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The impact of credit supply shocks and a new FCI based on a FAVAR approach

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The impact of credit supply shocks and a new FCI based on a FAVAR approach*

(Hitelkínálati sokkok hatása és pénzügyi kondíciós index egy FAVAR modell alapján)

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Abstract

In this paper, relying on a time-varying parameters FAVAR model, two credit supply factors are calculated, the first of which is identified as willingness to lend, while the second as lending capacity. The impact of these two types of credit supply shocks on macroeconomic variables and their changes in time is examined. The two types of lending shocks affect the macro variables rather differently; a positive lending capacity shock in a banking system mostly owned by non-residents influences GDP through the decrease in country risk and the easing of monetary policy, while willingness to lend primarily increases lending activity. The two financial shocks also differ in terms of their evolution over time: the change in the impact of willingness to lend was driven by foreign currency lending and one-off events (e.g. the outbreak of the crisis), thus the deviations occur usually for short periods of time and they are of small degree between the various quarters. On the other hand, in the case of lending capacity, trending processes can be observed: before the crisis the situation of the banking system plays an increasing role in country risk, while after 2008 it appears that monetary policy paid increasing attention to financial stability. Finally, a new type of financial conditions index is quantified based on our estimates, which measures the impact of the banking system's lending activity on GDP growth.

JEL: C32, C38, C58, E17, G21.

Keywords: dynamic factor model, dual Kalman-filter, financial conditions index, credit supply shocks, time varying parameter VAR.

Összefoglaló

Jelen tanulmányban egy időben változó paraméterű FAVAR modell segítségével két hitelkínálati faktort számítottunk, melyek közül az elsőt hitelezési hajlandóságként, a másodikat hitelezési képességként azonosítottuk. Majd megvizsgáltuk a kétfajta hitelkínálati sokk makrogazdasági változókra gyakorolt hatását, és ezek időbeli változását. A kétfajta hitelezési sokk meglehetősen eltérő módon hat a makrováltozókra: egy pozitív hitelezési képességi sokk egy túlnyomórészt külföldi tulajdonban lévő bankrendszerben a GDP-t az országkockázat csökkenésén és a monetáris politikai lazításon keresztül befolyásolja, míg a hajlandóság főleg a hitelezési aktivitást növeli. Időbeli változás szempontjából is eltér a két pénzügyi sokk egymástól: a hajlandóság hatásának változását a devizahitelezés, valamint egyszeri események (például válság kitörése) mozgatták, így az eltérések általában rövid időszakokra jellemzőek, és ráadásul kismértékűek a különböző negyedévek között. Ezzel szemben a hitelezési képesség esetén trendszerű folyamatok figyelhetők meg: az országkockázat alakulásában egyre nagyobb szerepet játszott a bankrendszer helyzete a válság előtt, míg 2008 után úgy tűnik, a monetáris politika növekvő mértékben vette figyelembe a pénzügyi stabilitást. Végül, becsléseink alapján egy újfajta pénzügyi kondíciós indexet számszerűsítettünk, amely a bankrendszer hitelezési tevékenységének GDP-növekedésre gyakorolt hatását méri.

1 Introduction

The financial crisis reached Hungary in 2008 and the credit crunch that followed highlighted the fact that the financial intermediary system and financial markets exert a large impact on real economic developments. Moreover, in Hungary foreign currency lending to households played an important role in the escalation of the crisis and the protracted recovery, which still hinders pick-up in domestic consumption through the indebtedness of households and large non-performing bank portfolios. Hence, after the crisis the stability of the banking system and financial markets gained higher importance compared to earlier periods. Macroeconomic policy makers and regulators also attach higher significance to the changes affecting this sector and spill-over effects. Issues related to the operation and effects of the banking system and the financial markets more and more often become the focus of research, just like in the case of economic decision-making.

Several time series are available for describing financial processes; however, the question arises whether the information content of these can be concentrated into one or two easy-to-interpret indicators, and if so, how it can be done. The pertaining literature refers to these information concentration indices as a financial conditions index (hereinafter: FCI), which provides a view of the general situation of financial markets. Each FCI is created by weighting certain financial time series together; however, their calculation has changed a lot in recent years. The indices start out from an ever broader set of information (even several hundreds of time series). In addition, initially the weighting together was a simple averaging, while the latest FCIs already come from estimation procedures, which consider, for example, the impacts on the macro economy.

This paper presents a new method of calculating an FCI for the Hungarian financial intermediary system, relying on a time-varying Factor-Augmented Vector Autoregressive (FAVAR) model. Considering the special features of the Hungarian financial intermediary system we depart from FCIs appearing in the literature in several aspects: firstly, upon estimating the financial factors only the indicators describing the banking system are taken into account. We use a bank panel database, as we wish to explore the underlying process of the banking system as accurately as possible. Secondly, although this is not unprecedented, we perform a time-varying parameter-based estimation, because on the one hand, an extraordinary event – the crisis – also forms part of the observed period, and on the other hand, as a result of the crisis some regulatory changes that fundamentally impact the banking system took place in this period, which also may have transformed the correlations between the banking system and the real economy. Thirdly, we combine two former FCI calculation methods: the impact of the factors received during the factor analysis on the real economy (specifically on GDP growth) is designated as FCI.

In addition, we also use the results from the FAVAR model to examine the impact of credit supply shocks. We differentiated between two financial factors, where one of them was identified as willingness to lend and the other one as lending capacity. We calculated factors also from the macroeconomic variables, and then the two types of factors were analysed in a VAR model, so as to measure the impact of the credit supply shocks on a wide range of macro variables. The two financial factors have material impact on the development of the macroeconomic variables, albeit in a different manner. The model used by us also showed how the probability of credit supply shocks and their impact have changed in the period under review.

Our most important results are: a capacity shock is similar to a negative risk premium shock, it influences GDP through the decrease in country risk and monetary policy easing. The willingness shock mostly changes lending activity. Moreover, the impact of capacity shocks is usually more persistent, while willingness shocks wear off faster. The two financial shocks also differ in terms of their evolution over time: the change in the impact of willingness was driven by foreign currency lending and one-off events. In the case of lending capacity, trend-like processes can be observed: before the crisis the situation of the banking system plays an increasing role in developments in country risk, while after 2008 it appears that monetary policy paid increasing attention to several aspects of financial stability. Based on the change in the variance of the VAR error terms it may be stated that the expected measure of financial shocks increased as a result of the crisis, and still increases, presumably as result of the new regulatory requirements that followed 2008. This paper is structured as follows: in Chapter 2 we review the literature related to the topic, specifically touching upon the analyses made on Hungarian data. Thereafter we present the data used by us and the selected methodological framework. Chapter 4 contains the estimated factors, the impulse responses of credit supply shocks and the FCI analysis. Finally, we summarise the most important thoughts of the paper.

2 Related literature

The application of factor models for macroeconomic purposes dates back to the 1970s (see e.g. Geweke (1977) or Sargent and Sims (1977)). The basic idea of these estimates is that the information in panel data comprising of a large number of macro variables can be presented well with a few (much fewer than the number of the original variables) factors, the use of which for further calculations leads to more stable results. Since then a number of studies were published on the various types of factor models, which are used more widely also for examining economic issues. This paper is confined only to the part of the factor models' literature that was used for the calculation of FCI or for the quantification of the impact of the financial and banking system shocks.

In terms of methodology, the first group of the articles use the factor model presented in the Stock and Watson (2002), which calculates factors by principal component analysis, and presents their dynamics by a VAR model. The analysis of financial conditions and shocks is combined in a number of publications with the review of monetary policy, as well as with the separation and comparison of the two types of shocks. The first of such articles was that of Bernanke et al. (2005), which estimated the impact of monetary policy shocks on other variables using a US dataset. Due to the use of factors, it was possible to involve much more time series in the examination than in the case of a classic VAR model. In addition to the factors derived from the macro variables, the short-term interest rate was also included in the VAR, while the impulse responses were calculated with the use of Cholesky decomposition. The authors of the Boivin et al. (2013) and Pellényi (2012) studies use a very similar approach; the first one examined the impact of lending shocks on US figures, while the latter one analyses the heterogeneity of the impacts of monetary policy by industries on the Hungarian data. The difference was in the methodology of the shock decomposition: the respective shocks were identified by the sign restrictions applied on the original variables used for the factors. Jimborean and Mésonnier (2010) quantified the bank balance sheet channel of monetary policy in the case of France, calculating the financial and macro factors for this by principal component analysis, the interaction of which (and the base rate) was examined in a VAR model. In this case the identification of the shocks took place by sign restriction on the impulse responses of the base rate. Buch et al. (2014) examined an issue of opposite direction compared to the previous ones, namely the impact of the macroeconomic shock on the banking system and on the individual banks; however, the estimation process is the same here as well.

From the second half of the 2000s the time-varying parameter FAVAR models became increasingly popular (see for example: Del Negro and Otrok (2008), Eickmeier et al. (2011a), Korobilis (2013)). Based on the results of the articles this appeared to be justified: significant differences were identified in the parameters of the models when examining different periods. There are much larger differences in the particular model specifications within this group in the various articles. They use different assumptions as to type of the model parameters that change in time, and whether the estimation was made by the Bayesian or the classic procedure (and within that by exactly which method). The Eickmeier et al. (2011b) study examines the effects of the international financial shocks with time varying parameter FAVAR model estimated by the classic method. The authors conclude that both the size and the impact of the shocks differ in various periods (they compared primarily the 2008 crisis with previous periods). The Prieto et al. (2013) study deems similarly important to consider the change in time when examining the relation between the real economy and financial intermediary systems, which obtained this result based on a Bayesian VAR model.

In recent years the financial conditions index methodology has changed a lot: the first FCIs were created as the simple average of the most important financial indicators (see ECB (2009), IMF (2008)). Second-generation FCIs were already more advanced in the sense that the various financial time series were weighted together based on their impact on the macro economy, primarily on GDP (this group includes e.g. Swiston (2008), Beaton et al. (2009), which were estimated on US figures). The impact on the macro economy was estimated based on the coefficients and impulse responses of a structural VAR. An FCI using this approach was also prepared for Hungarian data, which was based on the SVAR model described in the study of Tamási and Világi (2011).

The latest method applied for the FCI calculation is the principal component and factor analysis, the advantage of which compared to the former ones is that they use a broad set of information, thus they may provide a more comprehensive view of developments in the financial intermediary system. The first, pioneering study in this area was Hatzius et al. (2010), which estimated FCI also for the USA. First regressions were applied one-by-one to the financial indicators, where the time lags of GDP growth and inflation were used as explanatory variables (thereby trying to eliminate the endogenous effects of macro economy from the financial time series). The first principal component was calculated from the regressions' error terms and it was regarded as FCI. Darracq Pariès et al. (2014) calculates FCI for euro area data using the methodology of Stock and Watson (2002), and then they also quantify the impacts of the financial shocks relying on the FCI thus received and a VAR model. Brave and Butters (2011), as well as Matheson (2012) estimated dynamic factors for the data of the USA and the euro area, relying on state-space models. During their calculations they used the estimation process specified in Doz et al. (2012) and Doz et al. (2011), the advantage of these is that they are able to manage time series of different frequencies and the problems arising from missing data. The FCI methodology used by us is based on the Koop and Korobilis (2014)[1] approach. The authors generalized the estimation process described in Doz et al. (2011) for the varying parameters case, and of the variables used for the FCI they selected those that ensure the best possible forecast performance for the resultant FCI.

Finally, we should mention the study of Tamási and Világi (2011), which estimates the impact of credit supply shocks on the Hungarian data using a Bayesian SVAR model rather than a factor model, thus it will serve as a useful benchmark for the results obtained by us.

[1] More details on the methodology are provided in Chapter 3.

3 Data and methodology

3.1 FINANCIAL AND MACROECONOMIC DATASET

As we already mentioned in the introduction, separate factors are calculated from a financial and a macroeconomic dataset. In the case of the financial factors we use only banking system data, namely a panel database that contains the data on the ten largest banks in Hungary (more precisely we used the time series of nine banks, while the tenth bank is the remainder of the banking system). This solution differs from the method generally used for FCI calculation. We chose this procedure, because in Hungary the rest of the financial intermediary system and financial markets have a negligible role in the allocation of funds to the corporate and household sectors (see Banai (2016)). Accordingly, we focus on the bank credit markets: the FCI presented here may as well be referred to as a banking conditions index, and of the financial shocks we examine the impact of credit supply shocks.[2] Since the vast majority of the data are available only at quarterly frequency, we used quarterly data and the longest possible sample where data were available. Thus our time series extend from the 2001 Q2 to 2015 Q2.

Of the indicators describing the situation of banks we focused on those that have closer links with credit supply. Ten time series were considered for each bank, which may be allocated to three groups based on their content: solvency position, liquidity position and risk-taking indicators. Of the indicators capturing solvency position we used leverage (balance sheet total as a per cent of total capital), capital buffer (as a per cent of balance sheet total) and the parent bank's leverage. The third indicator follows from the special features of the Hungarian banking system, namely that the major part of the banking system is owned by foreign banks. It could be observed at these banks that they kept only as much capital with the Hungarian bank that just satisfied the regulatory requirements. If the capital level of the Hungarian bank fell below that, they supplemented the shortfall (see Bethlendi (2007)). Thus in fact the solvency position of these foreign-owned banks (and thereby their lending potential or willingness) is better captured by the parent bank's capital stock.[3] The liquidity position was captured by three indicators: liquid assets, stable funding and the value of foreign exchange swap portfolios as a per cent of balance sheet total. Of these it is the third variable that calls for some explanation: the banks solved the funding of foreign currency lending –which was rather significant before the crisis – by foreign exchange swaps, thus risks built up in terms of liquidity and problems arising from the crisis both could be mostly observed in developments in foreign exchange swaps. The entire list of the financial variables is:

1. Solvency
   - Leverage: balance sheet total/total capital
   - Capital buffer/balance sheet total
   - Parent bank's leverage: balance sheet total/total capital
2. Liquidity
   - Liquid assets/balance sheet total
   - Stable funding/balance sheet total
   - FX swaps/balance sheet total
3. Risk-taking
   - Difference of NPL-ratio
   - Loan loss provisioning/total loans
   - Risk weighted assets/balance sheet total
   - Interest and comission income/balance sheet total

[2] The use of banking panel databases is not typical in the FCI-related literature; however under the impact assessment of the financial shocks we find examples of these as well: Buch et al. (2014), Jimborean and Mésonnier (2010).

[3] In the case of the Hungarian-owned banks this indicator was substituted by the leverage of the bank group.

Two of the risk-taking indicators relate to the realisation of risks assumed in the past and their downward effect on lending. These are the portfolio-proportionate loan loss provisioning and the change in the ratio of non-performing household and corporate loans (NPL). The development in risk-weighted assets and the value of interest and commission income as a per cent of the balance sheet total provide a better view of the current risk appetite. The increase in these suggests that the bank moved toward a riskier lending segment. With the exception of the NPL ratio we considered the level of each indicator; in the case of NPL the model used the change thereof, because the stationarity (a necessary element of factor analysis) could be ensured only in this way.

For the macroeconomic factors we used altogether thirty-four time series, containing the most important information related to the Hungarian economy. These include, among others, GDP and its components, employment data, prices and deflators, confidence indicators, exchange rate, country risk indicators, outstanding amounts, lending rates and interbank short-term interest rates. (The full list is available in the Appendix together with the transformations applied to the variables). Where it was necessary, we used data after seasonal adjustment.

3.2 TIME-VARYING PARAMETER FAVAR

Having described the data, now we move on to presenting the methodology; with regard to notion we follow Koop and Korobilis (2014), wherever possible. The $n \times 1$ ($n = 100$) vector of banking variables is denoted by x_t ($t = 1, \dots, T$), $T = 56$ and $s \times 1$ ($s = 34$) vector of the macro variables is denoted by y_t. We wish to estimate the following model:

$$
\begin{aligned}
y_t &= \lambda^y f_t^y + \mu_t && (1)\\
x_t &= \lambda_t^f f_t + \lambda_t^y y_t^D + \upsilon_t && (2)\\
F_t &= B_{t,1} F_{t-1} + \dots + B_{t,p} F_{t-p} + \epsilon_t && (3)\\
\lambda_t^x &= \lambda_{t-1}^x + \eta_t && (4)\\
\beta_t &= \beta_{t-1} + \nu_t && (5)
\end{aligned}
$$

Four macro factors and two financial factors are estimated, the lag length of the VAR equation is two ($p = 2$). In this system, equation (1) describes the relation of the macro variables and the factors, λ^y is the 34×4 matrix of factor loadings and, f_t^y is the 4×1 vector of the latent macro factors, $\mu_t \sim N(0, S)$ is a 34×1 vector. As can be seen, we assume that both the loadings and the covariance matrix of the error terms are constant in time, as we believe that in this period material changes occurred primarily in the banking system and in the interaction of the banking system and real economy, thus we focus on these.

Equation (2) shows the connection of the financial factors and time series, where λ_t^f is the 100×2 matrix of the financial factor loadings, f_t is the 2×1 vector of the financial factors, $\upsilon_t \sim N(0, V_t)$ is a 100×1 vector. Equation (2) also includes some macroeconomic time series denoted by y_t^D, which is a 6×1 vector containing GDP growth, inflation, difference of EUR/HUF exchange rate and the lagged values of these variables. With this we intend to eliminate the impact of macro economy on financial factors, thereby reducing the endogeneity problem and getting purged credit supply factors. This procedure may be deemed standard among the FCIs based on factor analysis; the same type of cleaning was performed on the financial time series, for example, by Hatzius et al. (2010), Darracq Pariès et al. (2014) and Koop and Korobilis (2014). The 100×6 matrix of coefficients of the macro variables is denoted by λ_t^y. As you can see, in this case we assumed time-varying loadings and heteroskedastic error terms, where the change in loadings follows a multivariate random walk, described by equation (4) ($\lambda_t^x = [\lambda_t^y, \lambda_t^f]$). We assume, as it is common in the literature containing likelihood estimation, that the S and V_t matrices are diagonal, i.e. f_t^x és f_t^y contain the common information in the financial and macro time series.

Arranging the various types of factors in a single 6×1 dimension vector: $F_t = \begin{bmatrix} f_t^y \\ f_t^x \end{bmatrix}$,in equation (3) the factors are arranged in a common VAR model, where $B_{t,1}$ and $B_{t,2}$ are the 6×6 matrix of VAR coefficients, $\epsilon_t \sim N(0, Q_t)$. That is, both the VAR coefficients and the covariance matrices of the error terms are described by time-varying processes; for the coefficients we assume, similarly to the loadings, multivariate random walk. This is described by equation (5), where $\beta_t = (vec(B_{t,1})', \dots, vec(B_{t,p})')'$. The error terms of the equations describing the change in loadings and the VAR coefficients follow a joint normal distribution with zero expected value, with covariance matrices W_t and R_t. Respctively, if the β_t and λ_t^x were constant in time, we would get a heteroskedastic FAVAR model, and when the V_t and Q_t are also constant, we obtain a classic FAVAR model.

There are a few relevant differences between the models in Koop and Korobilis (2014) and those outlined by us. These are primarily attributable to the fact that while Koop and Korobilis developed their own FCI for forecasting, the purpose of this paper is to address structural issues. Firstly, no macroeconomic factors are calculated in the original article (equation (1) is missing), instead the VAR includes, in addition to the factors, three variables (the GDP deflator, the unemployment rate and the GDP growth rate) (i.e. the y_t dimension there is three). However, this procedure – although it would be easier to estimate the model – would considerably narrow the number of the variables compared to the 34 variables used by us. Secondly, Koop and Korobilis estimated several models differing from each other in the set of the financial variables used for the calculation of FCI. Thereafter, the models were weighted together based on the forecast performance, moreover in a time-varying manner, thus there the number of variables used for generating the FCI also changed.

The last difference that is worth mentioning arises from the number of factors. Koop and Korobilis calculate one factor from the financial time series, as it is usual in the FCI literature. However, in theory the question may arise whether with a single factor we indeed captured all relevant information. In the case of principal component analysis and the time-constant dynamic factors there is a test to decide this question; of these the most frequently applied one is the test described in Bai and Ng (2002) and Bai and Ng (2007). Since for the model applied by us we found no applicable test, but nevertheless we wished to examine this question as well (moreover, in this case the number of required factors is questionable not only in respect of the banking data, but also of the macro time series), we calculated the factors also with time-constant models. For these the above mentioned tests proposed an optimal number of factors between one and six. Finally – also taking account of the significance of the impulse responses to be described later[4] – we decided to use two factors for the banking database and four for the macro time series.

3.3 ESTIMATION OF THE MODEL

The full description of the estimation procedure is included in Doz et al. (2011) as well as in Koop and Korobilis (2014).[5] The article mentioned first presents a two-step estimation procedure for the calculation of dynamic factors. As the first step of this, the model parameters are defined by OLS estimation based on the principal components, while in the second step the factors are calculated by the Kalman filter. During our estimation the macro factors are first defined by this method.

The latter article is the form of this procedure generalised to time-varying parameters. For the estimation of the time-varying models the latest procedures usually use Bayesian methods, which require Markov Chain Monte Carlo simulation (examples of such models: Del Negro and Otrok (2008), Moench et al. (2013)). This substantially increases the compilation requirement of the model. As opposed to this the advantage of the procedure used here is that its runtime is significantly shorter. Its mechanism is as follows: it sets out from the principal component analysis just like the Doz et al. (2011) article, but this is followed by a dual Kalman filter procedure (because with a classic Kalman filter it would not be possible to calculate both the variable parameters and the factors simultaneously). First the principal component (and depending on the initial values) re-estimates the parameters and then in the second step it recalculates the factors from the parameters.

No simulation is required for this either; we used two types of variance matrix discounting procedures (following the solution of Koop and Korobilis): the exponentially weighted moving average (EWMA) for V_t and Q_t, and the forgetting factor procedure for the calculation of W_t and R_t (the details of these are described in: Koop and Korobilis (2013)). The EWMA may be regarded as the approximating procedure of an integrated GARCH model; the estimated matrices depend, in addition to the data, on the pre-defined so-called decay factors. The interpretation of decay and forgetting factors is very similar: these are numbers between 0 and 1, and the lower their value is, the more the value of the covariance matrix at the given point of time depends only on the data observed in that quarter. The further are the data from this point of time, the less important role the observation has in the value of the estimated matrix. If these equal to 1, the parameters of the model will be constant. Their value can be defined on expert basis and based on the model performance.

Accordingly, the steps of the estimation are as follows:

1. Estimation of the macro factors
   a) Calculation of the principal components

[4] We also performed the model estimation with just one banking and three or five macro factors. These did not modify the impact of the credit supply shocks materially.

[5] The model was estimated by the MATLAB programme, using the codes of Dimitris Korobilis, also available on the internet: https://sites.google.com/site/dimitriskorobilis/matlab/forecasting-tvp-favar. All errors left in the codes the responsibility of this paper's author.

   b) Kalman filter/smoother

2. Definition of the initial values
   a) For the parameters and financial factors: $\lambda_0^x, \beta_0, f_0^x, V_0, Q_0$
   b) Calculation of the principal components from the financial data

3. First step of the dual Kalman filter: estimation of parameters in addition to the principal components
   a) Estimation of the covariance matrices (V_t, Q_t, R_t, W_t) by EWMA and forgetting factor procedures
   b) Estimation of λ_t^x, β_t by Kalman filter/smoother

4. Second step of the dual Kalman filter: re-estimation of the financial factors under the parameters calculated in the previous step.

Before presenting the results, the definition of the initial values should be explained. Here we made efforts to ensure that the initial values are in harmony with the information gained from the data as much as possible (that is the change in the results is truly attributable to the change in the correlations deducible from the observation rather than to the convergence after the incorrect initial values). Thus we made the following choice: $\lambda_0^x \sim N(0,1)$, $\beta_0 \sim N(0, V_{min})$, where V_{min} a diagonal covariance matrix, the values in its diagonal equal $0.1/r^2$ (r denotes the time lag which the given coefficient belongs to; this assumption is similar to a Minnesota-prior). $f_0 \sim N(0,1)$, V_0 and Q_0 diagonal matrices; the diagonal of the first one contains 0.1 and that of the latter one contains 0.01. In order to eliminate the impact of the initial values the evaluation of the results is always performed from period 11 (2004 Q4).

Finally we need to define the forgetting and decay factors; the choice of Koop and Korobilis and our choice are shown in Table 1. κ_3 and κ_4 determine how fast the loadings and the VAR coefficients may change. Both the time-varying VAR (Cogley and Sargent (2005)) and the FAVAR literature assume of these that they change very slowly. Koop and Korobilis found that the forecast performance of the models deteriorates significantly when the value of these factors is less than 0.99. Since the aforementioned estimates were made for the US figures, and in Hungary the convergence, the financial deepening and the regulatory change of recent years justify a larger change in the parameters, we selected a slightly lower value for this. On the other hand, we also found that the significance of the results is reduced by the further decrease of κ_3 és κ_4, therefore we specified relatively high values. The smaller these factors are, the higher the risk of overfitting is.

The values of κ_1 és κ_2 determine the degree of the VAR error terms' heteroscedasticity and that of the error terms of equation (2). Koop and Korobilis found that the lower values of κ_1 and κ_2 do not deteriorate the models' forecast performance significantly, which supports the assumption of the heteroskedastic error term (even when a value below 0.96 is selected). We also found this at κ_1, however we permitted only a slower change at the VAR error terms' covariance matrix. This is due to the difference in the data selection: they calculated financial factors from financial market data and their VAR estimate contained macroeconomic times series. As opposed to this, we generated financial factors from banking time series and our VAR model contained macro factors. The latter ones are presumably less heteroskedastic than the former ones.

Table 1
Decay and forgetting factors

	$\kappa_1(V_t)$	$\kappa_2(Q_t)$	$\kappa_3(W_t)$	$\kappa_4(R_t)$
Koop and Korobilis	0.96	0.96	0.99	0.99
Hosszú	0.96	0.98	0.98	0.98

Source: Koop and Korobilis (2014)

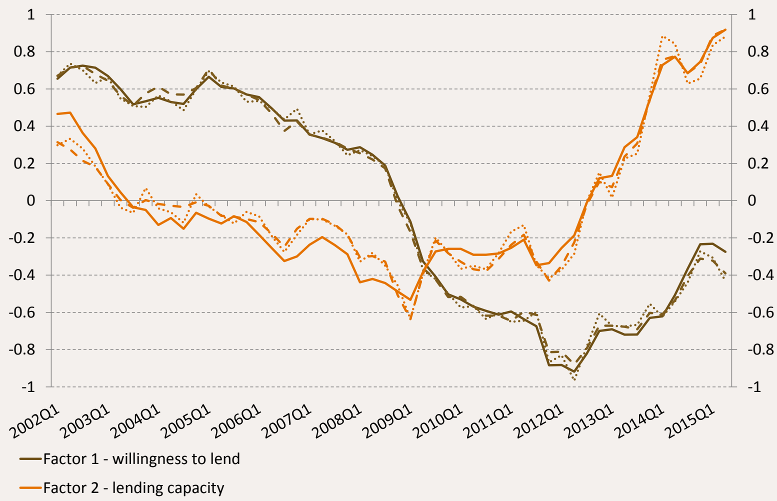
4 Estimation results

4.1 FACTORS

We start the presentation of the results with the factors (the two banking factors are shown in Figure 1). As we already mentioned, we estimated two factors from the banking data; in these two variables we managed to capture almost 50 per cent of the variance in the original data. We compared the results of our time-varying estimation with two other factor analysis procedures: with the principal component analysis and also with the dynamic factors described in the Doz et al. (2011) study. It may be stated generally that the factors gained from the three methods are very similar, which is in line with our assumption that although the parameters of our principal model change in time, they do so not too fast.[6] The factors from the time-varying model are less volatile than the time series of the other two estimations (this particularly applies to the principal component analysis); the one-off/extreme events generate minor swings in them.

Figure 1
Financial factors

(Note: the solid lines show time-varying parameter factors, the dashed lines show factors estimated with Doz et al. (2011) method, the dotted lines show principal components.)



We also examined which of the original variables move together more tightly with the gained factors and as a result of that how they should be interpreted. In order to decide the question we ran a regression for the standardised version of all banking variables, where the factors served as explanatory variables.[7] Table 2 presents the results of these, where the R^2 values of the regressions and the estimated coefficients of the factors are presented, averaged for the ten banks included in the sample. The bold characters show the coefficients, which are the four highest absolute values, thereby highlighting which of them determine the development of the factors the most.

[6] Although the time varying factors and principal components are very similar, the impulse responses of the two types of FAVAR are different. Macro variables react to financial shocks in a time-varying manner.

[7] We could have also used factor loadings for this; the average of these for the full period returns an almost identical result with the regression coefficients.

Table 2
Regressions with financial factors and variables
*(Note: * Relative to the balance sheet total, ** relative to total loans, *** leverage: balance sheet total/total capital)*

Variable name	R^2	Factor 1 - willingness to lend	Factor 2 - lending capacity
Liquid assets*	0.57	**-0.5**	**0.35**
Stable funding*	0.68	-0.19	-0.14
FX swaps*	0.33	-0.27	-0.22
Parent bank's leverage***	0.63	**0.55**	-0.27
Capital buffer*	0.32	-0.19	0.16
Leverage***	0.42	0.25	**-0.40**
Difference of NPL-ratio	0.16	-0.25	-0.25
Loan loss provisioning**	0.59	**-0.73**	-0.01
Risk weighted assets*	0.33	-0.20	**0.34**
Interest and commission income*	0.49	**0.43**	**0.30**

Source: MNB calculations

According to this the value of the first factor is high when the credit risk of the existing credit portfolio is low, interest and commission income on assets is high, the parent bank operates with high leverage and the ratio of liquid assets is low. Under the low level of the first two indicators (credit risks) the banks have the opportunity to move towards the riskier lending segments, while the higher level of the latter two indicators suggests that the banks are willing to undertake a larger lending volume and higher risks. Accordingly, we identified this factor as willingness to lend. The level of the second factor increases when the ratio of liquid assets and the banks' interest and commission income on assets go up, and their leverage decreases. Accordingly, this factor is higher when the banks' liquidity and capital position is more stable and their profitability is higher. Therefore, this factor is suitable for measuring the lending capacity. It is worth highlighting the result that in the case of the first factor the parent bank's leverage correlates stronger with the factor than the banks' own leverage (the coefficient of the first one is 0.55, while it is 0.25 at the latter one). This corresponds to our hypothesis according to which in the case of foreign-owned banks the capital position of the parent bank may be much more informative in respect of the credit supply than that of the subsidiary. It should be noted that this manner of interpreting the factors is supported by methodology only partially. However, as it will be presented in the next subsection, during the analysis of the impulse responses we may come to the same conclusion based on the macroeconomic consequences of the shocks caused by the two factors, and temporal developments in the factors is also consistent with the experts' opinion on willingness to lend and lending capacity.

In a theoretical framework, one possible interpretation of willingness to lend and lending capacity is the following: banks solve an optimisation problem with constraints in every period. The liquidity and capital requirements function as constraints, these determine the set of eligible outcomes for banks. The factor of lending capacity shows how near the actual choice of the banking system is to the constraints: the lower the factor becomes, the smaller the distance is. Therefore, in case the factor of lending capacity is lower, it has a more relevant effect on macro variables. On the other hand, the factor of willingness to lend shows how the banks change their choices inside the set of eligible outcomes. These changes can be explained by - among other things - profit maximization or shifts in risk appetite. For example, if banks have to suffer higher loan losses than the expected amount, as a result the rates of non-performing loans increase and their profitability diminishes. Therefore, they are willing to take less risk in the case of new loans.

Based on the time series of the first factor, willingness to lend was at a roughly constant high level until 2005, due to the parent banks' risk appetite and the low credit losses. Then it slowly started to decrease until 2008, when, as a result of the crisis, there was a considerable decline and it fell to a negative range, in parallel with the realisation of the losses on foreign currency loans and the contraction in funding. As of 2009 (with the exception of the quarters impacted by the final early repayment at preferential exchange rate[8]) it remained roughly at the same, rather low level, and in 2013 it gradually started to pick up; however, this process came to a halt in 2015. The lending capacity factor reached its highest level at the beginning

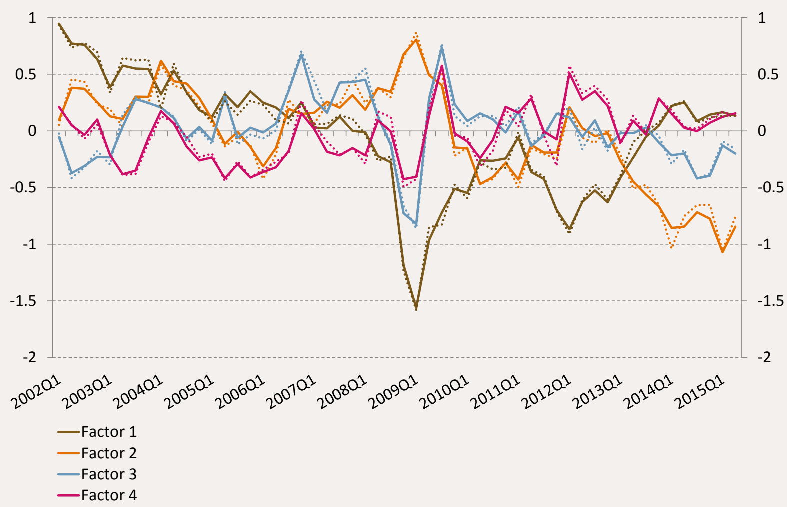
[8] One of the chapters of the Appendix summarises the most significant post-crisis government measures related to foreign currency lending.

of the sample, and then, in parallel with the soaring of foreign currency lending, banks' capital and liquidity position became increasingly stretched, which was coupled with the continuous weakening of lending capacity. The capital injections by the parent banks after the crisis and the measures aimed at improving liquidity significantly increased the institutions' lending capacity by 2009, which, due to the prudent behaviour of the banks and the moderate lending activity, moved to the positive range by 2011 and has been continuously increasing ever since then, and at the last point of time it was at its historic high.

As a robustness check, we estimated our model with just one financial factors, with one less and one more macro factor instead of four. We find that the number of factors does not affect the values of the estimated factors (results can be found in the Appendix B: Figure 8).

Figure 2
Macroeconomic factors

(Note: the solid lines show factors estimated with Doz et al. (2011) method, the dotted lines show principal components.)



We generated four factors from the macroeconomic variables (illustrated on Figure 2), with the static principal component analysis and the dynamic estimation of Doz et al. (2011) we once again arrived at very similar results. This time we managed to capture 65 per cent of the variables' variance by the factors; we performed regressions similar to the banking variables in this case as well; the R^2 thus received are included in the Appendix A.[9] However, we do not attempt to interpret these factors, as this would be rather cumbersome with 4 factors and 34 variables, and we do not need this for the evaluation of the additional results.

4.2 FINANCIAL SHOCKS

Having learnt about the factors we may move on to the analysis of the factor-augmented VAR model and the impulse responses. In the VAR model we used two time lags[10], and calculated the impulse responses by Cholesky decomposition. Since we chose this procedure it must be clarified which order we assumed at the shock decomposition and to what extent the model is sensitive to that. The first four places are occupied by 4 macro factors, followed by 2 financial factors. Due to the estimation of the factors, within each block (macro and financial) the factors, and thus also the error terms, are almost orthogonal and thus the results of

[9] The 5 and 95 confidence intervals belonging to these are included in the Appendix B both for the banking and the financial factors (Figure 5, Figure 6, Figure 7). The estimation of the factor is the more uncertain, the factor with the higher sequence numbers is estimated, which is also reflected by the confidence bands, especially in the case of the macro factors. On the other hand, these bands show relatively small estimation uncertainty, which corresponds to the result that we obtained similar factors with the use of other methods as well.

[10] If the FAVAR model is estimated by principal components, the Akaike and Schwartz information criteria both regard 2 time lags to be optimal.

the model for their ordering are fully robust. On the other hand, in the studies where a VAR that also contains financial factors is analysed by Cholesky decomposition, the usual procedure is that factor comes after the macro variables, thus we also used this approach.

The question arises what size of impact of a shock should be quantified, as the factors have no natural measure. In this case the usual solution is to calculate with a shock the size of which corresponds to the variance of the error terms. However, in our estimation the variance of the error terms also changes in time, thus if this procedure is followed, the impulse responses could change due to two reasons: the change in the extent of the shock and in the response given to the shock. However, we wish to separate these two impacts as both reasons may be interesting. Accordingly, at the impulse responses we examine the impact of a one unit shock for both factors at each point of time. Impulse responses of individual variables are calculated as the linear combinations of impulse responses of macro factors using factor loadings for weights.

Figure 3
Volatilities of the financial factors

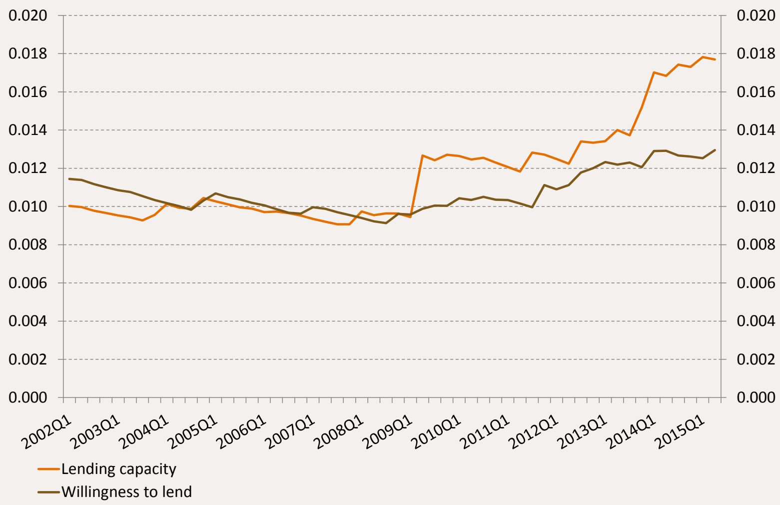


Figure 3 illustrates the variance of the error terms belonging to the banking factors; according to that no major change occurred to this indicator before the crisis. On the other hand, the post-crisis period shows a completely different picture: firstly, the volatility of lending capacity soars, and this growth is not adjusted downward in the next quarters, but continues and almost doubles compared to the pre-crisis level. The volatility of willingness to lend has also gradually increased in the period after 2008, albeit to a smaller extent. Thus, based on these, the increase in the degree or probability of the banking system's shock was not a one-off outlier at the outburst of the crisis, but rather a more persistent level shift. This is mostly attributable to the fact that since 2008 the macroprudential considerations gained increased importance, thus banks have to comply with a number of new capital and liquidity rules. As a result, the banking system is hit by significantly more regulatory shocks than before 2008. This is also reflected well by the fact that it was the volatility of the lending capacity that increased to a larger degree – which has tighter links to the regulatory environment – compared to the willingness to lend. It is also interesting to compare the variances of the macroeconomic[11] and financial factors' error terms: thus there was a large swing in the macro factors in the year of the outbreak of the crisis, after which the variances either did not increase further, or they start to return to lower levels. This difference also substantiates our finding with regard to the impact of the regulatory environment.

4.3 WILLINGNESS TO LEND

First we present the impulse responses given to the first factor, i.e. willingness to lend, and then perform the same for lending capacity (second factor) shocks.[12] It may be generally stated of impulse responses given to willingness to lend shocks that they

[11] The figure is included in the Appendix B (Figure 9).

changed relatively little on the observed sample (Figure 10, Figure 11). There was a minor wave between 2004 and 2008; this was the period of active foreign currency lending, as a result of which the non-performing household portfolio reached almost 20 per cent. In this period banks applied extremely accommodating lending standards, thus it is conceivable that compared to the other periods of the sample willingness had a stronger role then. The impulse responses depart from the average at three additional points of time: in 2008 Q4, 2012 Q3 and 2015 Q2. Each of this relates to a specific event: the outbreak of the crisis, final early repayment at preferential exchange rate and the settlement of unfair interest, the impacts of which are usually reflected in the macro factors with a lag of two quarters.[13] It may be generally stated that in the case of the willingness to lend the shocks are less significant and wear off faster than in the case of the lending capacity shocks.

Moving to the impulse responses of the macroeconomic variables, we get the following picture: as it can be expected of a willingness to lend shock, all credit portfolios increase, with the lending rates remaining practically unchanged, or there is a mild decrease in housing loan interest rates (Figure 14). These results are in accordance with conclusions of Király and Nagy (2008): before the financial crisis, credit supply of Hungarian banks were growing, they granted credit to increasingly risky households and corporates, while interest rates substantially did not change. That is, the banks are willing to lend to larger (riskier) clientele under constant interest rates. The main GDP components and industrial production increase as a result of the credit supply shock; however, this increase is smaller than in the case of the credit portfolio and it ceases relatively soon, thus no significant employment effect can be traced (Figure 15). Higher GDP growth reduces country risk, thus the government bond premium decreases, while the exchange rate slightly depreciates as a result of higher imports. Prices do not react to the shock to a significant degree, thus the base rate is not changed either; however, with the recovery of the housing loan market house prices also increase (Figure 16). As in the case of the macro factors, (naturally) no large difference can be traced in impulse responses in the case of the variables either along the time dimension. It is in consumption, GDP and house prices where it can be slightly felt that the impulse response of 2014 is greater than those followed later; most probably this is attributable to the impact of foreign currency lending.

The significant impulse responses are very similar if the model contains just one financial factor. The correlations between the fourth macro factor and credit amounts, interest rates on housing loans, exchange rate and export are high, therefore, if we use three macro factors for the estimation, the impulse responses of the mentioned variables become smaller. Adding one more macro factor and estimating the model with five factors does not affect significantly the results. (See Figure 20, 21 and 22 in the Appendix.)

4.4 LENDING CAPACITY

In the case of lending capacity shocks we get more persistent impulse responses than in the previous case. As it was stated before, the degree of capacity shocks increased after the crisis and based on the impulse responses it may be also stated that their impact increased as well. The impact on the first and fourth macro factors started to increase already since 2004 and in recent years it stayed at a higher level (Figure 12, Figure 13). On the other hand, the impulse response of the second macro factor shifted more after the crisis. Moreover, these changes cannot be tied to a specific event, but occurred in a trend-like manner during several years.

The impact of the lending capacity shock is rather different from that of the willingness to lend shock. With the improvement in the banking system's lending capacity, i.e. its capital and liquidity position, financial stability strengthens, which also significantly reduces country risk. If the banking system is more stable, the probability of banks' need for capital injection financed by the government is lower, which also reduces sovereign country risk. This is reflected by the large and persistent decrease in government bond premia (Figure 19). In response to this (and to the unchanged exchange rate), monetary policy also eases, followed by a decrease in corporate interest rates (Figure 17), which were tied to the Hungarian base rate. On the other hand, household interest rates do not change significantly (that of consumer credits even slightly increase), which is attributable to the fact that in the period under review the vast majority of outstanding borrowing of households sector was denominated in foreign currency or they were state-subsidised loans, the interest rate of which was not tied to the base rate (nor to any other market reference rate). As a result of declining corporate interest rates companies have access to cheaper funds, which also reduces prices and increases GDP (Figure 18), particularly internal items (consumption, investment). Employment rises

[12] The figures belonging to the impulse responses are included in the Appendix; the confidence intervals were generated on the basis of 10,000 runs.

[13] More details are provided on the latter two in the Appendix.

significantly in parallel with the GDP (Figure 19). Owing to the growth of households' disposable income, rents and house prices also increase. Finally, all this takes place without material growth in outstanding borrowing (Figure 17).

At first glance this latter result appears to be counterintuitive. On the other hand, we should once again refer to a feature of the Hungarian banking system, namely that a major part thereof is owned by foreign parent banks, thus the capital position of Hungarian subsidiaries is not necessarily informative. This result also reflects that willingness to lend is a determinant of developments in outstanding borrowing; the constraints posed by the lending capacity are ineffective, as the parent banks can easily remedy these due to their size. This is well illustrated by the fact that before the crisis many banks were fully stretched in terms of capital; however, during the period of foreign currency lending they continuously expanded their credit portfolio. We have to mention that using Cholesky-decomposition can result that the separation of lending capacity shock and risk premium shock is not perfect. The cause of similarity of the two types of shock could be that the identified lending capacity shock is actually a mixed shock of lending capacity and risk premium. If this is the case, the actual impulse responses could be smaller and less significant.

However, it should be noted that although the lending capacity shock has no significant impact on the credit portfolio, it exerts material and increasing impact on the macro economy, particularly through country risk and the monetary policy reaction. Although only the smaller part of the banking system is owned by residents, the bankruptcy and rescue of the larger Hungarian-owned banks would still represent high burden for the budget. Thus the stability of the banking system plays a major role in the perception of country risk and developments in government bond premiums. Moreover, with financial deepening and the increase in the ratio of the financial intermediary system to the macro economy this impact is stronger and stronger. This is reflected by the impulse responses of government bond premiums, which shows that premiums responded better to the lending capacity shock in the later years compared to 2004. This growth took place before the outbreak of the crisis and it did not continue thereafter. Based on the development of the interbank interest rates it may also be stated that the monetary policy response has changed in the period under review; however, here the shift took place after the crisis. Presumably, after 2008 developments in country risk and financial stability gained more importance for the monetary policy decision-makers than in previous years. The increasing impact of the lending capacity shock appears accordingly in corporate interest rates, GDP components, employment, inflation and also in house prices.

The significant impulse responses are very similar if the model contains just three macro factors, the only exception is the exchange rate, which becomes insignificant. With five factors, the impulse responses of GDP components, house prices and spread on government bonds are higher (See Figure 23, 24 and 25 in the Appendix). Based on the evolution of the impulse responses over time, the same conclusions can be derived independently of the number of factors.

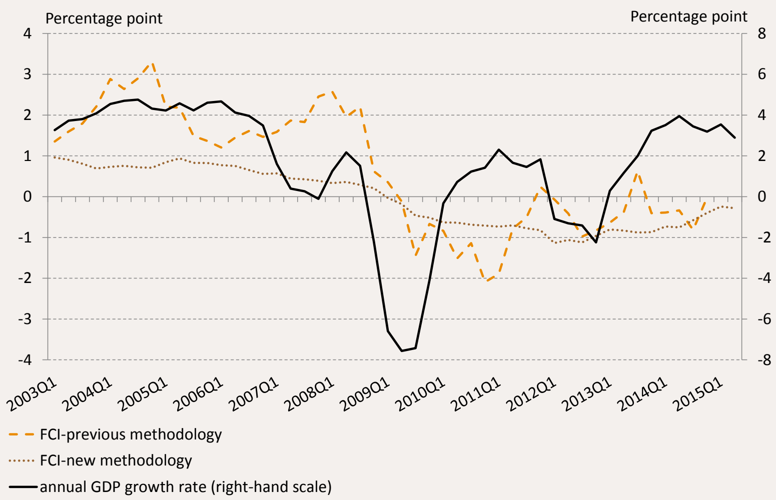
Our results derived from the impulse responses may be compared to a certain degree with the statements of previous surveys. Tamási and Világi (2011) examined the impact of supply shocks on the Hungarian corporate credit market within the framework of a Bayesian SVAR model. They identified two types of credit supply shocks: risk assessment and credit spread shocks. In this paper we narrowed the estimation not only to the corporate credit market, and the identification of the shock was also performed by different tools. On the other hand, the willingness to lend shock is also a credit supply shock, which impacts GDP through the change in outstanding borrowing; moreover, the impulse responses proved to be stable in terms of time. In Tamási and Világi (2011), both supply shocks increase corporate lending and GDP, strengthen the exchange rate and not affect CPI. Based on the impulse responses of a willingness to lend shock, the same conclusions can be derived except for the exchange rate. In the case of the risk assessment shock, credit spreads stay flat, while base rate increases, however, a credit spread shock does not affect the base rate. It means that interest rate on corporate loans does not react to a credit supply shock, which is also in accordance with our conclusions. According to their results, a 1 per cent growth in the outstanding corporate borrowing caused by the credit supply shock increases GDP by 0.1-0.2 per cent. Based on our calculations, a willingness to lend shock that results in a corporate credit portfolio increase higher than 1 percentage point, increases the GDP growth rate by 0.07-0.25 percentage point. Thus we can state that from the results of the two researches we came to similar conclusions.

4.5 FINANCIAL CONDITIONS INDEX

Until now the FCI of the Magyar Nemzeti Bank was calculated based on the SVAR model of Tamási and Világi (2011) (this article includes only the VAR model for corporate credits, and SVAR model for the consumer credits was estimated similarly to that of corporate one for the purpose of the FCI calculation). Thus it belonged to the group of those FCIs that weighted the most important financial time series together based on their impact on the macro economy, primarily on GDP. These times series included the corporate and consumer credit portfolio, as well as corporate and consumer credit interest rate spreads. The weights were calculated as the sum of two impacts: the lagged impact of the financial time series on GDP was determined by the coefficients of the VAR model's GDP equation, while the simultaneous impact was determined by the impulse responses of the identified shocks. The two SVAR models returned a corporate and a household (narrowed to consumer credit) sub-index, and the final FCI was the sum of these two. The index showed the banking system's contribution to the annual GDP growth rate.

The problem with the index thus created was that it considered only consumer loans in the household sector and often showed significant changes from one quarter to the other, while the position and behaviour of the financial intermediary system did not change materially. Presumably this was due to the fact that the index was compiled by the weighting of such variables that were greatly influenced both by credit demand and supply, thus it is a less accurate measure of the supply side. Hence, upon creating the new index we made efforts to set out from a wider information base and compile the database for variables that focus more on the credit supply side.

Figure 4
Financial conditions index



It was evident to use the factor models, especially because almost all of the latest FCIs come from factor analysis, and usually the first factor is regarded as FCI. On the other hand, it is against this usual procedure that the FAVAR model returned the result that the second factor also affects the macro economy; moreover the interpretation of the factors is cumbersome, it is their change rather than their level that carries information, which would be a disadvantage compared to the previous FCI. Hence we combined the advantages of the FCIs that are based on the factor models and the VAR models, and determined the impact of the willingness to lend factor on GDP as the final indicator. We ignored the impact of lending capacity, because based on the impulse responses this factor exerts no significant impact via the credit portfolios, while we expect the FCIs to provide us with a view on credit market developments.[14] The impact on GDP was calculated from the coefficients of the GDP equation of the time-varying FAVAR (Figure 4).[15]

Accordingly, prior to the outbreak of the crisis in 2008, the financial intermediary system's contribution to output growth was always positive, with the upswing in foreign currency lending the contribution to GDP also increased, and then, starting from

[14] In the future this assumption will be regularly reviewed, and if the impulse responses of the lending capacity change, both factors will be considered for the purpose of the FCI calculation.

[15] It is a change compared to the previous methodologies that we did not use the impulse responses; this difference comes from the different shock identifications, as with the Cholesky decomposition the simultaneous impacts are ignored.

2007, the contribution of lending to output became lower and lower. Starting from 2009, the banking sector's contribution to GDP was continuously, and increasingly negative until 2012 H2. Therefore, the Central Bank of Hungary's Funding for Growth Scheme[16] was started in 2013, the target of this program was to break the negative trend in credit supply. In 2013 and 2014 as well, the contraction effect of the banking sector declined gradually, which could sign the success of the Scheme. In 2015 H1 this trend came to a halt and a fall was observed in the index. The banking sector's contribution to the output continues to be moderately negative.

[16] For more information, see Endrész et al. (2015).

5 Conclusions

In this paper, relying on a time-varying parameter FAVAR model, two credit supply factors were calculated on Hungarian data, the first of which was identified as willingness to lend, while the second one was identified as lending capacity. Thereafter, the impact of these two types of credit supply shocks on macroeconomic variables and their change in time was examined. Finally, a new type of financial conditions index was quantified based on our estimates, which measures the impact of the banking system's lending activity on GDP growth.

For the performance of the calculations we used a banking panel database, where we considered the indicators describing banks' capital and liquidity position, as well as their willingness to take risks. Upon compiling the time series we also bore in mind that a major part of the Hungarian banking system is owned by foreign parent banks, thus the parent banks' capital position may be more determinant in terms of credit supply than the indicators of the Hungarian subsidiaries. These assumptions were supported both by the loadings of the factors and the conclusions drawn from the impulse responses.

In our model estimation the loadings of the factors, the VAR coefficients, as well as the variance of the factors and the VAR equation error terms appeared as processes that change in time. Based on the change in the variance of the VAR error terms it may be stated that the expected measure of both the macro and financial shocks increased as a result of the crisis; however, at the former ones this was a one-off sudden increase, which has started to return to its former level since then. On the other hand, the measure of expected shocks still increases at the latter ones, presumably as result of the new regulatory requirements that followed 2008.

The two types of lending shocks affect the macro variables rather differently. The most important of these is that a capacity shock in a banking system, which is mostly owned by non-residents, influences GDP through the decrease in country risk and monetary policy easing, but it generates no substantial growth in outstanding lending, as due to the foreign owner the capacity usually does not represent a constraint. On the other hand, the willingness shock mostly changes lending activity. Moreover, the impact of capacity shocks is usually more persistent, while willingness shocks wear off faster. In addition, similar conclusions may be drawn from the impulse responses received at willingness to lend as from the study of Tamási and Világi (2011) quantifying the impact of the credit supply shocks.

The two financial shocks also differ in terms of their evolution over time: the change in the impact of willingness was driven by foreign currency lending and one-off events (the outbreak of the crisis, final early repayment, conversion into forint), thus the deviations occur usually for short periods of time and they are of small degree between the various quarters. On the other hand, in the case of lending capacity, trend-like processes can be observed: before the crisis the situation of the banking system plays an increasing role in developments in country risk, while after 2008 it appears that monetary policy paid increasing attention to financial stability.

Using all these results we prepared a new FCI, which combines the advantages of the indices calculated from the factor and VAR models: using a broad set of information it returns an easy-to-interpret index. The index shows the impact of willingness to lend on GDP, which was calculated from the factor and the VAR coefficients. Since the lending capacity shock has no significant impact on developments in outstanding lending, we did not take it into consideration for the purpose of FCI calculation; on the other hand, if in the future our time-varying model shows a different result, the impact of this latter factor will be also included in the index.

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Appendix A Macro time series

Table 3
Macroeconomic time series

Variable name	Real/nominal	Transformation	Seasonal adjustment
Final consumption expenditure of households	real	growth rate	yes
Final consumption expenditure of general government	real	growth rate	yes
Gross fixed capital formation (households)	real	growth rate	yes
Gross fixed capital formation (non-financial corporation)	real	growth rate	yes
Gross fixed capital formation (government)	real	growth rate	yes
Gross fixed capital formation	real	growth rate	yes
Exports of goods and services	real	growth rate	yes
Imports of goods and services	real	growth rate	yes
GDP	real	growth rate	yes
Production in industry	real	growth rate	yes
Manufacturing	real	growth rate	yes
Whole-economy employment	real	growth rate	yes
Private sector employment	real	growth rate	yes
Disposable income	nominal	growth rate	yes
Core inflation	nominal	–	yes
Core inflation without indirect tax effects	nominal	–	yes
Inflation	nominal	–	yes
FHB houseprice index	nominal	growth rate	yes
Producer price index	nominal	growth rate	yes
3-month interbank interest rate	nominal	–	no
Interest rate on corporate loans	nominal	–	no
Interest rate on housing loans	nominal	–	no
Interest rate on consumer loans	nominal	–	no
Total loans	nominal	growth rate	exchange rate adjusted
Corporate loans	nominal	growth rate	exchange rate adjusted
Housing loans	nominal	growth rate	exchange rate adjusted
Consumer loans	nominal	growth rate	exchange rate adjusted
Spread on government bonds	nominal	–	no
EUR/HUF exchange rate	nominal	percentage change	no
Sentiment indicators: industry, services, construction, retail, building	nominal	–	yes

Source: MNB, European Commission

Table 4
Regressions with macroeconomic factors and variables

Variable name	R^2
Final consumption expenditure of households	0.68
Final consumption expenditure of general government	0.08
Gross fixed capital formation (households)	0.31
Gross fixed capital formation (non-financial corporation)	0.23
Gross fixed capital formation (government)	0.26
Gross fixed capital formation	0.28
Exports of goods and services	0.75
Imports of goods and services	0.61
GDP	0.80
Production in industry	0.82
Manufacturing	0.84
Whole-economy employment	0.41
Private sector employment	0.40
Disposable income	0.23
Core inflation	0.72
Core inflation without indirect tax effects	0.58
Inflation	0.75
FHB houseprice index	0.35
Producer price index	0.57
3-month interbank interest rate	0.91
Interest rate on corporate loans	0.93
Interest rate on housing loans	0.75
Interest rate on consumer loans	0.83
Total loans	0.92
Corporate loans	0.76
Housing loans	0.80
Consumer loans	0.95
Spread on government bonds	0.75
EUR/HUF exchange rate	0.57
Sentiment indicator: industry	0.57
Sentiment indicator: services	0.95
Sentiment indicator: construction	0.86
Sentiment indicator: retail	0.79
Sentiment indicator: building	0.87

Source: MNB calculation, European Commission

Appendix B Factors, its confidence intervals, robustness and volatilities

Figure 5
Financial factors and its confidence intervals

(Note: the solid lines show factors, the dotted lines show the 5 and 95 per cent confidence intervals.)

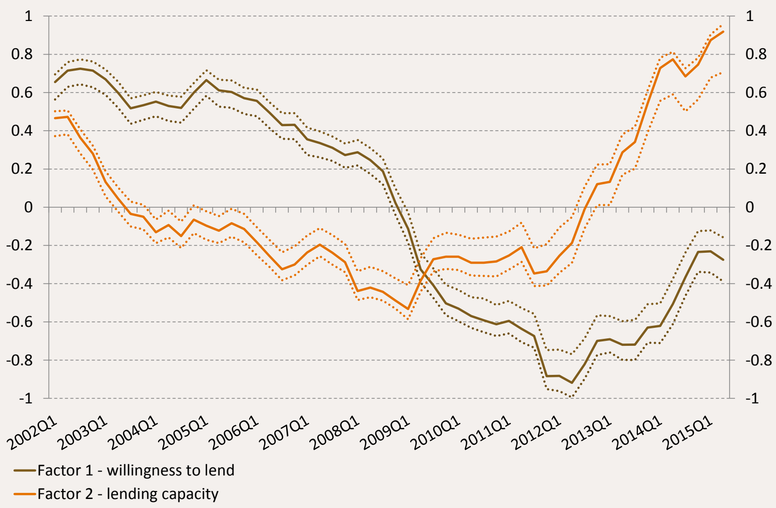


Figure 6
First, second macro factors and its confidence intervals
(Note: the solid lines show factors, the dotted lines show the 5 and 95 per cent confidence intervals.)

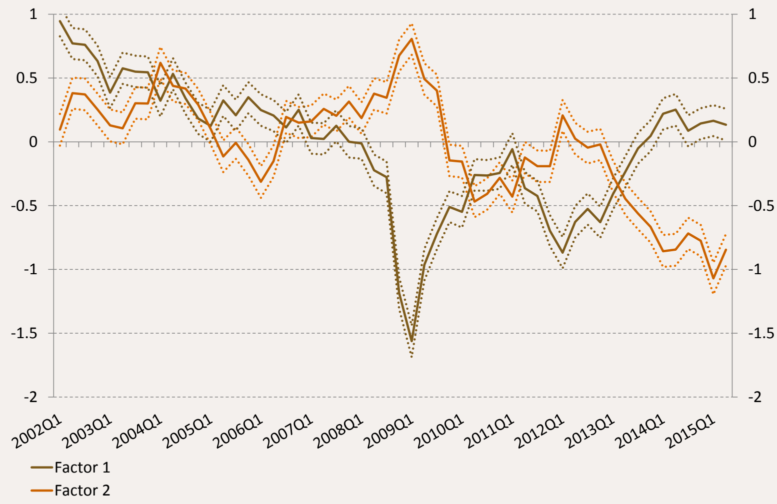


Figure 7
Third, fourth macro factors and its confidence intervals
(Note: the solid lines show factors, the dotted lines show the 5 and 95 per cent confidence intervals.)

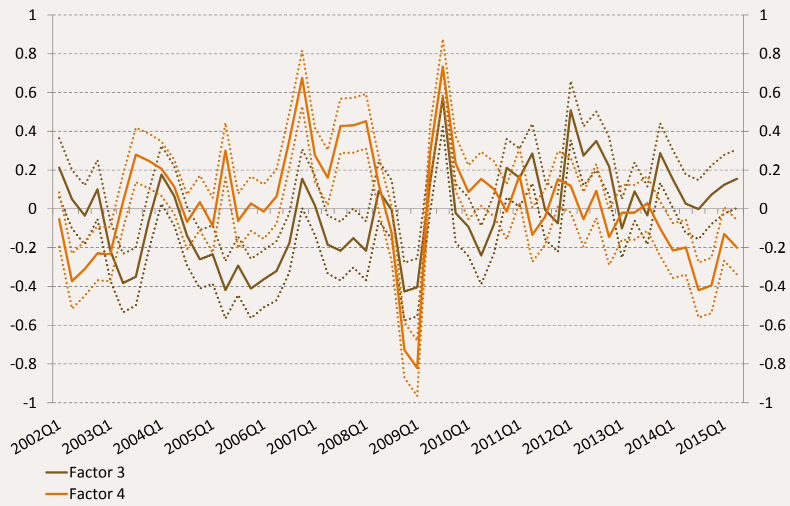


Figure 8
Financial factors' robustness

(Note: the solid lines show the financial factors, when the model contains three macro factors, the dashed lines: with four macro factors, the dotted lines: with five macro factors.)

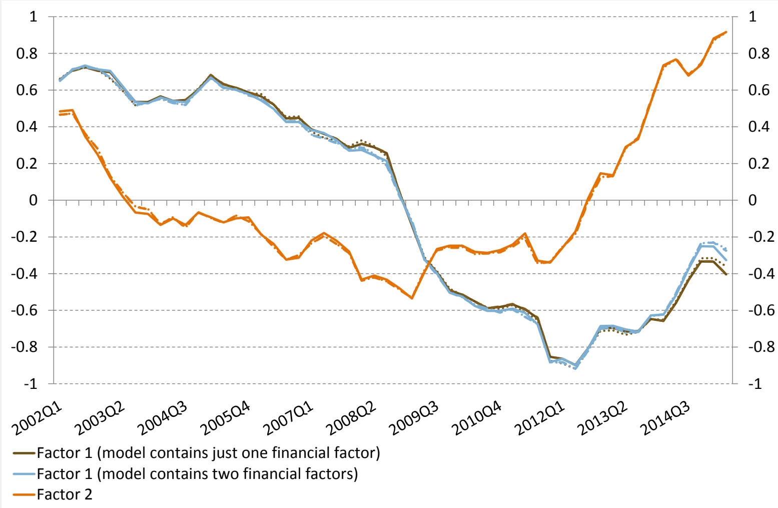
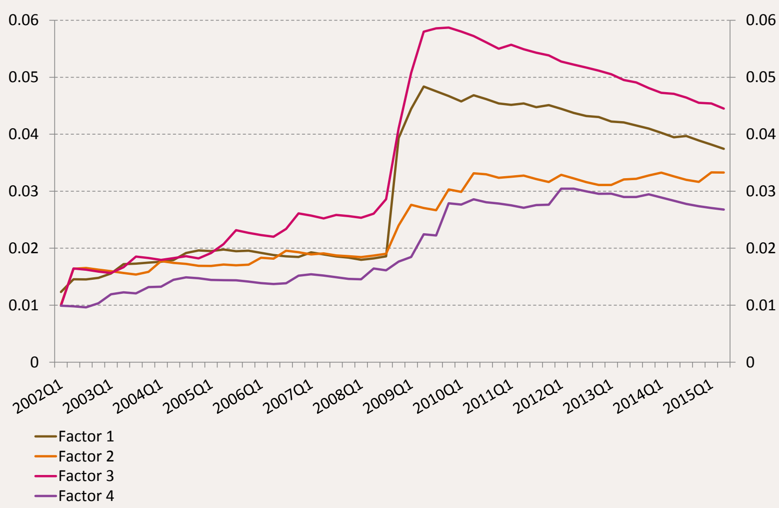


Figure 9
Volatilities of the macro factors



Appendix C Foreign currency lending to households and related regulatory measures in Hungary

Before the outbreak of the crisis in 2008, there was a significant lending boom in the Hungarian household credit market from 2004. Due to the high forint interest rates in this period, the clients drew down a large part of the loans in foreign currency, primarily under CHF and EUR-denominated schemes, while they had no foreign currency income at all. Moreover, these loans were variable-rate loans, i.e. banks could unilaterally change the interest rate payable on the loan at any time. In the beginning of the period, most of the loans placed under this scheme were housing loans; however, later on the volume of foreign currency-denominated home equity loans also soared. Particularly from 2007 banks' lending standards became more lax and even those low-income households of more uncertain labour market situation could have access to loans that formerly faced liquidity constraints. The result was a portfolio that had much higher probability of default than before; moreover both the exchange rate and the interest rate risk were borne by households.

By 2008 Q3 foreign currency loans accounted for two thirds of household loans. As result of the crisis, the forint depreciated several times to a great extent, unemployment increased, house prices plunged, which led to a fast increase in the household NPL portfolio. In order to cover their credit losses banks increased interest rates on the performing loan portfolio, thereby imposing additional burdens on borrowers. As a result, households decreased their consumption expenditures, which further exacerbated the recession caused by the crisis. As the debt overhang impacted several hundred-thousand households, the government adopted a number of measures to address the problem of foreign currency loans. Of these we discuss those that can be traced in the change of the impulse responses of the willingness to lend shock.

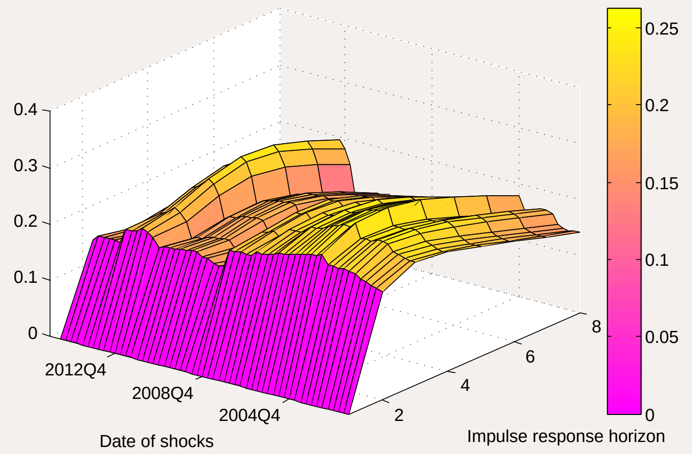
Final early repayment at preferential exchange rate: In order to reduce vulnerability arising from high foreign currency exposure, the government permitted foreign currency mortgage loan-holder clients to early repay their loans at a preferential exchange rate. In that period the CHF/HUF exchange rate was around 245, and instead of that the clients had the opportunity to repay their loans at an exchange rate of 180. The exchange rate loss was borne by the banks. The scheme applied to 2011 Q4 and 2012 Q1; loans in the amount of HUF 1,350 billion were repaid then, accounting for 24 per cent of the outstanding portfolio.

Settlement of unfair interest rate increases: In June 2014 the decision of the Curia declared variable interest rate lending facilities to be unfair; accordingly, in September the Parliament passed a law on banks' obligation to repay their income originating from the unilateral interest rate increase to the clients. The manner of this:„the overpayments of the clients resulting from the unfair conditions must be treated retrospectively as principal prepayments on all loans – with the exception of overdrafts, credit card debts and the state-subsidised loans – that were granted after 1 May 2004 and did not expire before 26 July 2009. The amount of clients' claims, that is the exchange rate spread and cost of the settlement of the unfair contract modifications, is derived as the difference between the original and the thus recalculated principal debt outstanding and the difference between the original and the recalculated overdue amounts. In the case of the still outstanding contracts the thus calculated amount must be settled against the overdue amounts, and then the principal debt"' MNB (2014). The settlements mainly took place in the last quarter of 2014, generating a loss of HUF 600 billion to the banking system.

Conversion of loans into forint: After the previous measure, this one entered into force in January 2015, and its purpose was to eliminate the exchange rate risk of the household mortgage portfolio. Foreign currency loans in the amount of about HUF 3,500 billion were converted into forint loans, where the maximum interest rate on the loans was regulated by law. (See further details on the programme: MNB (2014)).

Appendix D Impulse responses

Figure 10
Impulse responses of macro factors to a willingness to lend shock



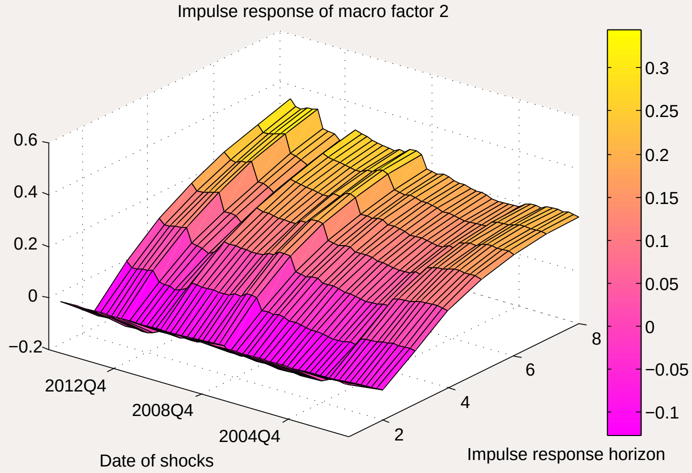


Figure 11
Impulse responses of macro factors to a willingness to lend shock

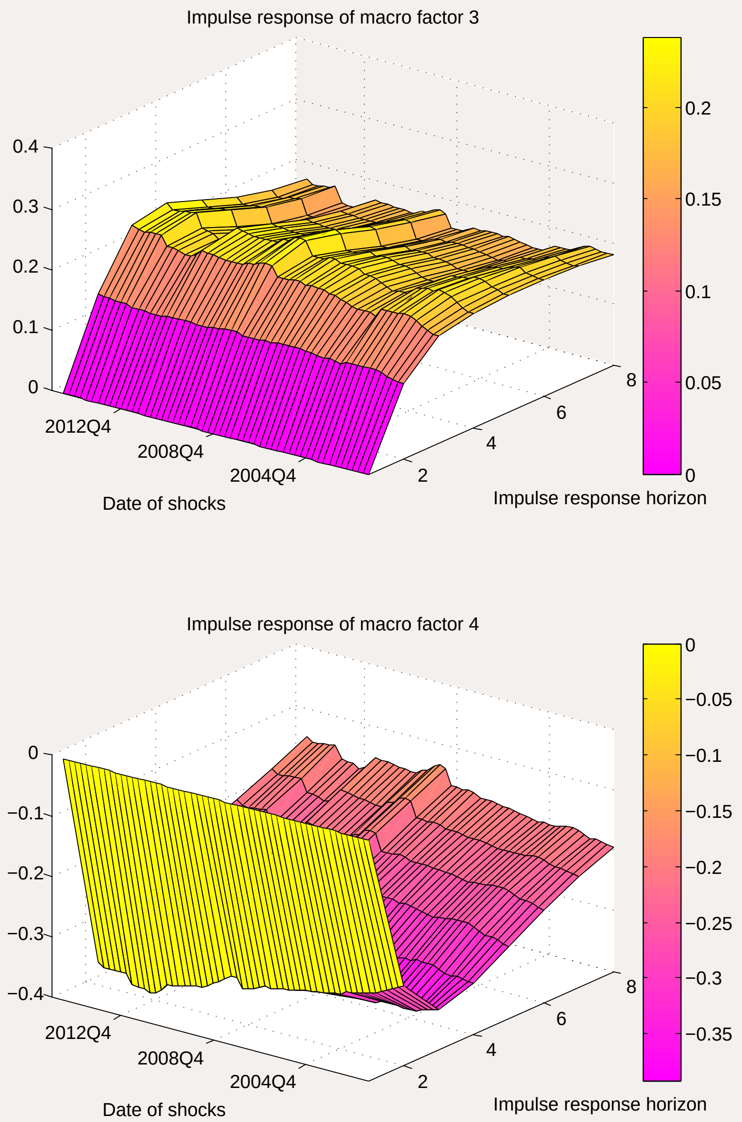
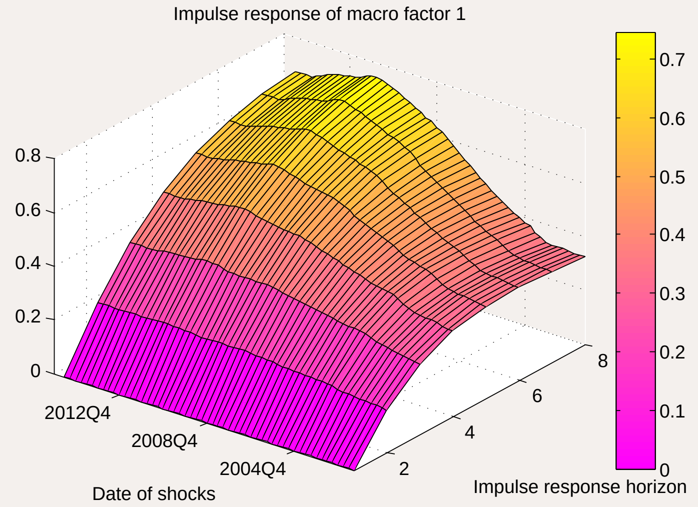


Figure 12
Impulse responses of macro factors to a lending capacity shock



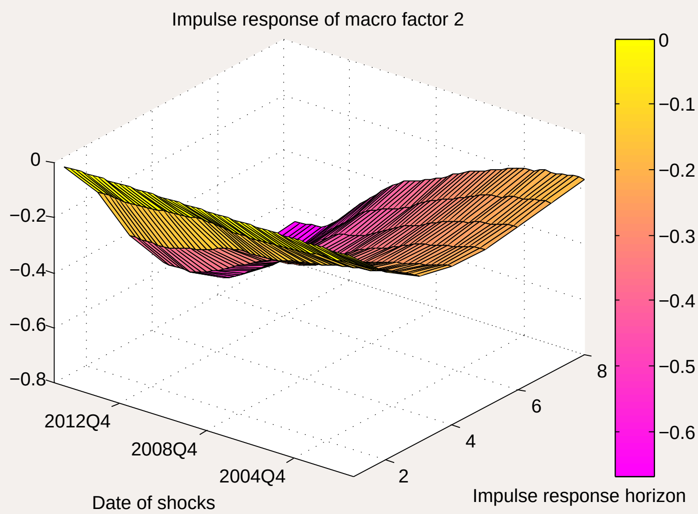
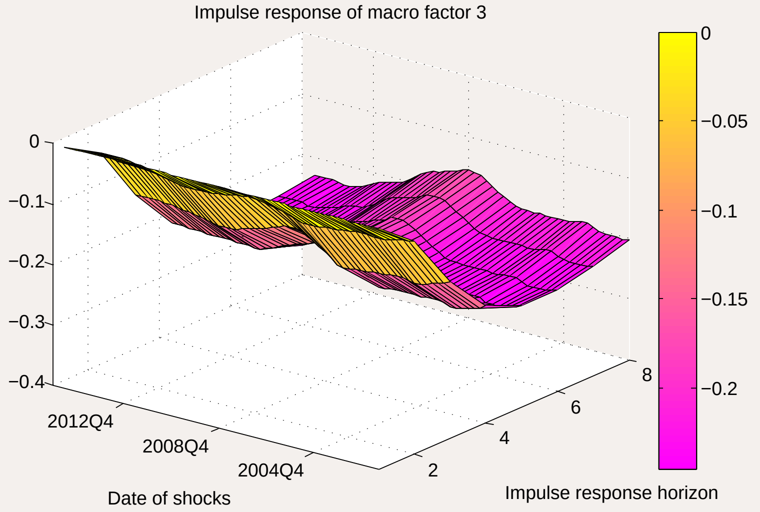


Figure 13
Impulse responses of macro factors to a lending capacity shock



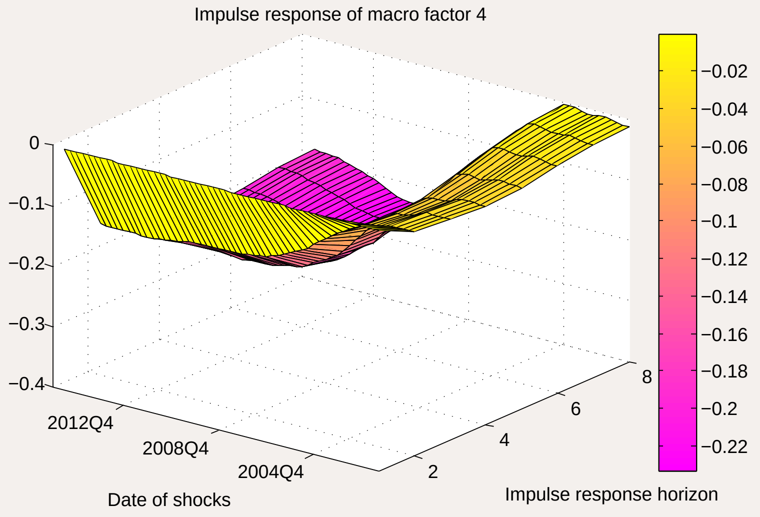


Figure 14
Impulse responses of credit amount and interest rates to a willingness to lend shock
(Note: solid lines show the impulse responses (blue=2004q4, red=2008q4, green=2013q4), dashed lines are the 16% and 84% confidence intervals)

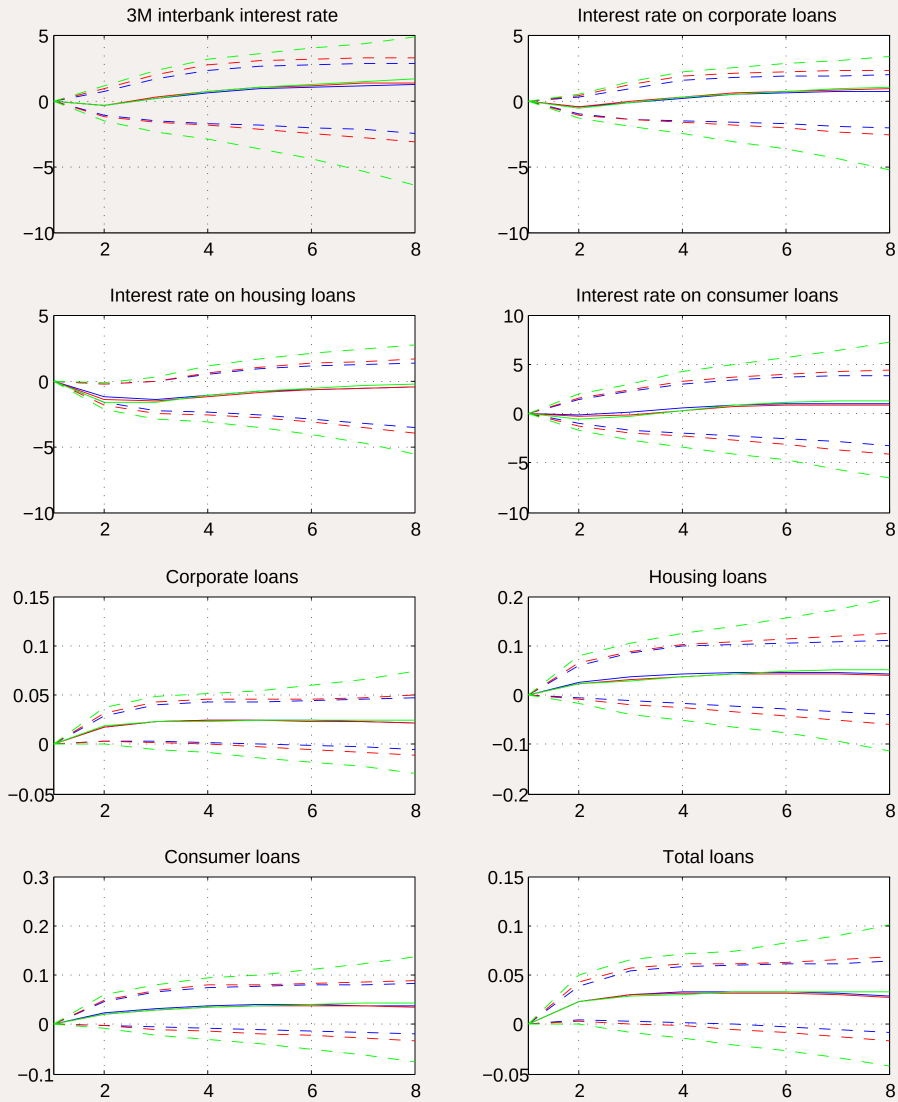


Figure 15
Impulse responses of GDP components and production in industry to a willingness to lend shock
(Note: solid lines show the impulse responses (blue=2004q4, red=2008q4, green=2013q4), dashed lines are the 16% and 84% confidence intervals)

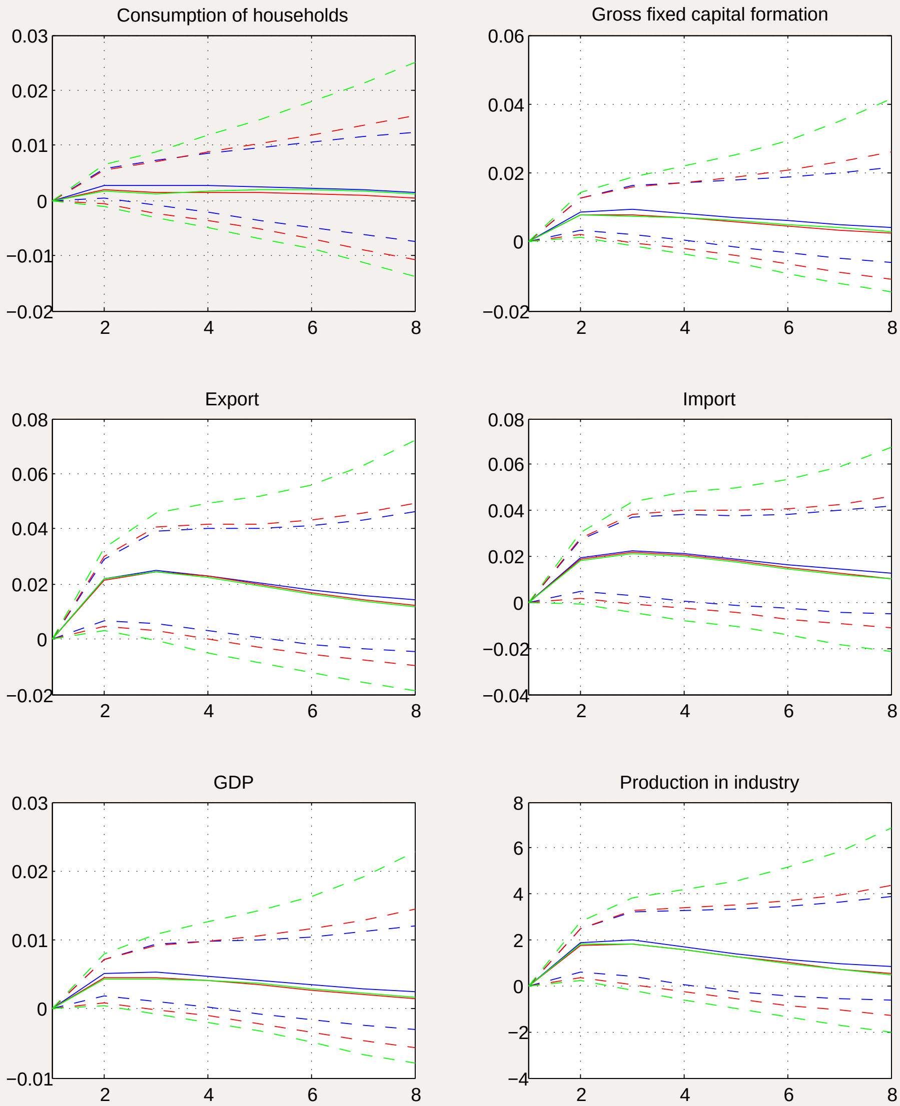


Figure 16
Impulse responses of employment, government bond spreads and prices to a willingness to lend shock
(Note: solid lines show the impulse responses (blue=2004q4, red=2008q4, green=2013q4), dashed lines are the 16% and 84% confidence intervals)

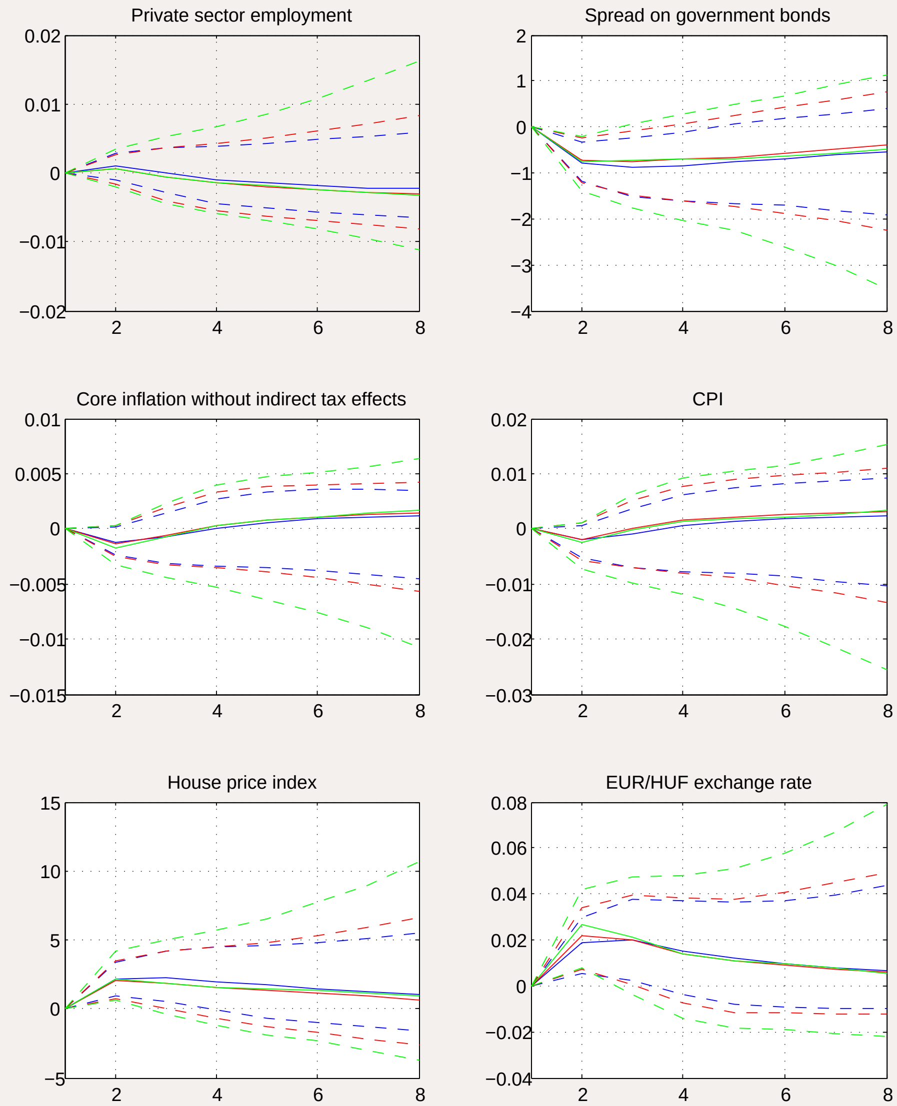


Figure 17

Impulse responses of credit amount and interest rates to a lending capacity shock

(Note: solid lines show the impulse responses (blue=2004q4, red=2008q4, green=2013q4), dashed lines are the 16% and 84% confidence intervals)

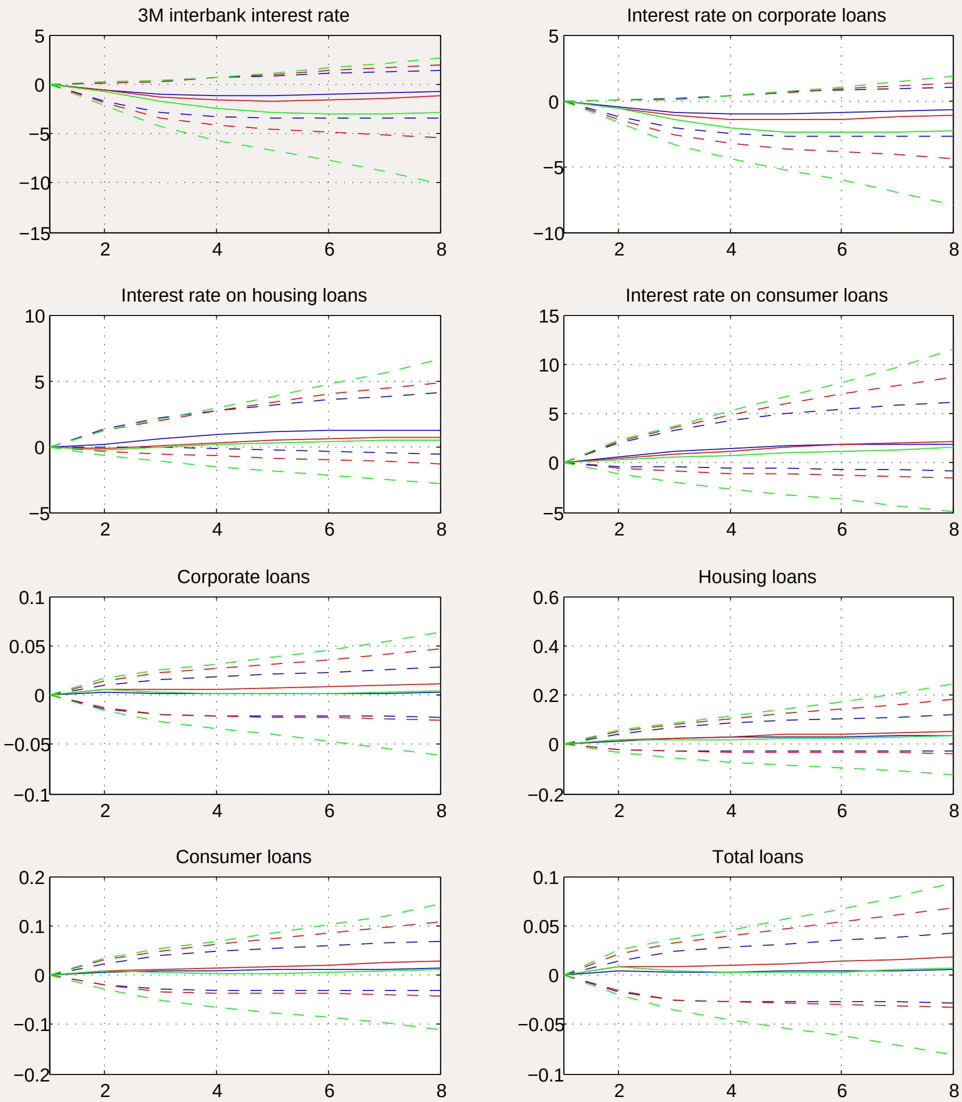


Figure 18

Impulse responses of GDP components and production in industry to a lending capacity shock

(Note: solid lines show the impulse responses (blue=2004q4, red=2008q4, green=2013q4), dashed lines are the 16% and 84% confidence intervals)

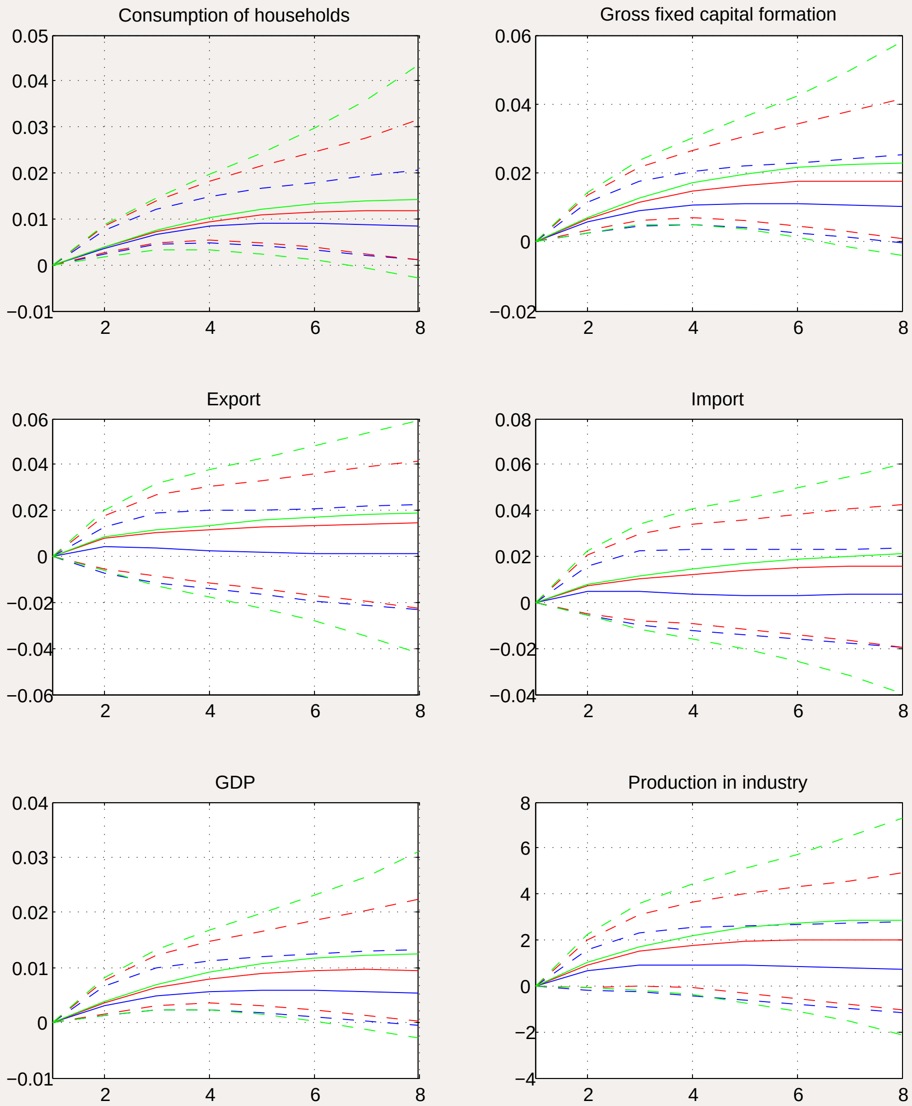


Figure 19

Impulse responses of employment, government bond spreads and prices to a lending capacity shock

(Note: solid lines show the impulse responses (blue=2004q4, red=2008q4, green=2013q4), dashed lines are the 16% and 84% confidence intervals)

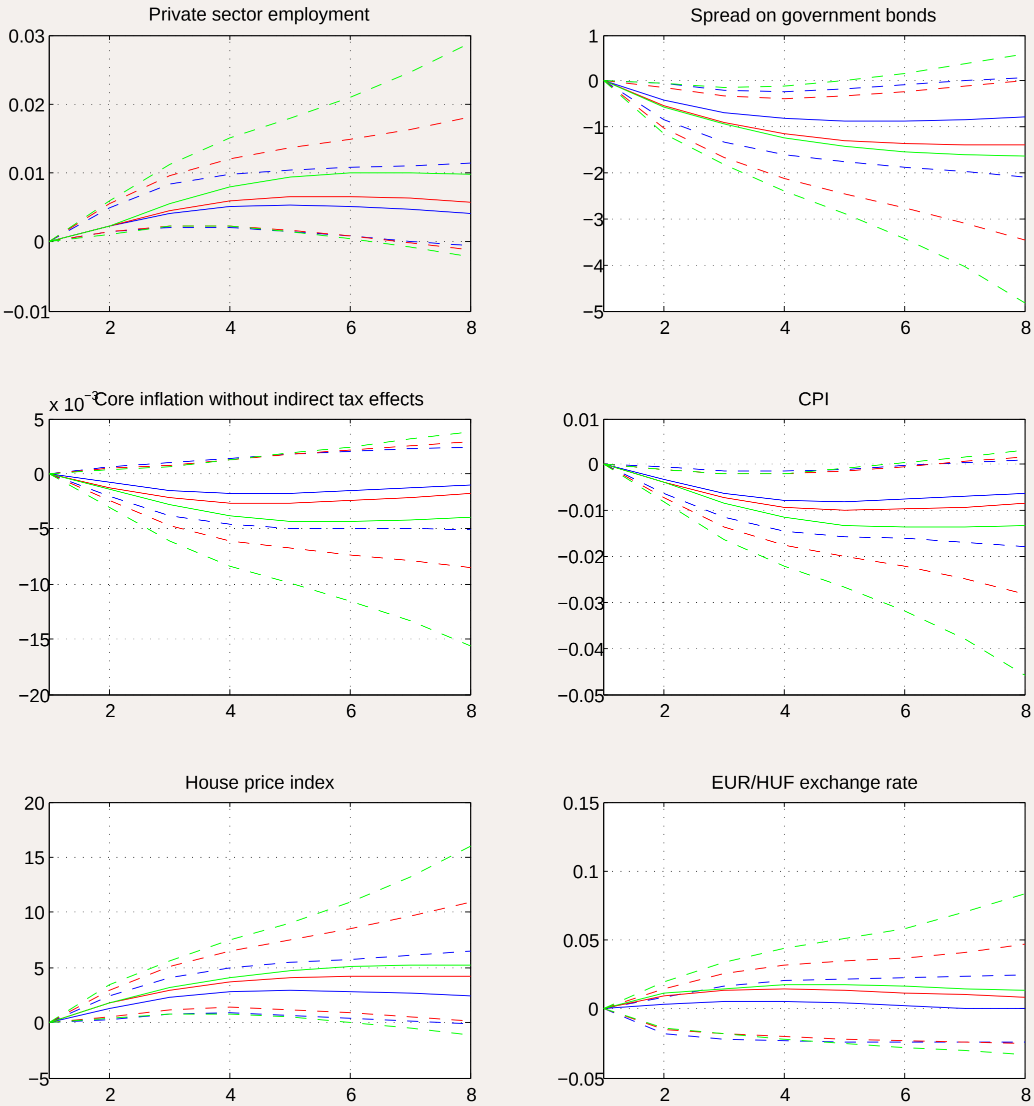


Figure 20
Impulse response of credit amount and interest rates to a willingness to lend shock (robustness check) in 2013Q4

(Note: solid lines show the impulse responses of the model estimated with two financial factors, dashed lines show the impulse responses of the model estimated with one financial factor (blue=with three macro factors, red=with four macro factors, green=with five macro factors))

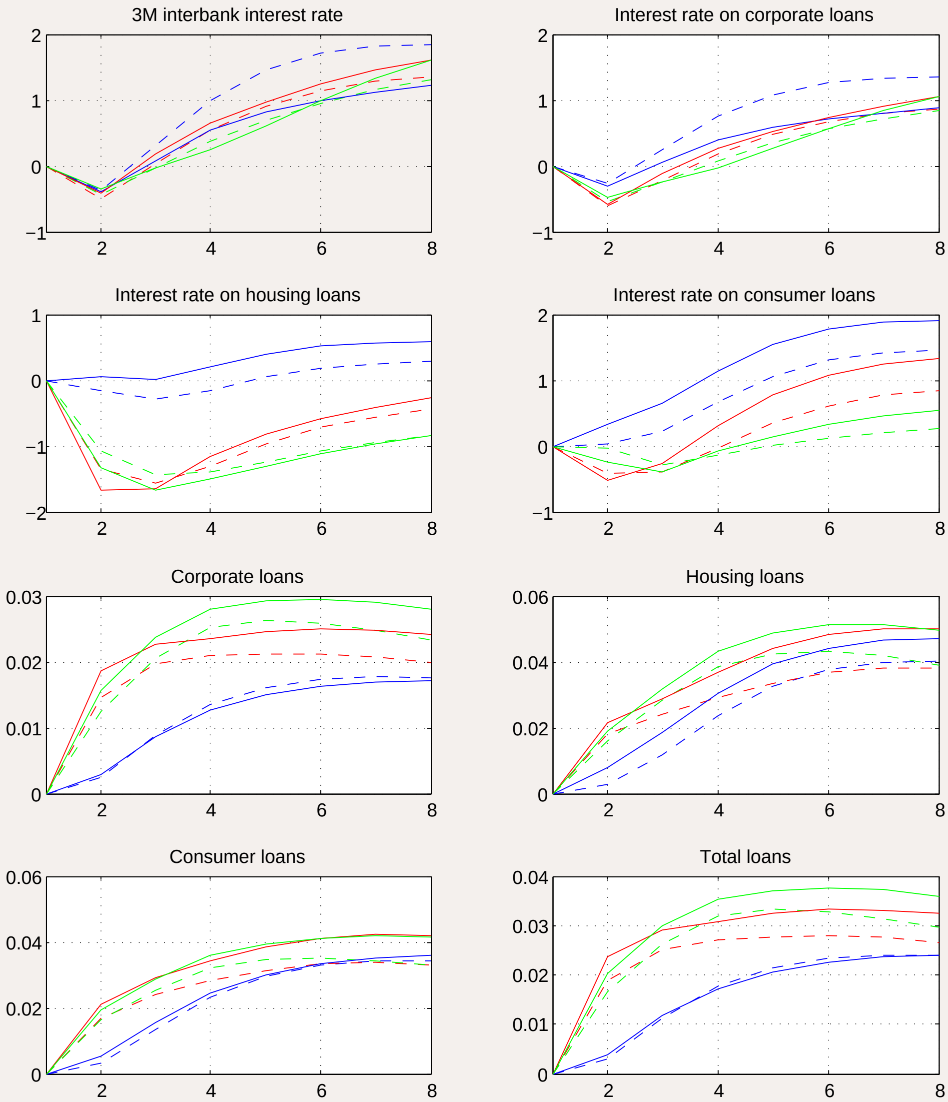


Figure 21
Impulse response of GDP components and production in industry to a willingness to lend shock (robustness check) in 2013Q4

(Note: solid lines show the impulse responses of the model estimated with two financial factors, dashed lines show the impulse responses of the model estimated with one financial factor (blue=with three macro factors, red=with four macro factors, green=with five macro factors))

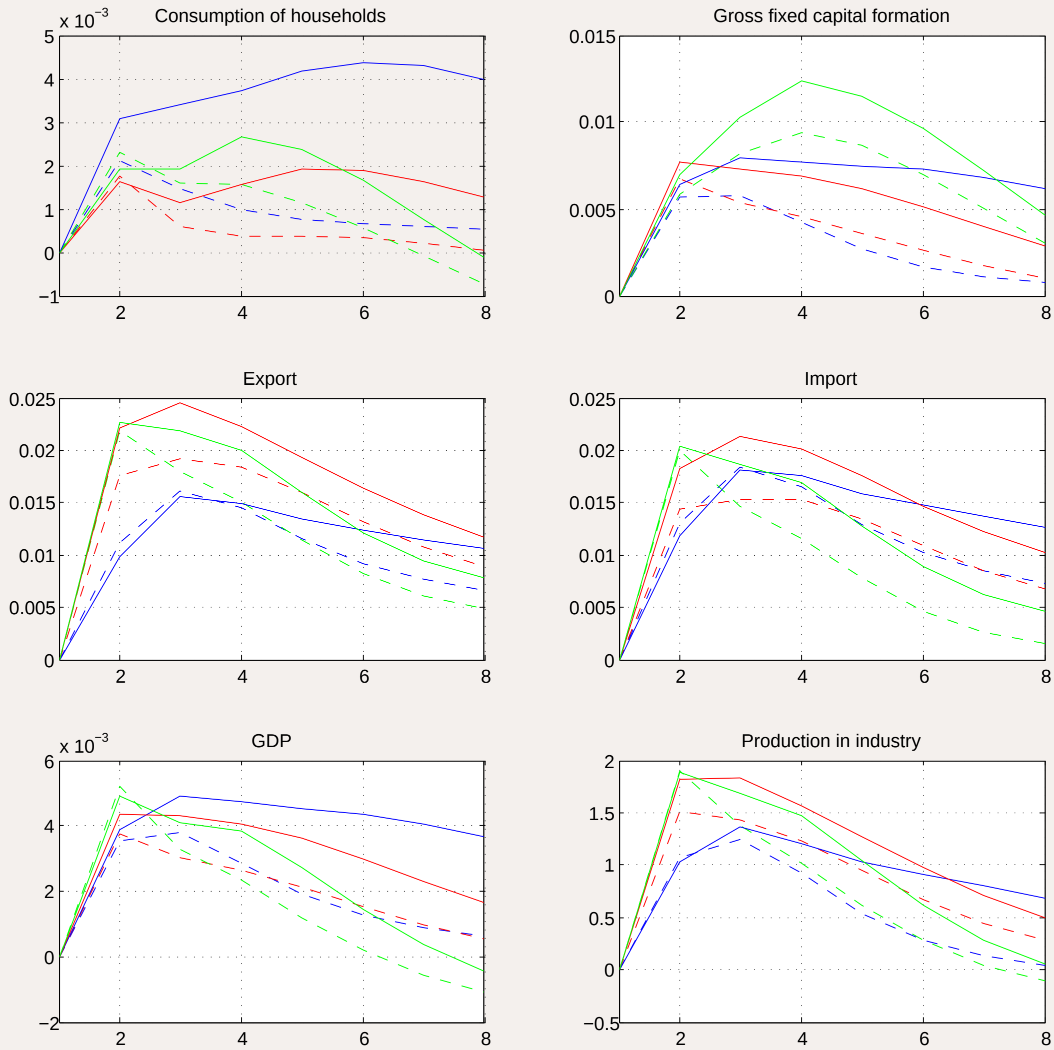


Figure 22
Impulse response of employment, government bond spreads and prices to a willingness to lend shock (robustness check) in 2013Q4

(Note: solid lines show the impulse responses of the model estimated with two financial factors, dashed lines show the impulse responses of the model estimated with one financial factor (blue=with three macro factors, red=with four macro factors, green=with five macro factors))

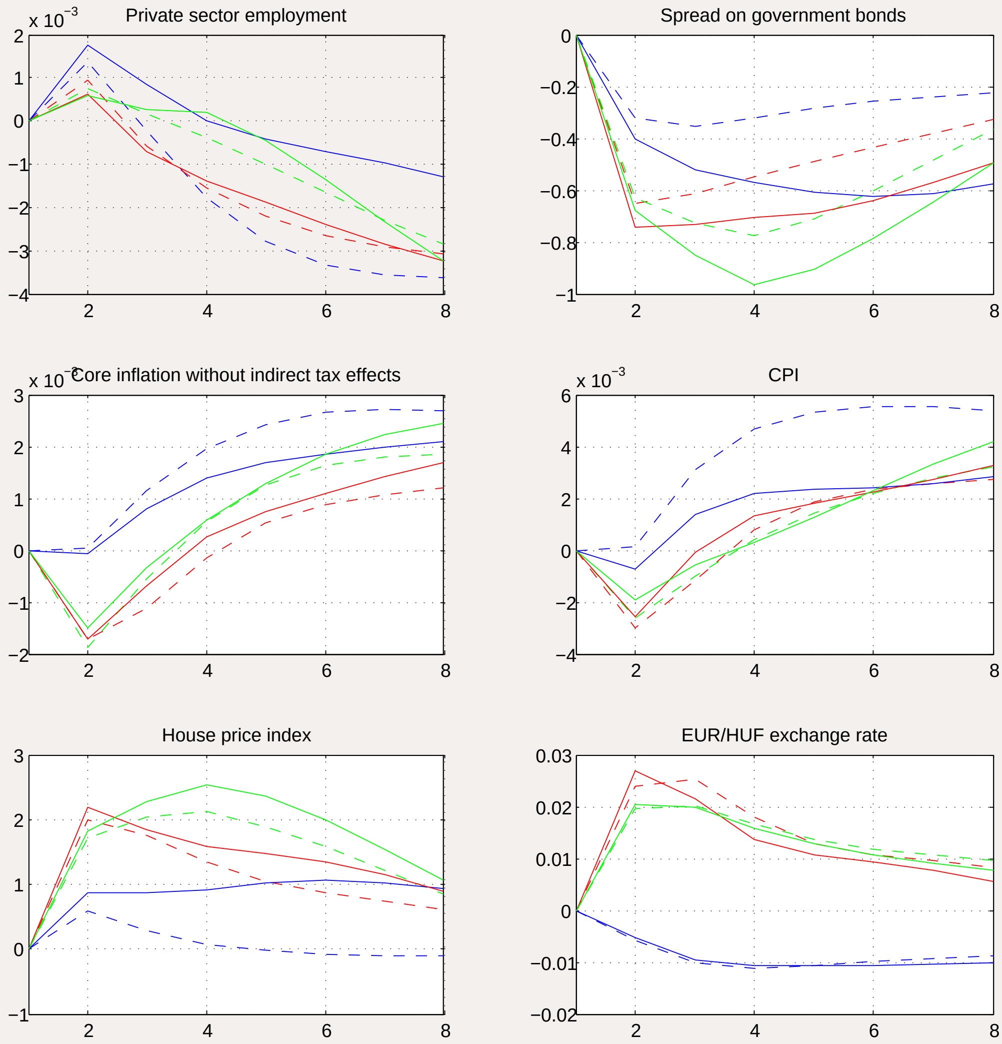


Figure 23

Impulse response of credit amount and interest rates to a lending capacity shock (robustness check) in 2013Q4

(Note: solid lines show the impulse responses of the model estimated with two financial factors and with three macro factors (blue) or with four macro factors (red) or with five macro factors (green))

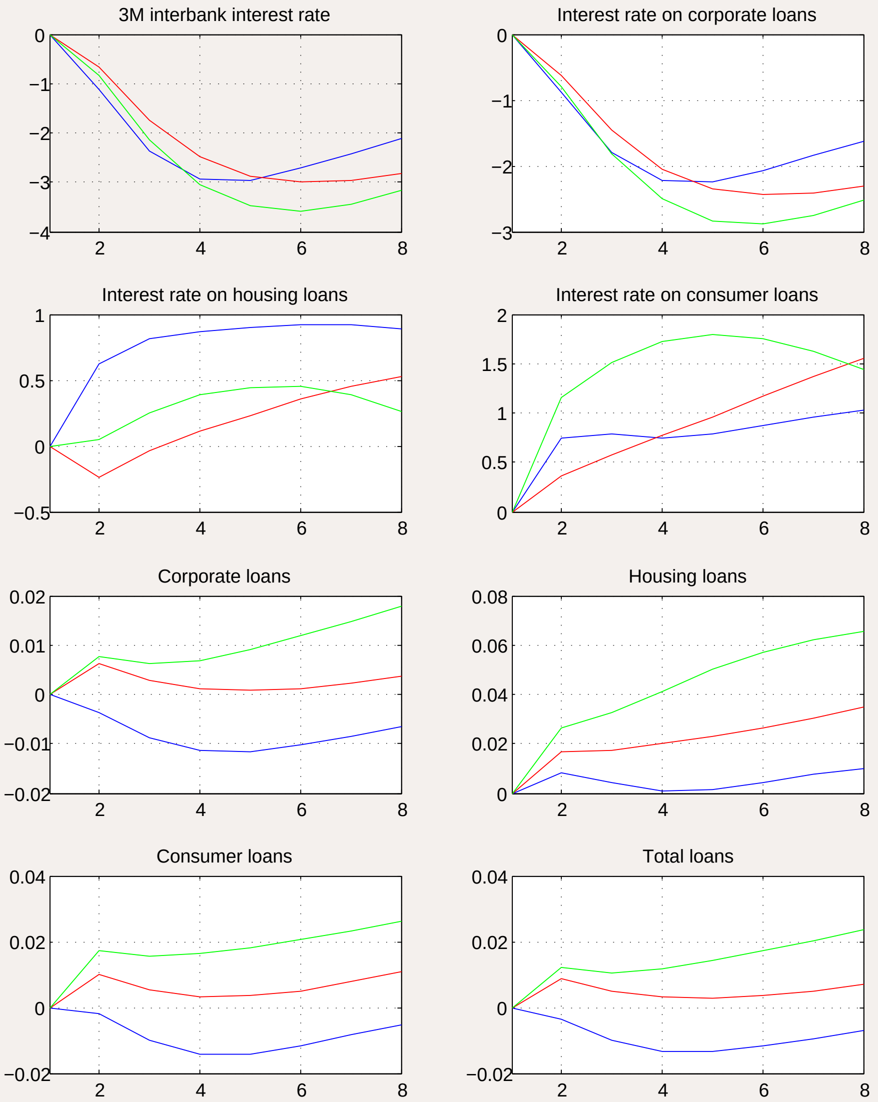


Figure 24
Impulse response of GDP components and production in industry to a lending capacity shock (robustness check) in 2013Q4

(Note: solid lines show the impulse responses of the model estimated with two financial factors and with three macro factors (blue) or with four macro factors (red) or with five macro factors (green))

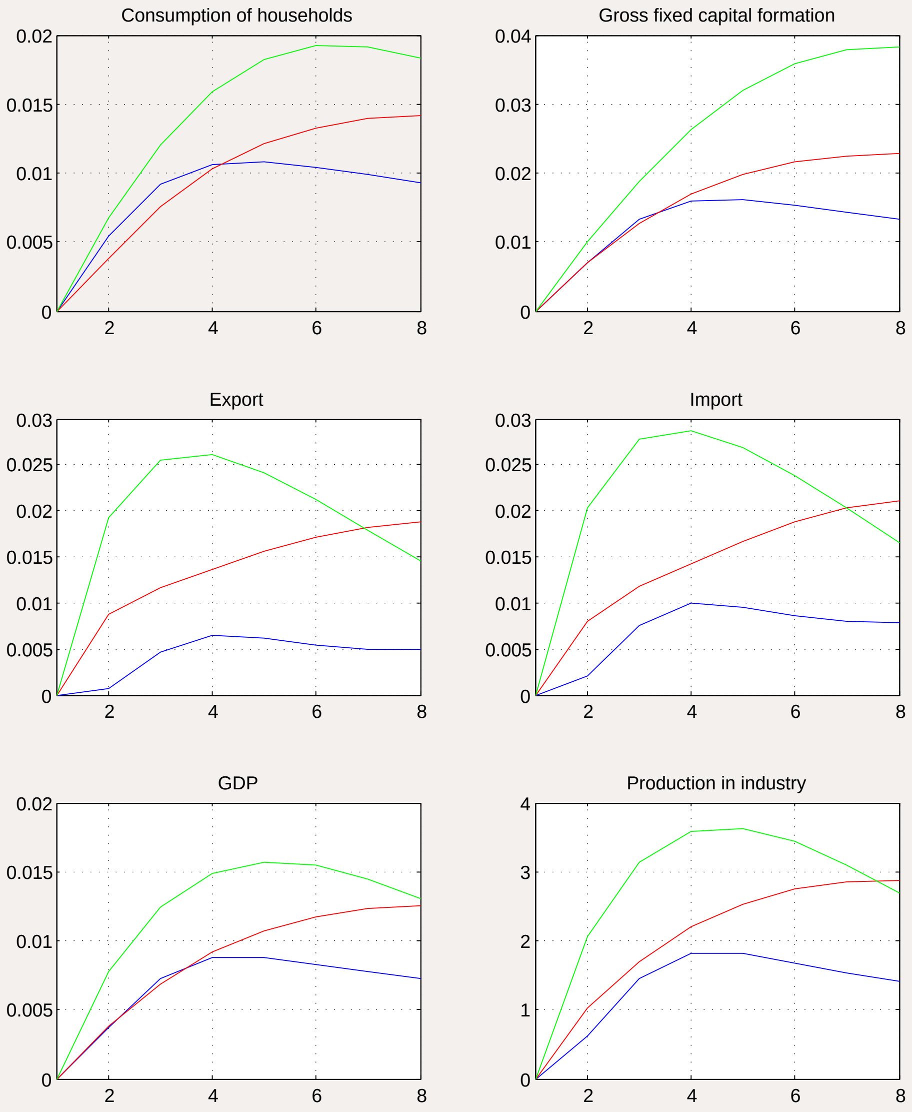
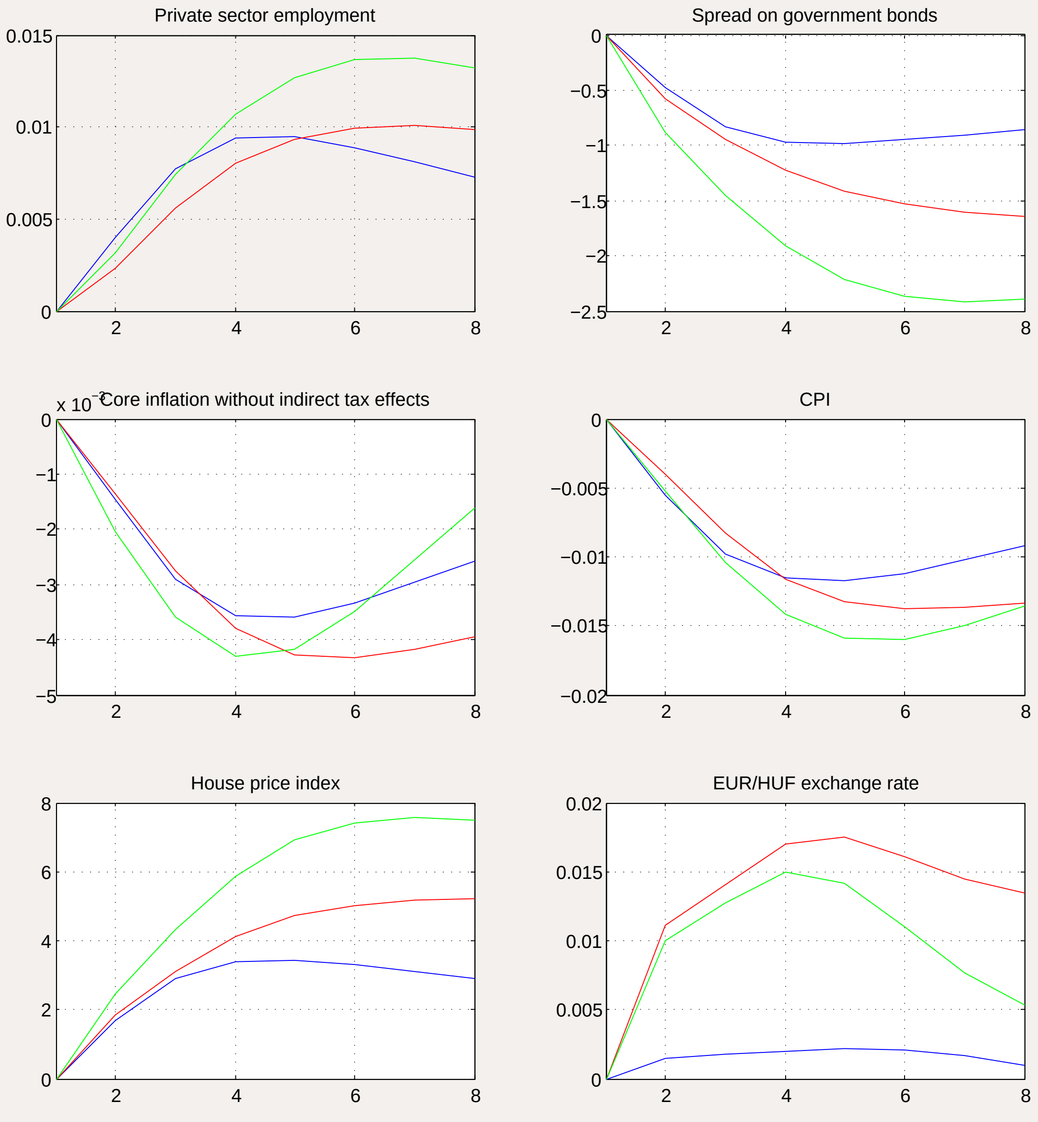


Figure 25

Impulse response of employment, government bond spreads and prices to a lending capacity (robustness check) in 2013Q4

(Note: solid lines show the impulse responses of the model estimated with two financial factors and with three macro factors (blue) or with four macro factors (red) or with five macro factors (green))



MNB Working Papers 1

The impact of credit supply shocks and a new FCI based on a FAVAR approach

Budapest, March 2016