried out separately for the household and corporate segments. Of the four methods, it is the results of the multivariate Hodrick–Prescott filter, which also uses the information content of other variables, that reflect experts' assessment relating to developments in lending in Hungary the most. In addition, endpoint uncertainty was also the smallest in this case, i.e. the receipt of new data caused the smallest changes in the values estimated for previous periods here.

JEL codes: C30, E32, G28
Keywords: countercyclical capital buffer, credit gap, trend filtering method

Summary

Pursuant to the MNB Act, in Hungary the Central Bank plays the part of macroprudential authority and operates the set of macroprudential instruments specified in the Act. One of its elements is the countercyclical capital buffer, which was introduced at international level within the framework of the Basel III capital regulation.

The primary objective of the countercyclical capital buffer is that banks accumulate a capital buffer in the periods when there is excessive credit growth at national economy level, because then significant systemic risks may build up. The capital buffer established this way may then facilitate the maintenance of loan origination in stress situations through strengthening the solvency of not only individual banks but of the banking sector as a whole. This may reduce the risk that in a stress situation, in order to meet the capital adequacy requirement, banks limit their credit supply, causing further loan losses to the banking sector through unfavourable real economy effects.

In its guidance, the Basel Committee on Banking Supervision (BCBS) focuses on the credit-to-GDP ratio, and proposes to adjust the setting of the countercyclical capital buffer to the cyclical component of the credit-to-GDP ratio.

The time series of the credit-to-GDP ratio may be decomposed to trend and cyclical components by applying univariate and multivariate filtering methods. There are different assumptions underlying each filtering method, resulting in different trend and credit gap time series. Univariate filtering methods take into account only the data of the time series intended to be filtered, while multivariate methods allow the inclusion of other information as well.

The European Systemic Risk Board requires the quantification of the cyclical component on the basis of the BCBS guidance, applying a standardised univariate Hodrick–Prescott filter, but the use of other tools is also allowed. Therefore, in addition to the univariate Hodrick–Prescott filter, three other filters are also presented in this study: the first one is the Christiano–Fitzgerald filter, the second one is the Beveridge–Nelson filter (both of them are univariate ones), whereas the third one is a multivariate Hodrick–Prescott filter, developed by us for this purpose. In the case of Hungary we consider the latter more suitable for quantifying the cyclical component than the univariate Hodrick–Prescott filter included in the recommendation.

As developments in lending in the household and corporate segments can be separated from one another, in order to obtain a more precise picture, we carried out the filtering processes in the case of both segments. Accordingly, the trend and the cyclical components of the credit-to-GDP ratio of the private sector become the sum of the two results.

With changes in the time series, incoming new data may considerably amend our assessment of the trend and the size of the gap. For this reason, as time goes by, one could consider significantly different levels of capital buffers as desirable for the various periods. Therefore, it is important that the credit gap received as the result should be as robust as possible to incoming new data. We have compared the filtering methods from this aspect: based on our findings, the univariate Hodrick–Prescott filter produces greater revisions than the Christiano–Fitzgerald filter, while the most stable method is the multivariate Hodrick–Prescott filter. In addition, the credit gap estimated by the multivariate filter is in conformity with our experts' assessment as well.

1 Introduction and motivation

Pursuant to the MNB Act,[1] in Hungary the Central Bank plays the part of macroprudential authority and operates the set of macroprudential instruments specified in the Act. One of its elements is the countercyclical capital buffer, which was introduced at international level within the framework of the Basel III capital regulation.

According to the guidance issued by the Basel Committee on Banking Supervision (BCBS, 2010), the primary objective of the countercyclical capital buffer is that banks accumulate a capital buffer in the periods when there is excessive credit growth at national economy level, because then significant systemic risks may build up. The capital buffer established this way may then facilitate the maintenance of loan origination in stress situations through strengthening the solvency of not only individual banks but of the banking sector as a whole. This may reduce the risk that in a stress situation, in order to meet the capital adequacy requirement, banks limit their credit supply, causing further loan losses to the banking sector through unfavourable real economy effects.

In addition to the primary objective, a further favourable effect of operating the countercyclical capital buffer may be that it may dampen the fluctuations of the credit cycle as well, as it may restrain excessive credit growth through increasing the cost of lending.

Upon setting the capital buffer ratio, many types of information and relationships have to be taken into account, so macroprudential authorities have to develop new methods and decision supporting frameworks for the introduction of this instrument. Several studies and international recommendations were made to support this. The afore-mentioned guidance of the Basel Committee on Banking Supervision focuses on the deviation of the credit-to-GDP ratio from the trend (credit-to-GDP gap): partly because of its direct relationship with the phenomenon of excessive credit growth, and partly because examining a wide international sample it was found to be a suitable indicator in connection with the build-up of system-wide risks.[2] Although the guidance contains really concrete calibration proposals as well, in order to reduce the chance of false signals, it is proposed that in addition to examining the credit-to-GDP ratio, authorities should take into account various other indicators as well when they make a decision. In addition, it is also mentioned that it is worth thinking of releasing the capital buffer not only when credit growth slows down, because sudden, crisis-like turning points of credit cycles are indicated earlier by other, market indicators. In these cases it may be worth releasing the capital buffer immediately, already on the basis of market indicators. By this, the issue of releasing the capital buffer may be prevented from causing further uncertainty.

The European Systemic Risk Board also formulated a recommendation in connection with the introduction of the countercyclical capital buffer.[3] In this, in addition to the calculation of the credit-to-GDP gap preferred by the Basel Committee on Banking Supervision, the development and parallel use of alternative calculation methods are also recommended if it is justified by the characteristics of the given country. Detken et al. (2014) also emphasise that although out of the examined variables it was the credit gap that indicated the periods of excessive credit growth the best, an even better set of indicators may be produced by combining various explanatory variables.

[1] Act CXXXIX of 2013 on the Magyar Nemzeti Bank

[2] The detailed results are contained in Drehmann et al. (2010).

[3] Recommendation of the European Systemic Risk Board of 18 June 2014 on guidance for setting countercyclical buffer rates (ESRB/2014/1); the related study by Detken et al. (2014).

In Hungary, we start developing the set of indicators necessary for setting the countercyclical capital buffer by examining the credit-to-GDP ratio, due to its prominent role. As the statistical methodology proposed for the identification of the credit gap in the afore-mentioned recommendations does not perform satisfactorily (as presented in detail in the following chapters of this study) on the short domestic data, which do not even comprise a complete credit cycle, we are trying to use other statistical approaches as well in order to receive more robust results. In our article, credit gap is quantified by other univariate filtering methods as well, and also by an extended, multivariate amendment to the original filtering method. Then we present that the results of these methods are more stable and more reliable than the ones in the recommendations.

The next chapter of the study provides a detailed description of the various methods available for quantifying the credit gap, followed by a presentation of the data serving as a basis for the analysis: household and corporate loans outstanding. Then some univariate filtering methods are reviewed and their characteristics observed on Hungarian data are examined. This is followed by a detailed presentation of the multivariate filtering method, whose results are compared to the credit gaps received using simpler methods. Finally, our major conclusions are summed up.

2 Methodological approaches to identify the credit gap

The idea of using the countercyclical capital buffer as a macroprudential instrument arose following the outbreak of the 2008 crisis; consequently, past observations of its practical functioning are not yet available, and relevant researches cannot be found either. At the same time, modelling and measuring the credit gap is important in respect of other economic issues as well; accordingly, various studies were prepared regarding this subject. The main differences between the studies and the methods used therein are in the notion of equilibrium used to determine the trend or long-term equilibrium of lending. Of them, now we are briefly reviewing the ones that are the most important for us.

Based on the data used, we can distinguish between univariate and multivariate methods. While univariate methods carry out the smoothing of the time series under review only by using the time series itself, for determining the trend, multivariate methods take account of other variables as well, selected on the basis of economic considerations.

One of the univariate methods is the Hodrick–Prescott filter, which is included in the international recommendations. The article by Drehmann et al. (2010) contains exact proposals for its use. In their study, Edge and Meisenzhal (2011) tested what performance would have been attained by this method if the regulations regarding the countercyclical capital buffer had been introduced earlier in the United States. Based on their findings, the Hodrick–Prescott filter makes significant measuring mistakes in real-time calculations, which would have had considerable real economy costs through the false signals. They carried out their calculations using other univariate trend filtering methods as well, and came to similar conclusions with them too. Their findings are also very informative because the Hungarian time series are much shorter than the US ones; therefore, the problems that arose may be greater in the case of Hungary. Detken et al. (2014) does not strive to correct the mistakes of the methodology based on the Hodrick–Prescott filter, but shows that although the credit gap calculated this way is one of the best crisis warning indicators, even better results may be received by applying systems that are based on several indicators. This result, however, is also relevant for the methodology of calculating the credit gap itself: it may be worth trying the multivariate filtering methods to be able to include as much information as possible in the credit gap calculation itself as well.

Regarding the multivariate methods, the most often applied method in the available literature is the estimation of error correction models (VECMs). Compared to univariate methods, VECMs are able to take account of certain economic considerations as well, and they can also be estimated on panel data made up of countries, which means a further advantage in the case of countries that have short time series (like Hungary). The credit cycle in Central and Eastern Europe is examined using error correction models by Backé et al. (2006) and Kiss et al. (2006) as well. As these countries are in a catch-up period, and only very short time series are available, the parameters of the cointegration equation are estimated on the basis of the data of euro area countries, assuming that they would be valid for the countries to be reviewed as well if their loans outstanding reached the level corresponding to their level of development. Long-term, equilibrium credit-to-GDP ratio is captured with the per capita GDP, the real interest and inflation through cointegration. The main problem with the estimation is that for the CEE countries there is no estimate from the long-term relationship for the constant typical of them; therefore, the authors use various assumptions for it. The uncertainty of the calculation stemming from this and from the assumptions regarding the parameters of the cointegration equation are offset by the examination of different types of equilibrium notion in the studies. Kiss et al. (2006) carry out the estimation of the equilibrium level of credit at sectoral level (corporate and household).

Endrész (2011) also estimated a VECM model that takes account of lending as well on Hungarian data. During that, she examined the impact of the corporate credit market and whole-economy investment on one another within the framework of an error correction model. The primary objective of the study is the examination of the relationship between lending and real economy and not the estimation of the credit gap. However, equilibrium corporate credit path can be derived from the equations describing the long-term relationship in this case as well.

Finally, from this part of the literature, the article by Buncic and Melecky (2014) needs to be mentioned, in which the credit gap estimate (which was also carried out on panel data) received from the VECM was expressly used for the calculation of the countercyclical capital buffer. The study calculates equilibrium credit by substituting cycle adjusted explanatory variables (GDP and GDP deflator) into the received relationship following the estimation of the long-term relationship of cointegration. Based on theoretical considerations, this through-the-cycle (TTC) approach is the suitable one for setting the countercyclical capital buffer, but from a practical aspect the use of cycle adjusted explanatory variables causes difficulty. Firstly, because they are variables that cannot be observed, the time series can be obtained from a separate estimate. Secondly, the potential GDP estimate obtained independently of the credit gap disregards certain impacts of the credit market on the real economy, so it may be distorted. As it is seen from the presented studies as well, estimates from VECM were often used for determining the credit gap, even on Hungarian data, but these calculations would require strong limitations and assumptions to be suitable for setting the countercyclical capital buffer as well (therefore, another kind of approach is applied in our study).

Another type of econometric method is used for determining the periods of excessive credit growth, and thus the level of the countercyclical capital buffer, in the study by Kelly et al. (2013), in which a Markov switching regime model is estimated on the data of Ireland. This approach is able to decompose the observed sample to two regimes: equilibrium, sound state and overheated periods (with high credit growth), and in each period it estimates the probability of staying in the individual regimes. The parameter estimation is greatly facilitated by the fact that the calculations were carried out on an adequately long sample available as of 1983, containing two periods of excessive lending. Based on their results, this method provides a better and more reliable performance on the Irish data than the Hodrick–Prescott filter.

Finally, we have to mention the articles that use state–space models (primarily Kalman filter) to capture the equilibrium connection between the real economy and lending and their impact on one another. Such models to calculate expressly the countercyclical capital buffer have not been made yet, but the potential output of the USA as well as the equilibrium GDP of North American and developed European countries are estimated also taking account of the financial cycle in the studies by Compton and Silva (2005) and Sarno et al. (2005), respectively. Compared to the above described models, state–space models have the advantage that they are able to take into account structural and economic relationships as well during the estimation; moreover, in a more general manner than VECMs. At the same time, the more relationships we would like to include in a state–space model, generally the greater the number of the parameters to be estimated is. Therefore, the size of the sample is a significant risk factor in this case as well, which can be offset by the application of panel data and Bayesian estimation techniques.

Further on in our study we also review the credit gaps of the most often applied univariate filters calculated on Hungarian time series. Their results already outline the peculiarities and information content of the Hungarian time series. A multivariate amendment to the Hodrick–Prescott filter is also known. It is already able to take into account certain simple economic relationships as well. Thus the credit gap and the trend can be brought into connection with certain real economy and bank variables. A state–space representation of this method also exists, so the economic relationships behind the estimate are identical with those of a model that can be stated with a simple Kalman filter. The difference is in the estimation method: while compared to a Kalman filter the multivariate Hodrick–Prescott filter may be able to estimate relatively many parameters on a small sample as well, the former requires fewer assumptions (the assumptions are presented in the chapter that deals with the multivariate filter). We consider the change-over to state–space models a possible further development of the results presented here.

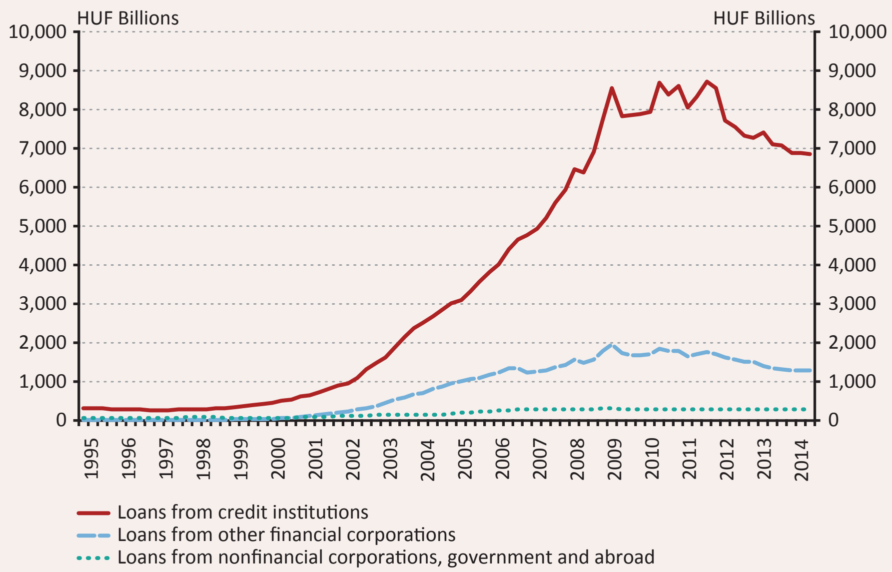
3 Data on loans outstanding

The primary objective of the countercyclical capital buffer is that the build-up of systemic risks be accompanied by an increase in banks' capital level. Consequently, on a theoretical point of view the examination of the widest possible loan categories is proposed in order to cover the largest possible scope of potential risks. Nevertheless, empirical experiences, such as Detken et al. (2014), show that narrower definitions of loans outstanding may also be good bank crisis warning indicators. Namely, it may happen that the build-up of systemic risks does not take place in the same way in the various credit markets: a large portion of risks may be concentrated only on a narrower partial segment, which may be concealed by the analyses carried out on completely aggregated data. At the same time, banks' deteriorating solvency may lead to the contraction of the whole credit market in a stress situation. This duality appeared in our case as well upon designating the loans outstanding to be examined. On the one hand, in any case, we wanted to separate corporate and household loans outstanding. On the other hand, we strived to analyse the loans outstanding taken in the widest possible sense according to creditors, also considering the statistical consequences of the data content.

We deem it important to separate corporate and household loans outstanding because developments in lending in the two sectors may be very different, and it may already entail serious consequences if lending to one of these sectors is inadequate. Examining the two loan portfolios separately and summarising the results subsequently may lead to a loss of less information than if we analysed the portfolios together. This is the simpler solution from a modelling aspect as well, because due to their different economic roles, different indicators may help to identify the cycles observed in the two loan portfolios.

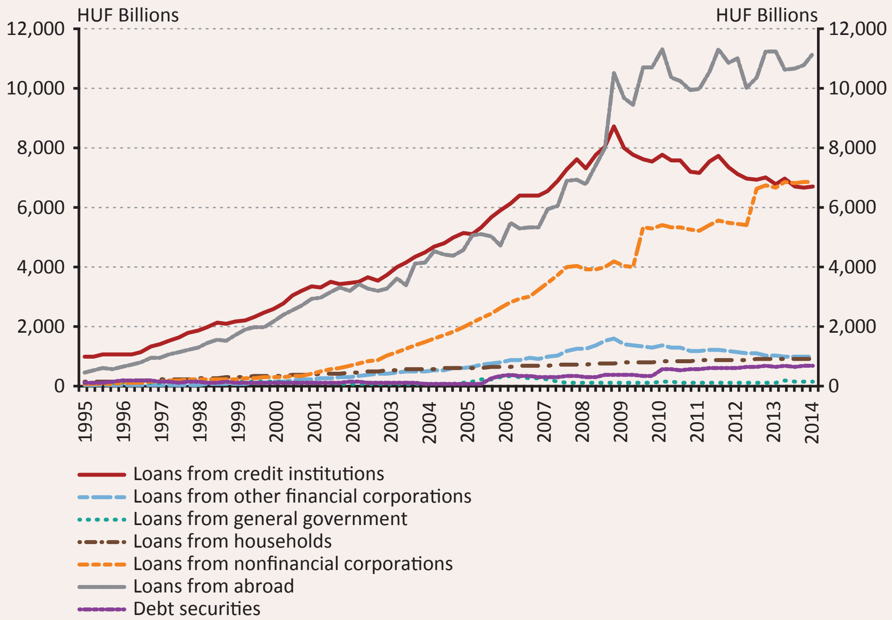
We started determining the widest possible scope according to creditors by examining and interpreting financial accounts data. In Hungary, most of household loans are extended by credit institutions and other financial corporations. Therefore, whether to include the loans extended by non-financial corporations, the general government and the non-resident sector in the analysis is of theoretical importance only, and there is no practical stake for the time being (Chart 1). However, in the case of non-financial corporations' loans the situation is different (Chart 2).

Chart 1
Breakdown of household loans outstanding by creditor sectors



Source: MNB.

Chart 2
Breakdown of corporate loans outstanding by the form of lending and creditor sectors



Source: MNB.

Intra-sector loans constitute a considerable portion of non-financial corporations' loans. Although we know that the excessive magnitude of supplier credit and the increase in circular debts may cause liquidity difficulties, which adds to the credit risk of the sector, we still decided not to treat this problem within the framework of the countercyclical capital buffer. Namely, it may happen that the circular debts increase considerably in a sector, and the solving of the problem would be hindered if the lending capacity of the banking sector was narrowed exactly then.

Borrowing from abroad constitutes another large portion of non-financial corporations' loans. These loans are mostly intra-group loans. Accordingly, so significant flows may take place that hardly or not at all influence the risk of the Hungarian non-financial corporate sector's risk. Transactions like this may be when a parent company provides funds through its Hungarian subsidiary to one of its subsidiaries operating in another country, but it may also result in significant flows if the parent company changes the capital to loan ratio within the financing it provides. As we cannot adjust for the afore-mentioned cases in our data series and, due to their negligible credit risk consequences, upon setting the countercyclical capital buffer, we would not like to take into account the significant flows generated by them, non-financial corporations' foreign loans are not included in the credit aggregate under review.

The share of non-financial corporations' loans from households is low in the financing of corporations in Hungary, and no significant fluctuations are observed in the amount of loans outstanding either. The main underlying explanation is that the Hungarian financial system is strongly bank-oriented, capital markets are less developed, and only a limited number of companies reach the size where, for example, issuing a listed bond may come into question. Outstanding corporate bonds are mostly held by non-residents, and a smaller portion of them by financial corporations. In view of all the above, the inclusion of loans extended by households in the analysis, or disregarding them, would not cause any fundamental changes in our results.

The share of loans extended by the general government is very low in the financing of non-financial corporations, so in terms of our analysis there is no practical importance of taking this item into account. Based on theoretical considerations, disregarding may be luckier if we wanted to exclude the possibility of influencing the result of our analysis by the choice of the state as owner between modes of financing (lending or capital increase).

Although household and non-financial corporations loans are examined separately, we want to ensure in any case the possibility of summarising the results. Therefore, it is worth designating the scope of loans under review in the two sectors in the same manner. In line with the above, finally we examine the loans from credit institutions and other financial corporations below.

Upon the examination of data on loans outstanding in Hungary it is a key issue how to treat the forint exchange rate. Not only because a significant portion of the loans outstanding is FX-denominated, but also because a considerable part of them does not even have natural hedge, so the exchange rate risk appears in the credit risk directly. The risk itself exists already from the moment of loan disbursement, and the shift in the exchange rate means 'only' the realisation of the risk. Therefore, we strived to find methods that are able to signal the risk in the build-up period of the loans outstanding, if possible, and do not identify the automatic revaluation due to the shift in the exchange rate as excessive lending.

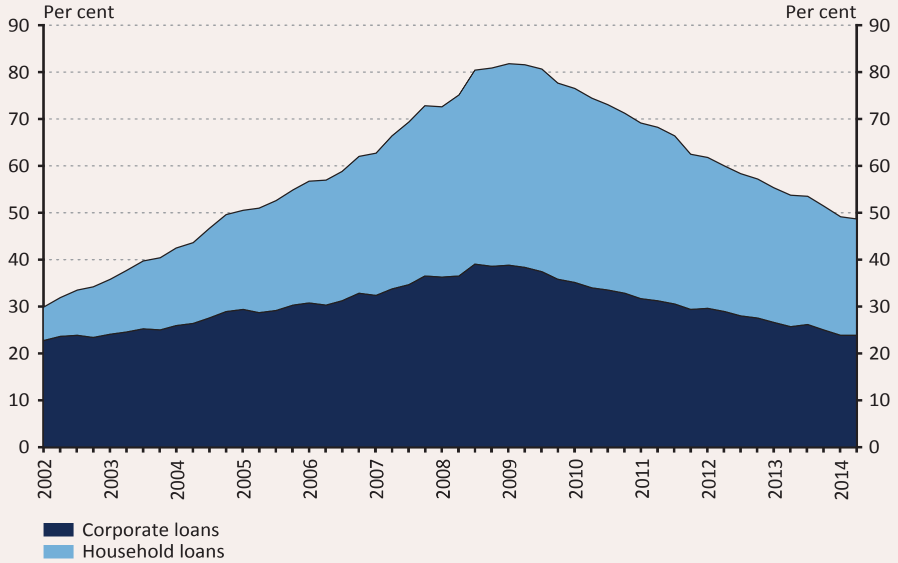
Accordingly, there are two basic possible directions of treating the exchange rate: we either apply exchange rate adjustment or – if the methodology allows it – model the relationship between the exchange rate and the loans outstanding without exchange rate adjustment. In the case of univariate cycle filtering methods it is not possible to model the exchange rate, and it would be relatively complicated in the case of the multivariate Hodrick–Prescott filter as well. Therefore, partly for the sake of comparability as well, we decided to apply exchange rate adjustment.

The 31 December 2010 exchange rates were used for the exchange rate adjustment. The data on FX loans outstanding stated in the financial accounts were decomposed to currencies assuming that within the FX loans outstanding of credit institutions and other financial corporations the ratios of individual currencies are identical with the current values observed at system level in the case of banks, mortgage banks as well as home savings and loan associations.

The value of the exchange rate adjusted loans outstanding at the end of the period under review was examined as a proportion of the seasonally adjusted nominal GDP in the past four quarters; therefore, inflation does not cause a problem in the indicator either.

In connection with the time horizon of the analysis, household loans represent a bottleneck. Although data are available as of December 1989, lending to households was of low importance until the turn of the millennium. Material increase in household loans outstanding started only with the introduction of housing loans with interest subsidy, so we decided to start our analysis as of early 2002. Based on the above, the evolution of the credit-to-GDP ratio is shown in Chart 3.

Chart 3
Exchange rate adjusted household and corporate loans borrowed from credit institutions and other financial corporations as a proportion of GDP



Source: MNB.

4 Univariate filters

This chapter is an overview of the most frequent univariate trend filtering methods, and it also examines the results of their application concerning the credit-to-GDP ratio. It also contains a presentation of the advantages and disadvantages of using or neglecting these filters. Many univariate trend filtering methods are known and used for the examination of economic time series. Their name originates from the fact that for determining the trend they set out exclusively from the time series under review, and do not use any other information or economic relationship. This property is at the same time the advantage and disadvantage of this group of methods: advantage, because it has a low data requirement, and disadvantage, because it disregards much information that helps the decomposition, so these methods often lead to false results. In each filtering method of this type, the trend–gap decomposition is based on some mathematical/statistical property of the time series under review. The distinction between the methods is made on the basis of exactly what property of the time series is examined.[4] They are usually easy to calculate and it does not take much time.

In addition to the variable intended to be decomposed, every method requires some external information: we usually have to give how long we think the average cycle that appears as a parameter in the models is. These parameters are usually determined on the basis of empirical experiences, simulations and the results of other trend filtering methods. In the case of certain methods and time series there is already a consensus on optimum parametering. In many cases, however, the various approaches do not harmonise. Different parameters may be justified for different countries and time series; therefore, parametering may cause significant estimation uncertainty in less examined cases.

Using univariate methods, a time series may be decomposed in a one-sided and two-sided manner as well. In the case of a one-sided decomposition, for determining each point of the trend only the information available until that time is used, while in the case of the two-sided decomposition the trend values are estimated on the basis of the whole sample. The advantage of the one-sided calculation is that with regarding new data the earlier received trend–gap decomposition does not change. In contrast, in the two-sided case each new observation may have an impact on the past value of the trend as well, but usually one may obtain a more accurate picture of the changes in the trend and the gap, as in this case a wider set of information is used for the estimation. We are compelled to use the two-sided method for the calculation of the first some periods of the trends calculated in the one-sided manner, as it is not possible to fit a trend on very few data points in a sensible way.

Finally, we need to mention a very important problem of these methods: univariate filters are usually characterised by high endpoint uncertainty, due to which our assessment of the past may change significantly with the receipt of new data. This causes significant revision in the case of two-sided decompositions, which makes the conclusions that can be drawn from the magnitude of trends and gaps as well as the economic decisions based on them uncertain. Although the one-sided decompositions are not revised technically, the problem caused by the endpoint uncertainty remains in this case as well, just it is concealed by the one-sided approach. In the case of a strong endpoint uncertainty the one-sided filters link uncertain endpoints into a time series instead of determining the trend.

The advantages and disadvantages of univariate methods are summarised in Table 1.

Table 1
The characteristics of univariate methods

	Advantages	Disadvantages
Data requirement	low data requirement (one time series)	uses little information
Parametering	one or two parameters given from outside	size may be uncertain
Methodology	easy and fast to produce	significant endpoint uncertainty

[4] More details are given in the presentation of each filter.

4.1 HODRICK–PRESCOTT FILTER[5]

Of the univariate methods, we start presenting the concrete cases with the Hodrick–Prescott filter (hereinafter: HP filter), which is the most frequently applied filter to economic time series. In this case the trend is the result of the following expression, where r_t indicates the time series under review, and $\overline{r_t}$ indicates its trend in the t^{th} time period:

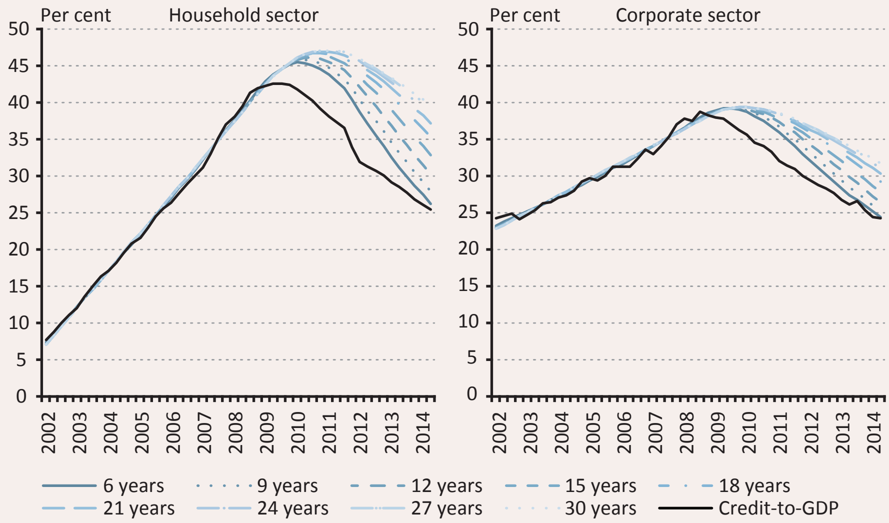
$$\min_{\overline{r_1}\ldots\overline{r_T}} \sum_{t=1}^{T}\left(r_t-\overline{r_t}\right)^2+\lambda\sum_{t=2}^{T-1}\left(\left(\overline{r_{t+1}}-\overline{r_t}\right)-\left(\overline{r_t}-\overline{r_{t-1}}\right)\right)^2 \qquad (1)$$

The purpose of the first sum is that the trend can match the actual data, while 'the smoother the trend', i.e. the more even its growth rate, the smaller the value of the second sum. The relative importance of the two aspects is expressed by the λ parameter. If there was only the first sum in the expression ($\lambda=0$), the trend would correspond to the fact, whereas if only the second part was considered (λ approaches the infinite), the trend would be completely linear.

In the case of a time series, the longer the assumed average length of cycle, the greater the value of λ. The average length of economic cycles was found to be approximately 6–8 years. In the case of quarterly data a λ of approximately 1600 corresponds to it. In contrast, much longer cycles were observed in the case of financial cycles; their average length was around 30 years, corresponding to a λ of 400,000. In the case of the Hungarian financial cycle, usable data are available from 2002 to the first half of 2014, i.e. the length of our sample is 12 and a half years, during which a complete financial cycle was probably not closed. Therefore, it is not clear what λ should be chosen.

In Chart 4 we calculated the one-sided HP filtered trends for the credit-to-GDP time series assuming nine different cycle lengths (between six and thirty years). Until end-2008 the filter was calculated in a two-sided manner; from then we switched over to the one-sided method. Based on our results, both in the corporate and household segments until 2010 the HP filter estimates an almost completely flat, linear trend, then the estimated trends take decreasing values with the decline in lending. The smaller the value of the lambda, the better the filtered trend follows the changes in actual data, and thus the faster it moves back to the actual data: by the end of the sample, the trend that assumes a six-year cycle length is nearly identical with the actual data, while in the case of a thirty-year cycle length the credit gap is 15 and 7 per cent, respectively. Consequently, the obtained results are greatly influenced by the chosen value of the lambda.

Chart 4
One-sided HP trend of household and corporate credit-to-GDP at various cycle lengths

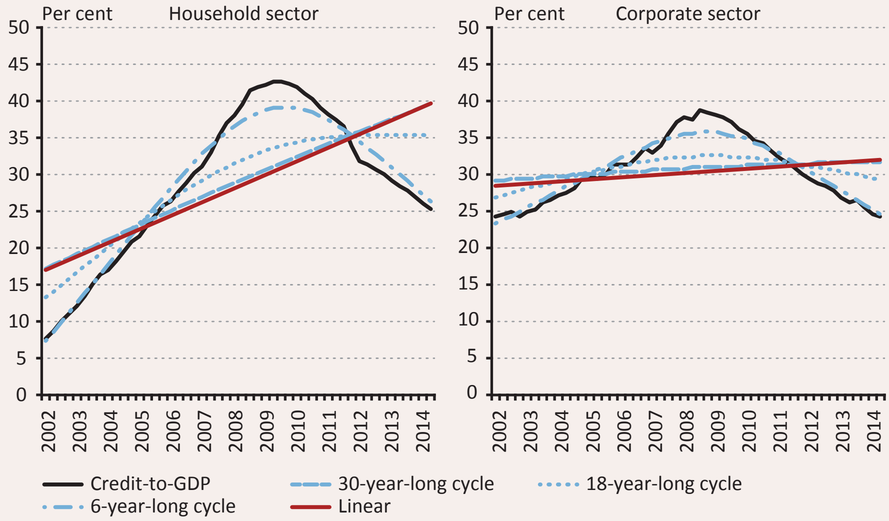


Source: MNB.

[5] For more details on the methodology see the article by Hodrick and Prescott (1997).

Examining the results of the HP filters calculated in the two-sided manner instead of those of the one-sided ones (Chart 5) reveals that using a six-year cycle length the estimated trend almost completely fits the data; a major difference is observed only in the period between 2008 and 2010. In contrast, at the greatest cycle length the trend is nearly linear. As in the case of trend estimate neither a perfect match, nor a completely smooth trend is desirable, we would like to see the optimum ratio of the two aspects; therefore, the proper cycle length may be somewhere between the two values, i.e. between 15 and 20 years (on the existing sample).

Chart 5
Two-sided HP filters calculated with various cycle lengths



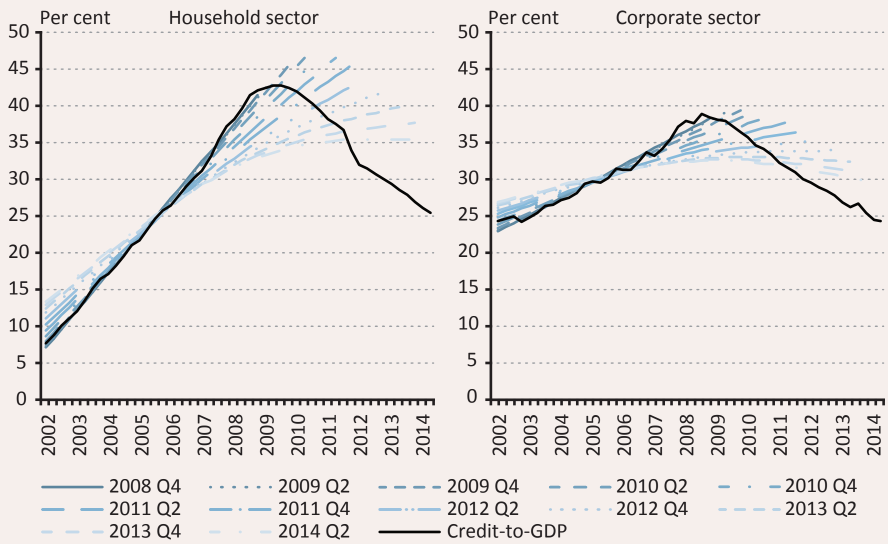
Source: MNB.

A comparison of Charts 4 and 5 reveals that the HP trends prepared in one-sided and two-sided manners show rather different pictures. As it was mentioned in the general presentation of the univariate methods, in their case the arrival of new data may significantly change our assessment of the past as well.

Chart 6 shows the testing of the revision due to new data. Here the trends were calculated in a two-sided manner. First only the data received until end-2008 were taken into account, then the observation period was always extended by two quarters.[6] As it can be seen, already the receipt of two new datapoints may result in a change of as much as 3 percentage points in the endpoint of the previous period, while in the longer run a difference of even more than 10 percentage points can be observed between the trend values calculated on the different periods. The charts also clearly show that although the use of the one-sided HP does not entail a revision of the trend, it does not provide help in the identification of the credit cycle. Neither the household, nor the corporate segment shows any sign of excessive lending (without revisions not even at a longer period); the trend moves together with the actual data almost entirely. Since the outbreak of the crisis, however, except for the trend with the smallest λ, the actual data are much smaller than the estimated trend in both sectors, i.e. the credit gap is in a significantly negative territory. Therefore, with the help of the currently available data the univariate HP filter is not suitable for the identification of financial cycles with any λ.

[6] As the filter provides too extreme solutions at the too low and too high lambda values, in this calculation we assumed a medium-size, 18-year cycle length, which is slightly longer than our existing sample.

Chart 6
Two-sided HP trends in various periods



Source: MNB.
Note: The legend of the chart shows the last quarter known upon the calculation of the individual trends.

4.2 CHRISTIANO–FITZGERALD FILTER[7]

Considering that the HP filter does not provide reliable performance upon the identification of the credit cycle, it is worth testing other filtering methods as well (still univariate ones for the time being). Below is a presentation of two filtering methods other than the HP and an examination of what results they lead to on our credit-to-GDP ratio time series.

The first one is the Christiano–Fitzgerald filter (hereinafter: CF filter), which belongs to the group of 'band-pass' filters, aka frequency filters. The logic behind these filtering methods is as follows: individual time series are composed of parts with different frequencies, and the trend may be obtained by removing the parts that can be characterised with the given cycle length. Therefore, in the case of these filters, a lower and an upper bound have to be given for the cycle length, based on which the parts of time series whose length is between the two values are considered a cycle, the part above the upper bound is considered a trend, whereas the part below the lower bound is noise. These methods produce the trend by some kind of two-sided weighted moving averaging of the original time series. The difference between the frequency filters is in how they exactly determine the weights for the averaging.

They have two groups: symmetric and asymmetric methods. In the symmetric case, at a given point the filter uses the same number of periods for calculating the trend value from before the point of time as from after the point of time; therefore, these weights are independent of the time. Consequently, symmetric methods are unable to give trend values for the first and last some observations of the time series. As the last periods of the sample are also important for us, we need an asymmetric filter. In this case the weights used for the average depend on the point of time for which we would like to calculate the value of the trend and they also depend on the data, i.e.:

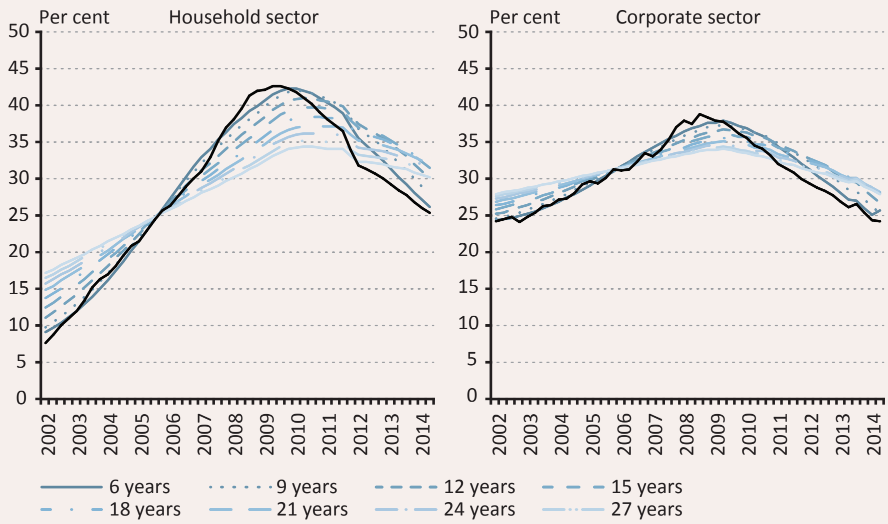
$$\overline{r}_t = \sum_{c=1}^{T} w(t,c) r_c \qquad t = 1,\cdots,T \qquad (2)$$

where $\overline{r}_t$ indicates the value of the trend at the t^{th} point of time, r_c is the c^{th} observation of the time series, and w is the weight used for the averaging. Of the asymmetrical frequency filters we have chosen the CF filter.

[7] For more details on the filter see the article by Christiano and Fitzgerald (2003).

As in the case of the HP, we present the sensitivity to the assumed cycle length and the extent of the revision observed upon the receipt of new data here as well. Chart 7 illustrates the impact of the assumed cycle length. Similarly to the HP, first we calculated the trends in a two-sided manner until end-2008, from where we extended the time series with a one-sided method. In our calculations, always two quarters were given as lower cycle length value (i.e. the part outside the trend is not decomposed separately to noise and cycle), while we altered the upper value between six and thirty years. Compared to the HP filter, the difference in interpretation in this case is that, for example, the six years in the case of the HP trend meant the assumption that the average cycle length is six years, while in the case of the CF filter the periodic movements not longer than six years are considered part of the cycle. Comparing the CF filter with the HP filter there is a visible difference between the charts: while in the case of the HP until 2010 there was no difference at all between the trends with different λ, in the case of the CF filter there are differences between the trends of various parametering already from the beginning of the sample.[8]

Chart 7
One-sided CF trend of household and corporate credit-to-GDP at various cycle lengths



Source: MNB.

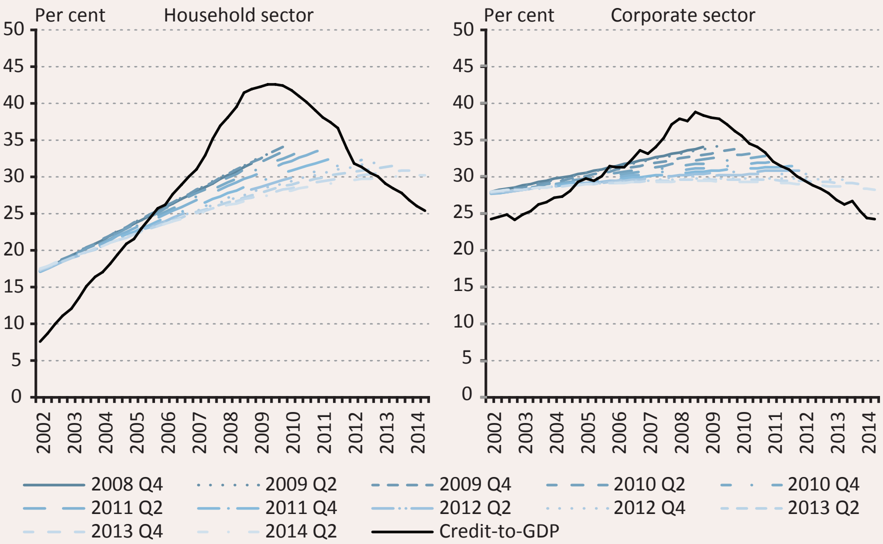
The chart also shows that in the household segment the trend had exceeded the actual data at almost every parameter value until 2006 (i.e. the credit gap was negative), then the value of the actual data was higher from 2006 until 2010/2012 (positive credit gap). Since then a negative credit gap has been observed again. Furthermore, the higher the allowed upper bound of the cycles, the greater the difference between the observed and trend time series on a large part of the sample is. Therefore, the signs of excessive lending to the household sector prior to the crisis are mainly seen in the trend time series that allows a 30-year-long cycle as well. In the corporate sector, developments in the relationship between trend and observation was similar to that of the household sector, only the difference between the two is smaller, so there are no signs of excessive lending in this segment.

As the trend with the thirty-year parameter results in the largest credit gap in the household sector, this trend was examined from the aspect of revisions (Chart 8). As in the case of the HP filter, the filter was run here as well until end-2008 first, then always two quarters were added to the estimation sample. With the receipt of two new periods, the past value of the trend usually changes only to a small extent. There is one exception from

[8] It needs to be mentioned that certain conditions applied to the CF filter influence these results considerably. Upon estimating a CF filter, a detrending condition has to be given, for which there are several possibilities. In the case of the results presented here we used the assumption that the trend is a random walk starting from a constant. If we assume instead that the trend is a random walk with a drift, the results will be very similar to the HP filter (Appendix: Chart 15). However, we do not consider this assumption right, as based on economic considerations, sustainable loan/GDP may take a value only between certain limits.

this in the household time series: the receipt of the 2011 H2 data. These two quarters, however, were special, as household loans outstanding fell considerably at that time due to the early repayment of FX loans, which reduced the value of the trend by 1–2 percentage points retroactively. Nevertheless, both in the household and corporate segments the revision caused by new data for five and a half years did not exceed 6 percentage points anywhere, and the overall size of revisions is approximately half compared to the HP filter. This probably indicates that the CF filter method is able to better treat the inconsistency that our observation sample at present is probably shorter than the length of a credit cycle. In addition to the size of revisions, this advantage is also seen in the fact that the trends obtained with the CF filter are closer to our conceptions of the trend of the lending cycle on the shorter sample periods as well.

Chart 8
Two-sided CF trends in various periods



Source: MNB.

4.3 BEVERIDGE–NELSON FILTER[9]

As the third one, we examine a univariate filtering method that – due to its approach that is different from the methods described above – does not require a parameter relating to the length of the cycle. According to the assumption of the Beveridge–Nelson filter, the trend follows a random walk (with or without drift), whereas the cycle is stationary, and is described by an ARMA(p,q) process. If we allow that the trend contain a drift, and we apply ARMA(2,2) specification, (under certain conditions) the following equation has to be estimated, from which the trend–gap decomposition can already be derived:

$$d\left(r_t\right)=\mu+\alpha_1\cdot d\left(r_{t-1}\right)+\alpha_2\cdot d\left(r_{t-2}\right)+\varepsilon_t+\beta_1\cdot\varepsilon_{t-1}+\beta_2\cdot\varepsilon_{t-2} \qquad (3)$$

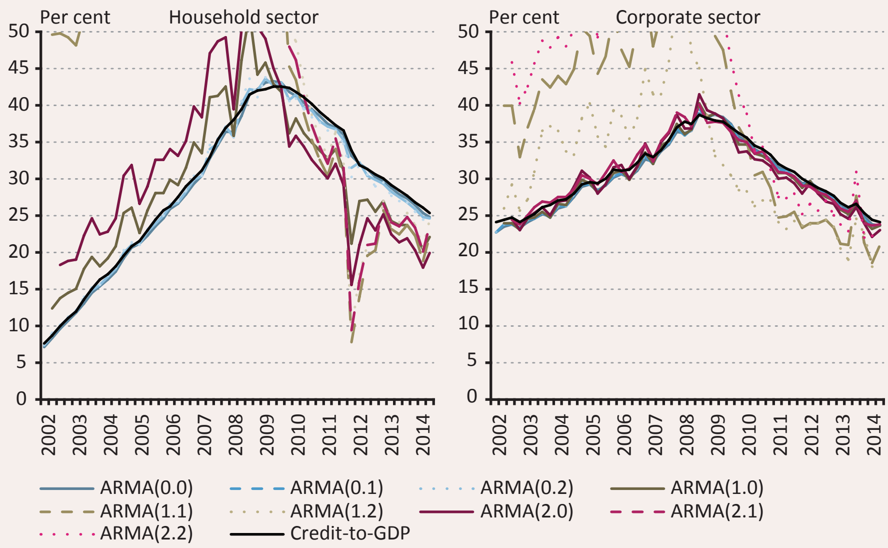
where $d(r_t)$ indicates the difference of the time series in the t^{th} period, and ε_t is the error term of the estimation. As it was mentioned before, in this method there is no parameter relating to the length of the cycle, but instead it has to be given whether it contains a drift (indicated by the μ in the equation) and how many of the AR and MA terms should be included in the estimation. In order to present the various specifications, we performed the calculations in several versions.

Chart 9 depicts the BN trends calculated with the two-sided manner, in each case where the number of both AR and MA terms is maximum two. There are two groups of the trends obtained: some of the trends fit almost

[9] For more details see Beveridge and Nelson (1981).

completely close to the observed time series (e.g. estimations that do not contain an AR term), while others continuously and to an unrealistically great extent deviate from that (e.g. the ARMA(1,2), ARMA(2,1) and ARMA(2,2) estimations). As increasing the AR and MA terms obviously had resulted in unbelievable trends, we did not even try to increase them further. It can also be observed that the trends that significantly deviate from the fact had continuously indicated a negative credit gap prior to the crisis, then they indicated a positive one, which completely contradicts our expectations and our assessment of the developments in lending. Therefore, the BN filter seems to be unsuitable for determining the Hungarian credit cycle. Consequently, we stopped using it. Probably the shortness of our observed sample and the length of the financial cycle compared to the economic cycle explain the bad performance of the BN filter.

Chart 9
BN trends with various parameters of the credit-to-GDP ratio



Source: MNB.

Overall, of the examined three univariate filters, the performance of the CF filter was the most promising, showing relatively moderate revisions on our sample and resulting in a trend that was largely in line with our expectations. In view of its completely counterintuitive results, the BN filter cannot be used on our data for the examination of the lending cycle; therefore, we are not discussing it any longer. The univariate HP filter already provides a more realistic result, but it is unable to adequately handle the shortness of our sample relative to the length of the cycle, so it produces great revisions, leading to distorted results in real time.

5 Multivariate Hodrick–Prescott filter

Multivariate methods allow us to take into account information obtained from other variables as well in addition to the target variable upon determining the gap. The literature mainly contains multivariate HP filter methods for the estimation of the trends of GDP time series. Laxton and Tetlow (1992) tried to quantify the GDP trend of Canada by improving the univariate HP filter: they completed the expression to be minimised of the HP filter with two additional relationships, the equation of the Phillips curve and the equation that captures Okun's law. The Phillips curve captures the relationship between the output gap and inflation, while Okun's law captures the relationship between the output gap and unemployment. Accordingly, the time series of inflation and unemployment may be used as additional information for the estimation of the output gap. Hirose and Kamada (2013) estimated the potential output and the Phillips curve in the case of Japan in a simultaneous manner by applying a multivariate HP filter, where potential output was to be understood as the output level in the case of which inflation is constant.

5.1 METHODOLOGY OF THE MULTIVARIATE HODRICK–PRESCOTT FILTER

In the case of the multivariate HP filter the univariate one is expanded by new relationships: we state regression equations between the trend and one or more variables on the basis of economic considerations, and these equations are also taken into account when filtering the time series. The direction of the logical connection between the trend and the variable involved may be discretional: we can state the regression relationship even if the changes in the trend influence the evolution of the variable involved, since it is possible to conclude the value of the trend from the value of the variable involved in this case as well.

Similarly to the univariate case, when the deviation of the trend from the observation is included as an error term in the expression to be minimised, upon stating the multivariate filter, the error term of the regression relationship between the trend and the explanatory variables is taken into account. As we think that the relationship stated with the regression must exist, any deviation from that is punished. If the existence of several relationships is assumed at the same time, the error term of several regression equations have to be used. We do not have to know the coefficients of the regression relationship in advance; we may estimate them together with filtering the trend.

Upon determining the trend of the credit-to-GDP ratio, we take account of two regression equations: some variables may explain the cyclical component (credit gap), i.e. the deviation of the observed data from the trend, while other variables explain directly the size of the trend. Accordingly, the multivariate HP filter applied can be given with the following formula:

$$\min_{\{\overline{r}_t\}_{t=1}^{T},\{\beta_i\}_{i=1}^{N},\{\gamma_i\}_{i=1}^{M},c_C,c_T} \left\{ \lambda_c \sum_{t=1}^{T} \left(r_t - \overline{r}_t\right)^2 + \lambda_{HP} \sum_{t=2}^{T-1} \left(\Delta\overline{r}_{t+1} - \Delta\overline{r}_t\right)^2 + \lambda_\varepsilon \sum_{t=1}^{T} \varepsilon_t^2 + \lambda_\nu \sum_{t=1}^{T} \nu_t^2 \right\} \quad (4)$$

$$r_t - \overline{r}_t = c_c + \sum_{t=1}^{N} \beta_i x_{it} + \varepsilon_t \quad (5)$$

$$\overline{r}_t = c_T + \sum_{i=1}^{M} \gamma_i y_{it} + \nu_t \quad (6)$$

where (4) is the expression to be minimised during the filtering, (5) and (6) are the regression equations that can be stated for the cyclical component and the trend, respectively; r_t is the value of the credit-to-GDP ratio indicator, while $\overline{r}_t$ is the value of the trend of the credit-to-GDP ratio, x_{it}s are the variables explaining the cyclical component, whereas β_is are their coefficients, y_{it}s are the variables explaining the trend, while γ_is are their coefficients, and c_c and c_T are the constants of the estimated equations. In addition to the two components of the univariate HP filter, the expression to be minimised contains two more terms: the error terms of the regression relationships stated for the cyclical component and the trend. As the coefficients of the explanatory variables are unknown in the equations of the cyclical component and the trend, they also have to be estimated, together with the value of the trend. Accordingly, (4) is minimised not only on the basis of the trend values for individual periods, but on the basis of the coefficients of explanatory variables as well. During the minimising, the ε_ts and v_ts in (4) have to be substituted with expressions originating from (5) and (6).

During the estimation we have to determine the explanatory variables that are in the equations and the values of the weights belonging to each term and applied during minimising (λs). At the same time, the determination of the value of λs is not self-evident: it may, for example, depend on the dispersion of individual time series, the notions regarding the length of the cycle or the interaction of individual time series in the regression equations. The determination of explanatory variables is not definite either, as their various combinations lead to different results. In order to manage the problems we decided to run the multivariate HP filter in many different ways – with adequate combinations of potential explanatory variables and λs – and average the ones that meet certain expectations of ours.

Our expectations regarding the trend time series involved in the averaging were as follows:

1. by 2008 Q2, the value of the trend should be between 60 and 95 per cent of the actual data, as on the basis of our experts' assessment upon the outbreak of the crisis lending was already excessive.

2. In the regression equations used for the filtering, the sign of the coefficient of the explanatory variables involved should be economically justified.

3. The impact of the explanatory variables involved should be significant. Due to the peculiarities of the estimation, on the basis of the standard errors of the explanatory variables we cannot draw a conclusion concerning significance; therefore, we considered as significant the variable that has an at least 2 percentage point impact on the value of the trend during the time horizon under review. It means that substituting the highest and lowest values of the given explanatory variable into the right equation there should be an at least two percentage point difference between the effects concerning the trend of the credit-to-GDP ratio.

4. The applied estimation should be robust: if we change (shorten) the length of the horizon used for the estimation (by max. two years), the value of the trend received for the last period of the shorter time series should not deviate by more than 2 percentage points from the value concerning the given period of the trend estimated on the basis of the whole time horizon, and conditions 1–3 should also materialise for the trend time series estimated on the shorter time series.

During the filtering of the time series of the household credit-to-GDP ratio, the following variables were used for the equation of the cyclical component:

- Global credit gap[10] – the estimated coefficient has to be positive, because global trends may pass through into a small, open economy.

- Cyclical component of real GDP (Hungarian output gap)[11] – the estimated coefficient has to be positive.

- Weighted interest rate on housing loans and consumer credit outstanding – the estimated coefficient has to be negative, because an increase in interest rates makes borrowing more difficult and reduces the demand for loans.

[10] For calculating the global credit gap, the credit-to-GDP ratios of 12 OECD member states (United States of America, Australia, Belgium, South Korea, United Kingdom, Finland, France, Japan, Germany, Norway, Spain and Switzerland) were weighted at purchasing power parity between 1980 and 2014, and from the thus obtained time series we determined the credit gap using a one-sided univariate Hodrick–Prescott filter (comp. Alessi and Detken, 2011).

[11] The GDP time series can also be divided into trend and output gap: the output gap presumably adds to lending or borrowing rather in the short run only, while the long-term equilibrium level of lending is probably more determined by potential GDP.

- BUBOR – its coefficient also has to be negative, as a rise in the BUBOR is usually accompanied by an increase in borrowing rates.

- Leverage (the ratio of total assets of the banking sector to equity) – the estimated coefficient has to be positive, because an increase in leverage may indicate an upturn in lending.

- Loan-to-deposit ratio for the banking sector as a whole – the estimated coefficient has to be positive, because a rising loan-to-deposit ratio may indicate an upturn in lending.

- Marketing costs (at banking sector level, in real terms, with moving averaging for the adjustment for seasonal effects) – the estimated coefficient has to be positive, because banks usually use significant marketing campaigns to let their clients know about the increase in household loan supply.

During the filtering of the corporate credit-to-GDP time series, the global credit gap, output gap, BUBOR, leverage and loan-to-deposit indicators used in the case of the household credit-to-GDP time series were included in the equation of the cyclical component as well. In addition to them, we also examined the interest rates of new corporate loans and the GKI business confidence index. In the case of the interest rate we specified a negative, while in the case of the business confidence index we specified a positive coefficient.

The logarithm of real GDP was included in the household and corporate trend equations, and the coefficient had to be positive, because, based on empirical experiences, a higher GDP may justify an increase in borrowing in terms of its ratio as well over the long term (comp. Kiss et al., 2006). Logarithmic transformation was necessary for two reasons: firstly, the impact of GDP growth on the credit-to-GDP ratio may be declining; secondly, the interpretation of the obtained coefficient is also more obvious: the obtained coefficient shows by how many percentage points a one per cent GDP growth increases the long-term value of the credit-to-GDP ratio. In addition to the logarithm of real GDP, the trend of this same time series obtained with a Kalman filter was also examined in the trend equation. In addition, the logarithm of real earned income was also included with a positive sign in the household trend equation, as higher earned incomes allow higher borrowing for households.[12]

In addition to the listed variables, during both the household and corporate estimations we took all the possible combinations when the equation of the cyclical component included one, two or three variables, but in the equation of the trend we used only one variable at a time. We also examined the possibilities when the regression of the cyclical component or of the trend was not used.

The formula of the filter contains four λs, but only their size compared to one another matters, so we can choose one of them upon discretion. Accordingly, λ_{HP}, i.e. the value of the component containing the evenness of the growth of the trend was taken as 1. As the third component explains the deviation from the actual data, if the regression of the cyclical component is included in the estimation, it is needless to punish the absolute deviation from the actual data, i.e. the first component, with a positive weight. Accordingly, of the first and third components, hereafter we always take into account only one of them at a time: if the regression of the cyclical component is included in the estimation, λ_ε is positive, and the value of λ_v is 0, otherwise vice versa. Hereinafter, of the first and third components the one with a positive weight will be called the cyclical component of (4). Therefore, in aggregate, we only have to determine two λs at most: that of the cyclical component and the one belonging to the trend equation (when there is a trend equation). For simplicity, we only changed the magnitude of the λs; in both cases the following λ values were examined: 0.0001; 0.001; 0.01; 0.1; 1; 10; 100 and 1000.

As both the regression of the cyclical component and the trend equation contain constants, the value of the objective function would be the same in the case of a discretionary shifting of the obtained trend as well, i.e. the minimising task would not be well-determined. To avoid this, the value of the trend has to be fixed for one of the quarters, thus making the solution unequivocal. The value of the trend of the first period was fixed in the case of the household and corporate time series as well: as it was in line with our experts' assessment, we took

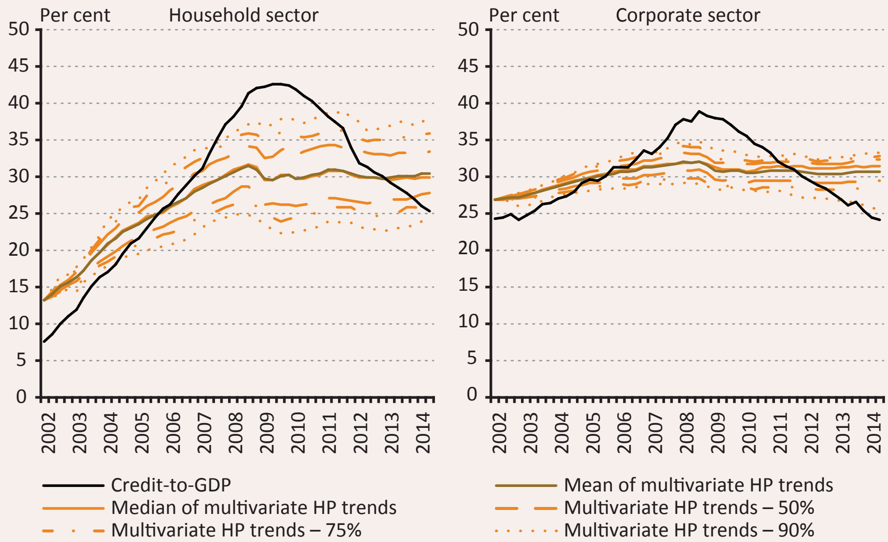
[12] Here we only list the variables that were included in the estimation of at least one of the trend time series that met the conditions. The appendix lists all the examined variables, together with their expected coefficients.

the value of the trend obtained with the univariate HP filter, i.e. upon the estimation of the household loan-to-GDP trend the value of the first period trend was fixed at 13.2 per cent, while in the case of the corporate time series it was fixed at 26.8 per cent.

5.2 PRESENTATION OF THE RESULTS

Chart 10 shows what trend the applied methodology estimates for the household and corporate credit-to-GDP ratios in the period between 2002 Q1 and 2014 Q2. Many time series meet the given conditions; in addition to the average and median of the time series we also indicated into what interval 50, 75 and 90 per cent of the estimated trend values fell in the given period. Based on the results of the middle 90 per cent, the extent of the interval in the case of the household time series is approximately 14 percentage points for the last period, and roughly 8 percentage points in the case of the corporate time series. If we interpret the trend calculated with the help of the multivariate methodology as the average of the time series obtained, in the case of the household time series, after an initial growth the household trend peaks at approximately 31 per cent, followed by some decline, while – following a slight increase – the corporate trend is stagnant around a level of 30 per cent.

Chart 10
Trends estimated by the multivariate HP filter



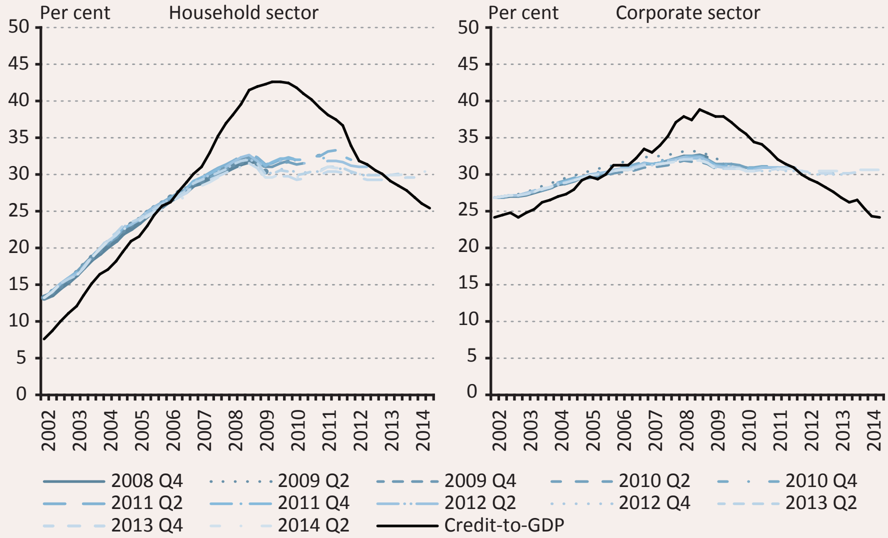
Source: MNB.

The result would change to a slight extent if another significance criterion were applied instead of the minimum two percentage point effect in connection with the variables involved in the estimation: in the case of a one or three percentage point criterion the size of the change is negligible in the household segment, while in the corporate segment it amends the results for individual quarters by approximately half to one percentage point. (Appendix: Chart 16) It means that in the case of the household segment the effect of the variables involved is adequately large, whereas in the corporate segment several variables drop out of the estimation with the increasing of the expected effect.

If the given initial value is increased or reduced by 2 percentage points, the obtained trend values converge during the build-up stage in the household segment, but they rather shift in the case of the corporate segment. (Appendix: Chart 17)

It is worth examining how robust the applied multivariate filter is if the averages are looked at. Chart 11 shows developments in the estimated trend as the length of the time series used for the filtering – and in parallel with that for the estimation – is increased from 2008 Q4 until 2014 Q2. A comparison with our previous charts reveals that the multivariate HP filter produces more robust results than the other filters.

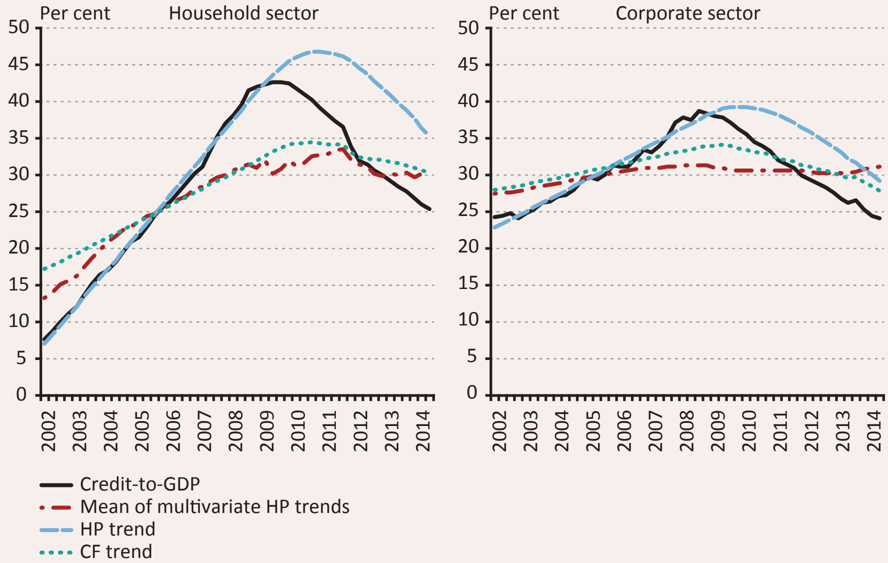
Chart 11
Trends of credit-to-GDP estimated with multivariate HP filter on various intervals



Source: MNB.

The trend obtained can be compared to the results estimated by the univariate methods (Charts 12 and 13), namely, the univariate HP filter, and to the result of the Christiano–Fitzgerald filter, the univariate method that seems to be the best for filtering the credit-to-GDP time series. Upon the comparison we set out from the values calculated in a one-sided[13] manner in order to see how big credit gap would have been indicated by the individual indicators at various points of time. The charts reveal that the univariate HP filter does not indicate any excessiveness. In fact, due to a decline in the holding, it shows a very large negative credit gap following the crisis. However, the CF filter and the multivariate HP filter signal the build-up of the positive credit gap.

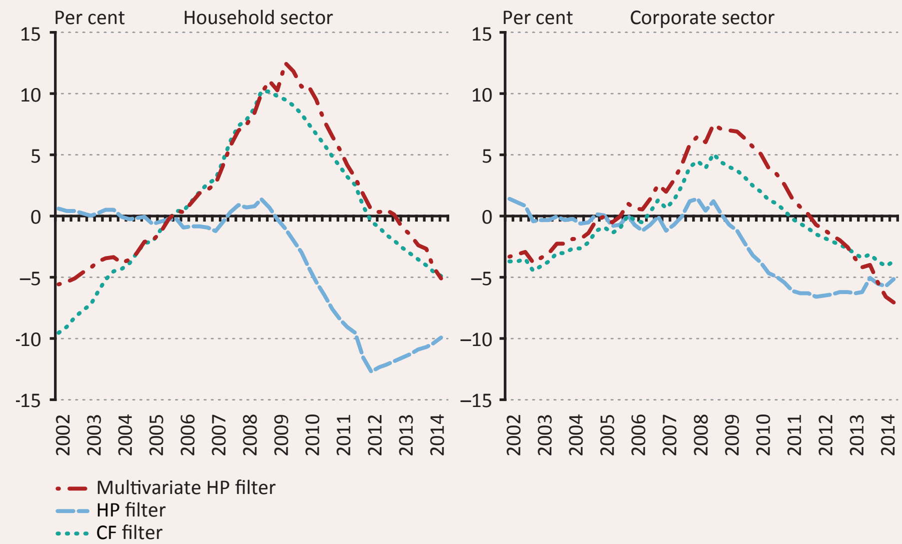
Chart 12
Comparison of univariate filters with the multivariate HP filter – trend



Source: MNB.

[13] As an initial sample period is needed for the estimation of the regression equations of the multivariate HP filter, until end-2008 the filters were estimated in a two-sided manner, before being extended in a one-sided manner from then on.

Chart 13
Comparison of univariate filters with the multivariate HP filter – credit gap

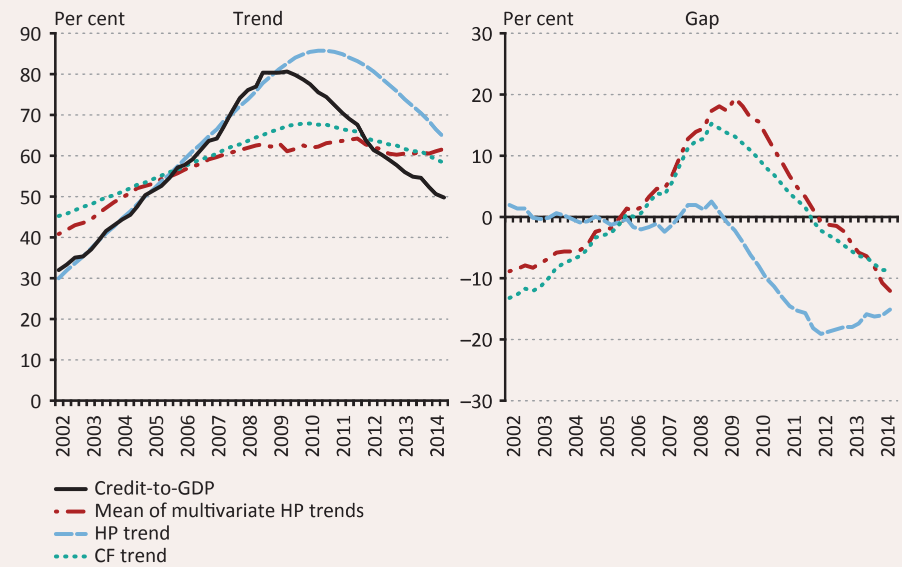


Source: MNB.

Upon the outbreak of the crisis, in the household segment the credit gap amounted to a mere 1 percentage point according to the univariate HP filter and to approximately 10 percentage points each on the basis of the other two filters. In the corporate segment, the univariate HP filter estimated a credit gap of one percentage point, while the other two filters estimated 5 and 7 percentage points, respectively. Summarising the household and corporate segments (Chart 14), in the case of the univariate HP filter the size of the credit gap would have reached the 2.5 percentage point value that means the introduction of the countercyclical capital buffer only upon the outbreak of the crisis, while the CF filter and the multivariate HP filter would have shown 15 and nearly 17 percentage point credit gaps, respectively. Both values are above the 10 percentage point credit gap that means the maximum capital buffer.

Following the outbreak of the crisis, the trend of the multivariate HP filter falters in both segments, and in parallel with the early repayment its value declines by some 3 percentage points in the case of households. Due

Chart 14
Comparison of univariate filters with the multivariate one for all loans outstanding



Source: MNB.

to the pause in the trend and the large credit gap existing at the time of the outbreak of the crisis, the fall in loans outstanding almost completely entails a decline in the credit gap, which is already in negative territory in 2014. The developments are similar in the case of the CF filter as well, although the pause in the trend occurs a little bit later, and in the corporate segment the trend also adjusts. However, as it did not signal a positive credit gap at the peak of lending, initially the univariate HP filter perceives the decline in loans outstanding as a very large credit gap, then the negative credit gap closes slightly as a result of the decline in the trend value.

The three filters are worth comparing in terms of robustness as well. Therefore, in the case of all the three filters we compared the results of the longest time horizon, i.e. the one lasting until 2014 Q2, with the results of the shortest and the second longest horizons (lasting until 2008 Q4 and 2013 Q4, respectively) under review. In the case of both comparisons we examined the average deviations in absolute value of the trends estimated for individual periods from the results obtained on the longest horizon and we also examined the size of the greatest deviation (Table 2). Another way of interpreting the obtained results is to what extent the run on the longer period would change the previous values obtained for the trends of individual periods. The results reveal that on the whole the multivariate HP filter can be deemed the most stable over time: the results of the run until 2008 Q4 were modified by the run on a five and a half years longer horizon by only 0.4 percentage point and 0.2 percentage point in the household and corporate segments, respectively, compared to the approx. 2 percentage point and 2.5–3.5 percentage point values of the Christiano–Fitzgerald filter and the univariate HP filter, respectively. Taking account of the maximum absolute deviation, the difference is even more striking. In the case of the results of the run until 2013 Q4, due to the shorter distance in time the size of revisions is smaller, and again the results of the multivariate HP filter change the least (except for the average absolute deviation of the household segment, where the difference is minimal compared to the CF filter).

Table 2
Comparison of univariate filters with the multivariate one – robustness

		Univariate HP	Christiano–Fitzgerald	Multivariate HP
Average absolute deviation until 2008 Q4 (percentage points)	household	3,65	1,98	0,39
	corporate	2,41	2,04	0,24
Max. absolute deviation until 2008 Q4 (percentage points)	household	8,42	4,82	0,85
	corporate	5,73	4,60	0,78
Average absolute deviation until 2013 Q4 (percentage points)	household	0,61	0,26	0,29
	corporate	0,32	0,21	0,12
Max. absolute deviation until 2013 Q4 (percentage points)	household	2,25	0,72	0,09
	corporate	1,18	0,57	0,28

Source: MNB.

6 Summary

For the application of the countercyclical capital buffer set out in the Basel III capital regulation the macroprudential authority has to monitor developments in the private sector's credit-to-GDP ratio to be able to impose a capital buffer of adequate size in the case of excessive credit growth. In order to be able to establish the extent of excessive credit growth, the time series of the credit-to-GDP ratio of the private sector has to be decomposed to trend and cyclical component (credit gap). There are various filtering methods available for the decomposition. Four of them were examined in detail: the univariate Hodrick–Prescott filter, the Christiano–Fitzgerald filter, the Beveridge–Nelson filter and the multivariate Hodrick–Prescott filter. The decomposition was carried out separately for the household and corporate time series, then the obtained values were summarised. In the case of the Beveridge–Nelson filter, however, only the household and corporate time series were decomposed and no other calculations were made due to the unsuitability of the results.

The advantage of univariate filters is the low data requirement, as only the values of the time series under review are used, few parameters have to be given from outside, and they can be produced easily and fast. At the same time, endpoint uncertainty may be significant when applying this method. As a result, with the receipt of more recent data the values estimated for previous periods also change. In the case of the univariate HP filter the magnitude of the change was so high that it made the use of the methodology unreliable, whereas in the case of the Christiano–Fitzgerald filter this effect seemed much smaller.

The multivariate Hodrick–Prescott filter allows the inclusion of other information in the filtration, providing a more precise picture of the developments. Setting the filter, however, requires several decisions of experts, which also has an impact on the value of the obtained trend as well. Within certain limits, the multivariate filter was run in various possible ways, and finally the average of the results was used as the value of the trend during the comparison. We experienced that the endpoint uncertainty is the smallest in the case of the multivariate Hodrick–Prescott filter, and the obtained results roughly reflect our experts' assessment to date concerning developments in the credit gap.

The extent of the countercyclical capital buffer has to be announced 12 months in advance, allowing banks to have enough time to prepare for the change in the requirement. For setting the capital buffer, the size of the current credit gap needs to be known, but in the case of the filters described above, always only the information available until the given point in time can be used. Therefore, it is a problem if the image of the size of the credit gap changes considerably with the receipt of new data. Unfortunately, with the methods described above we cannot present to what extent they would have been able to facilitate the setting of the countercyclical capital buffer, as only the rising phase of the lending cycle would have been available for the filtering. However, in view of the endpoint uncertainty and the forward-looking regulation, it is expedient to use a filter that is robust over time, and the multivariate Hodrick–Prescott filter presented above may meet this condition.

Based on the multivariate Hodrick–Prescott filter, in the early 2000s, during the financial deepening, the initially negative credit gap closed, but the further increase in loans outstanding resulted in a significant positive credit gap both in the household and corporate sectors. Upon the outbreak of the crisis, according to the filter the value of the credit gap amounted to 11 and 7 percentage points in the household and corporate sectors, respectively. During the adjustment following the crisis, the credit gap closed again. In fact, due to the considerable decline, its value became negative again.

In addition to the quantifications of the credit gap presented here, monitoring other indicators is also necessary for operating the countercyclical capital buffer. The build-up of risks can be signalled by a number of other indicators as well. Therefore, for a more detailed overall picture, it is worth monitoring other time series as well, even if the credit cycle is filtered by a multivariate method. In addition, the examination of the variables to be applied for the release of the capital buffer also deserves special attention. As it is mentioned in the Basel recommendation as well, it might as well take place already on the basis of market indicators that signal crisis phenomena earlier. However, the compilation of these sets of indicators and linking them to the capital buffer requirement are subject to further research.

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8 Appendix

A DIFFERENCES BETWEEN THE MULTIVARIATE HP FILTERS USED BY US AND FOUND IN THE LITERATURE

As it was mentioned in Chapter 5, there are several types of multivariate HP estimation solutions, of which we selected the Laxton–Tetlow and the Hirose–Kamada methods. Laxton and Tetlow completed the univariate HP with two regression relationships, and included the error terms of the regression equations in the objective function of the task to be solved. Hirose and Kamada, in turn, replaced the term of the univariate HP that prescribes matching with the data with a regression equation. Therefore, the latter method can take account of only one economic relationship. In terms of its stating, the model used by us corresponds to the Laxton–Tatlow solution, but it is different from that in two of its important properties. These are mainly technical features, which do not play an important role in understanding our article, but help in the deeper understanding of the model.

In both of the previous articles the estimation of the models was carried out through iterative steps. In contrast, we solved the optimisation task in an analytical manner. Therefore, we reached the results faster in terms of runtime. The optimal parameter and trend values may be obtained in one step by rearranging the two regression relationships and displacing them into the objective function.

The other significant difference compared to earlier studies is in the determination of regression equations. In the two above-mentioned studies the potential GDP was estimated, and one or two concrete economic relationships were adjusted to it: the Phillips curve and Okun's law. In contrast, we looked for variables that can move together with the trend or cycle of lending, and thus may help in identification. As we did not know exactly which variables would work properly, we tried several specifications and, contrary to previous articles, accepted the estimation results only on certain conditions. As we did not create the equations on a cause and effect basis, but were only looking for co-movement, there may be spurious regressions among the regression equations. Therefore, we could not use the p values upon the selection of the variables. Nevertheless, in our case the spurious regression does not lead to completely unusable results. As in this estimation the target variable is latent (therefore, it is to be estimated), a relationship that captures the connection between the latent variable and the observed explanatory variable may help in its identification.

B EXPLANATORY VARIABLES EXAMINED FOR THE EQUATIONS OF THE MULTIVARIATE HP FILTER

1.A) Household segment – regression of cyclical component

Explanatory variable	Applied transformation	Expected sign	Was it included in a run that met the conditions?
global credit gap	none	positive	yes
cyclical component of real GDP (based on Kalman filter)	logarithm	positive	yes
weighted interest rate of stock of housing loans and consumer credit	none, the data for year 2002 were modified because of the linearity of the model	negative	yes
BUBOR	none	negative	yes
leverage	none	positive	yes
loan-to-deposit ratio	none	positive	yes
real marketing costs	moving average	positive	yes
FHB real housing price index	none	positive	no
number of flats to be built	seasonal adjustment	positive	no
number of dwellings to be built	seasonal adjustment	positive	no

Source: MNB.

1.B) Household segment – regression of trend

Explanatory variable	Applied transformation	Expected sign	Was it included in a run that met the conditions?
real GDP	logarithm	positive	yes
trend of real GDP (based on Kalman filter)	logarithm	positive	yes
real earned income	logarithm	positive	yes

Source: MNB.

1.C) Summary table of the cycle and trend equations of the household segment

Variables of the cycle equation	Variable of the trend equation	Number of equations	Minimum of cyclical λ	Maximum of cyclical λ	Minimum of trend λ	Maximum of trend λ
global credit gap	–	1	0,001	0,001	–	–
loan–to–deposit	–	1	0,01	0,01	–	–
global credit gap, output gap	–	1	0,001	0,001	–	–
global credit gap, interest rate	–	1	0,001	0,001	–	–
global credit gap, loan–to–deposit	–	2	0,001	0,01	–	–
interest rate, leverage	–	1	0,001	0,001	–	–
–	real GDP	10	0,0001	0,01	0,001	1000
–	trend of real GDP	9	0,0001	0,001	0,001	1000
global credit gap	real GDP	23	0,0001	1000	0,0001	1000
global credit gap	trend of real GDP	10	0,0001	0,01	0,0001	1000
global credit gap	earned income	4	0,0001	1000	0,01	100
interest rate	real GDP	7	0,001	1000	0,0001	0,1
BUBOR	real GDP	6	0,001	0,1	0,01	1000
leverage	real GDP	12	0,0001	1	0,0001	1000
leverage	trend of real GDP	4	0,0001	0,001	0,001	10
leverage	earned income	1	0,0001	0,0001	0,01	0,01
loan–to–deposit	real GDP	5	0,01	1000	0,0001	0,1
loan–to–deposit	trend of real GDP	1	0,01	0,01	0,0001	0,0001
loan–to–deposit	earned income	1	0,01	0,01	0,0001	0,0001
marketing cost	real GDP	2	0,001	0,01	0,01	1
global credit gap, interest rate	real GDP	18	0,001	1000	0,0001	1000
global credit gap, interest rate	trend of real GDP	7	0,0001	0,01	0,0001	1000
global credit gap, interest rate	earned income	9	0,0001	1000	0,001	100
global credit gap, BUBOR	real GDP	25	0,0001	1000	0,0001	1000
global credit gap, BUBOR	trend of real GDP	6	0,0001	0,01	0,001	1000
global credit gap, BUBOR	earned income	1	0,0001	0,0001	0,01	0,01
global credit gap, leverage	real GDP	4	0,0001	0,01	0,0001	0,01
global credit gap, leverage	trend of real GDP	10	0,0001	0,01	0,0001	1000
global credit gap, leverage	earned income	3	0,0001	0,001	0,001	1
global credit gap, loan–to–deposit	real GDP	6	0,01	1000	0,0001	0,1
global credit gap, loan–to–deposit	trend of real GDP	9	0,001	1000	0,0001	1
global credit gap, loan–to–deposit	earned income	1	0,01	0,01	0,0001	0,0001
global credit gap, marketing cost	real GDP	1	0,001	0,001	0,0001	0,0001
global credit gap, marketing cost	trend of real GDP	2	0,0001	0,001	0,0001	0,0001
global credit gap, marketing cost	earned income	3	0,0001	10	0,001	1
interest rate, leverage	real GDP	3	0,001	0,1	0,0001	0,01
interest rate, leverage	trend of real GDP	3	0,0001	0,001	0,0001	1
interest rate, leverage	earned income	1	1000	1000	10	10
interest rate, loan–to–deposit	real GDP	4	1	1000	0,01	0,1
BUBOR, leverage	real GDP	22	0,0001	1000	0,0001	1000
BUBOR, leverage	trend of real GDP	2	0,0001	0,0001	0,001	0,01
BUBOR, leverage	earned income	1	0,0001	0,0001	0,01	0,01
BUBOR, marketing cost	real GDP	5	0,001	0,1	0,001	1000
leverage, marketing cost	real GDP	2	0,0001	0,001	0,0001	0,0001
leverage, marketing cost	trend of real GDP	4	0,0001	0,001	0,0001	10
leverage, marketing cost	earned income	1	0,0001	0,0001	0,01	0,01
global credit gap, interest rate, BUBOR	real GDP	3	0,1	1000	0,1	1
global credit gap, interest rate, BUBOR	trend of real GDP	4	0,0001	0,01	0,001	1000
global credit gap, interest rate, leverage	real GDP	1	0,001	0,001	0,0001	0,0001
global credit gap, interest rate, leverage	trend of real GDP	6	0,0001	0,01	0,0001	1000
global credit gap, interest rate, leverage	earned income	1	0,0001	0,0001	0,001	0,001
global credit gap, interest rate, loan–to–deposit	real GDP	4	1	1000	0,01	0,1
global credit gap, BUBOR, leverage	real GDP	25	0,0001	1000	0,0001	1000
global credit gap, BUBOR, leverage	trend of real GDP	9	0,0001	0,01	0,0001	1000
global credit gap, BUBOR, leverage	earned income	2	0,0001	0,0001	0,001	0,01
global credit gap, BUBOR, marketing cost	earned income	1	0,0001	0,0001	0,01	0,01
global credit gap, leverage, marketing cost	trend of real GDP	1	0,0001	0,0001	0,0001	0,0001
global credit gap, leverage, marketing cost	earned income	1	0,0001	0,0001	0,001	0,001
interest rate, BUBOR, leverage	trend of real GDP	2	0,0001	0,001	0,001	1
BUBOR, leverage, marketing cost	real GDP	1	0,0001	0,0001	0,0001	0,0001
BUBOR, leverage, marketing cost	trend of real GDP	3	0,0001	0,0001	0,0001	0,01
BUBOR, leverage, marketing cost	earned income	1	0,0001	0,0001	0,01	0,01

Source: MNB.

2.A) Corporate segment – regression of cyclical component

Explanatory variable	Applied transformation	Expected sign	Was it included in a run that met the conditions?
global credit gap	-	positive	yes
cyclical component of real GDP (based on Kalman filter)	logarithm	positive	yes
interest rate on new corporate loans	none	negative	yes
BUBOR	none	negative	yes
leverage	none	positive	yes
loan-to-deposit ratio	none	positive	yes
GKI business confidence index	none	positive	yes
GKI economic sentiment index	none	positive	no

Source: MNB.

2.B) Corporate segment – regression of trend

Explanatory variable	Applied transformation	Expected sign	Was it included in a run that met the conditions?
real GDP	logarithm	positive	yes
trend of real GDP (based on Kalman filter)	logarithm	positive	yes
real earned income	logarithm	positive	yes

Source: MNB.

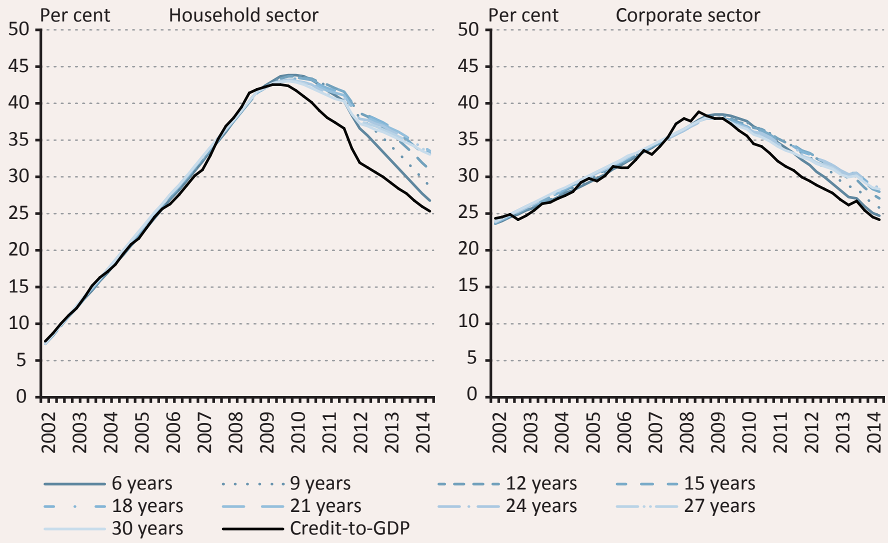
2.C) Summary table of the cycle and trend equations of the corporate segment

Variables of the cycle equation	Variable of the trend equation	Number of equations	Minimum of cyclical λ	Maximum of cyclical λ	Minimum of trend λ	Maximum of trend λ
global credit gap	–	2	0,0001	0,001	–	–
leverage	–	1	0,0001	0,0001	–	–
loan-to-deposit	–	1	0,01	0,01	–	–
global credit gap, output gap	–	2	0,0001	0,001	–	–
global credit gap, leverage	–	2	0,0001	0,001	–	–
global credit gap, loan-to-deposit	–	2	0,001	0,01	–	–
output gap, leverage	–	1	0,0001	0,0001	–	–
global credit gap, output gap, leverage	–	2	0,0001	0,001	–	–
global credit gap, leverage, business confidence index	–	1	0,0001	0,0001	–	–
–	real GDP	19	0,0001	10	0,0001	1000
–	trend of real GDP	28	0,0001	100	0,0001	1000
global credit gap	real GDP	29	0,0001	1000	0,0001	1000
global credit gap	trend of real GDP	30	0,0001	1000	0,0001	1000
leverage	real GDP	12	0,0001	0,1	0,0001	1000
leverage	trend of real GDP	7	0,0001	0,001	0,0001	1000
loan-to-deposit	real GDP	4	0,01	10	0,0001	0,1
loan-to-deposit	trend of real GDP	1	0,01	0,01	0,0001	0,0001
global credit gap, leverage	real GDP	24	0,0001	1000	0,0001	1000
global credit gap, leverage	trend of real GDP	15	0,0001	0,01	0,0001	1000
global credit gap, loan-to-deposit	real GDP	30	0,01	1000	0,0001	1000
global credit gap, loan-to-deposit	trend of real GDP	1	0,01	0,01	0,0001	0,0001
interest rate, leverage	real GDP	1	0,01	0,01	10	10
BUBOR, leverage	real GDP	4	0,0001	0,01	0,001	10
BUBOR, leverage	trend of real GDP	3	0,001	0,001	10	1000
leverage, loan-to-deposit	real GDP	17	0,01	1000	0,01	1000
global credit gap, leverage, business confidence index	trend of real GDP	24	0,0001	1000	0,0001	1000

Source: MNB.

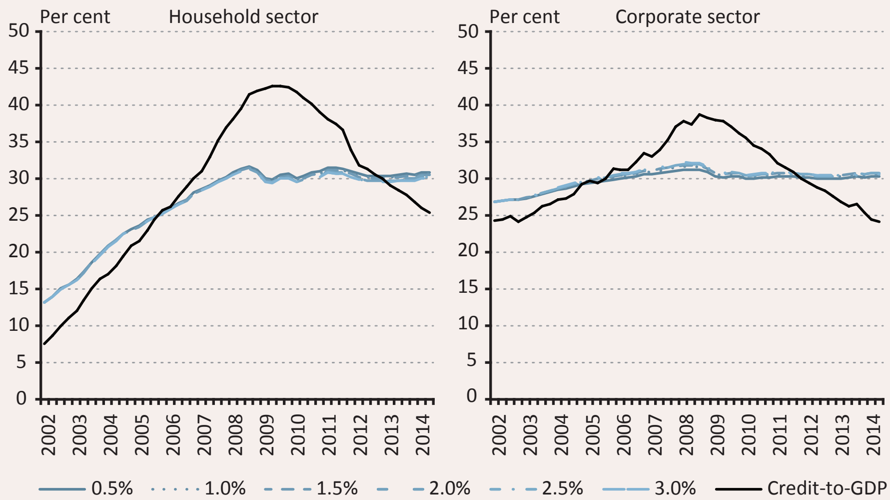
C ROBUSTNESS CHECK CONCERNING THE ASSUMPTIONS

Chart 15
One-sided CF trend of household and corporate credit-to-GDP with various cycle lengths, assuming drift upon detrending



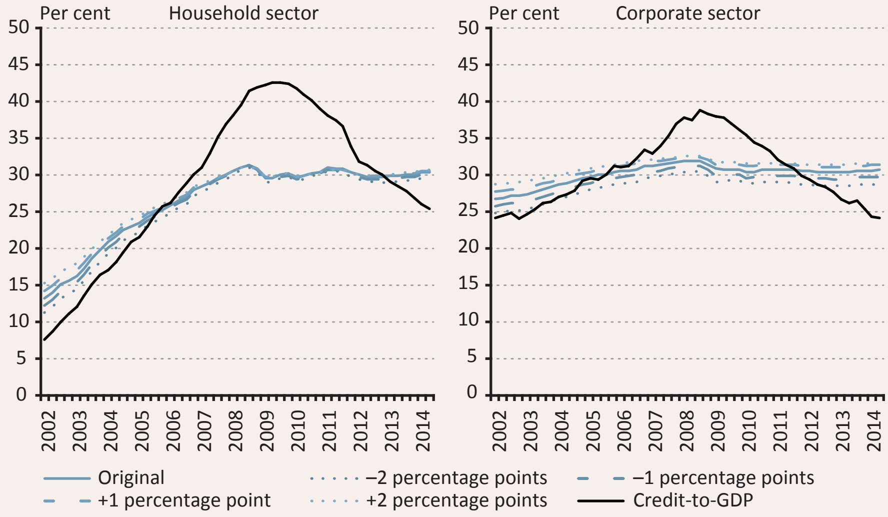
Source: MNB.

Chart 16
Two-sided multivariate HP trend of household and corporate credit-to-GDP with various significance criteria related to the variables



Source: MNB.

Chart 17
Two-sided multivariate HP trend of household and corporate credit-to-GDP with various starting values



Source: MNB.

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