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Macroeconomic Fluctuations and Private Debt in the Euro Area: A FAVAR Approach

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Abstract

I estimate a Bayesian FAVAR model for the Euro area to investigate the impact of supply and demand shocks to private sector debt on the currency block's macroeconomic dynamics. The approach has the advantage to study the shocks' repercussions on a wide range of variables. I identify the shocks via sign restrictions on private sector debt and on an interest rate spread. I find that while positive supply debt shocks have positive short-run effects on GDP, positive demand shocks do the opposite. My findings imply that correctly uncovering whether debt shocks are supply or demand driven is crucial for optimal macroprudential policy responses.

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Keywords: Business Cycle, Private Debt, Credit, Financial Stability, Euro Area

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1 Introduction

The recent Great Financial Crisis and the subsequent Euro crisis have highlighted the importance of debt dynamics for macroeconomic fluctuations and hence underlined the linkages between the financial sphere and the real economy. As the US economy saw a stark increase in private debt prior to Lehman's collapse, research has shown its prominent role in driving the economic cycle, e.g. Mian and Sufi (2014). As banks fueled additional spending via credit creation, growth was strong prior to 2008 (Turner, 2016). This led to a historical bust due to household over-indebtedness. Debt mattered for macroeconomic dynamics.

In this regard, this paper takes on the case of the Euro zone. In line with Helbling et al. (2011) I ask 'Do credit shocks matter?'. More specifically, this paper sheds light on the extent to which the European macroeconomy is driven by private debt and investigates how the Euro area economy reacts to supply and demand shocks in private sector debt, following Mian and Sufi (2018). I employ a Bayesian FAVAR framework in a similar fashion to Amir-Ahmadi and Uhlig (2012) to study this question.

This advances the existing literature in at least two ways. First, a FAVAR model approach has not been used within this branch of literature and has the advantage to study the impact of different kinds of debt shocks on a wide range of macroeconomic variables. Second, Mian and Sufi (2010) and other studies focus on the US economy or individual countries as in Koo (2009) for Japan or certain events, such as the railroad crises in the 19th century, as in Vague (2019). This paper is an attempt to provide a framework for an entire currency block, the Euro area.

Even more important, in a recent study Jordà et al. (2020) investigate the macroeconomic effects of corporate debt overhang and find that booms in business credit do not have a long-term impact on the macroeconomy. Yet they do not distinguish between credit supply and demand effects and my results suggest that this matters for the nature of short-run macroeconomic dynamics. In this regard I challenge current research by accounting for the role of company debt rather than solely private household debt as well as by introducing supply and demand shocks. Studying the macroeconomic effects of private sector debt in its aggregate in the context of the European currency block is indeed novel.

My results have implications for the wide field of financial stability and monetary policy reform. Private debt plays a key role for financial stability, since banking crises tend to be preceded by pronounced increases in private sector debt (Dembiermont et al., 2013). This establishes a case for macroprudential policy. The results of this paper allow me to discuss the implications of private debt for financial stability, adding to IMF (2017).

The main output in form of impulse response functions is presented in the paper and further details with respect to the data set and the model's robustness checks are attached in the appendix. The remainder of the paper is organized as follows: Section 2 provides a review of the relevant literature and some background. Section 3 describes the data and methodology employed. Section 4 discusses the results of the empirical analysis. Section 5 presents a robustness check for the initial empirical setup via re-specifications of the baseline model. Section 6 considers the implications of the paper's results with respect to macroprudential policy. Finally, section 7 provides concluding remarks.

2 Literature review

This paper builds on a stream of literature which has advocated the prominent role of private debt in the macroeconomy (Mian et al., 2017; Schularick and Taylor, 2012; Koo, 2009; King, 2017; Turner, 2016; Mian and Sufi, 2014). From the point of view of economic history, Vague (2019) shows the devastating repercussions of private debt cycles for six major economic crises in history. Likewise, Mian and Sufi (2014) demonstrate how the Great Depression, the Great Recession and Europe's economic turmoil of the past decade were caused by a surge in household debt in the boom period which was followed by a remarkable decline in household spending. Similarly, the IMF (2012) shows that run-ups in household debt before housing crises and recessions had the tendency to make them more pronounced and prolonged for advanced economies over the past three decades. In the same regard, Mian and Sufi (2010) find that the household leverage in 2006 acts as a significant predictor of the severity of the 2007-09 recession across the US. In addition, they show how household spending fell already before September 2008. Mian and Sufi (2013) investigate the consumption consequences of the Great Recession's housing slump in the US, finding a sizeable elasticity of consumption with respect to housing net worth. Hence households decreased their consumption substantially after the crisis, adding to the negative economic spiral. The existence of predictable credit cycles that sow the seeds of fluctuations in real economic activity is a robust finding in the literature; compare Mian and Sufi (2018). Using a sample of European households, the IMF (2017) finds a large drop in consumption in the wake of household debt expansions. Those who take on the most debt during the upswing phase of the credit cycle reduce spending the most during the subsequent downturn. See Andersen et al. (2016) for the case of Denmark and Bunn and Rostom (2015) for the United Kingdom. Irving Fisher (1933) first pointed towards a channel of high household indebtedness resulting in a fall in demand via his debt-deflation hypothesis: an economic downturn would increase the real burden of debt and this further suppresses economic activity through reduced aggregate demand. Hence the real economic impact of debt on macroeconomic fluctuations. For this also compare Cecchetti et al. (2011) on the real effects of debt for growth, whose analysis focuses on the debt levels of governments, coorporates and households in a sample of 18 OECD countries from 1980 to 2010.

Employing a sample of 30 countries over the past 40 years and estimating a vector autogression in the level of household debt to lagged GDP, non-financial cooperation debt to lagged GDP, and log real GDP, Mian et al. (2017) find that an increase in the household debt-to-GDP ratio in a country results in a three-year increase in the household debt-to-

GDP ratio with a subsequently sharp decline over the next seven years. They show that increases in household debt are followed by predictable declines in household debt after the shock. The business cycle is found to be closely interrelated to the household debt cycle. They demonstrate that a shock to household debt initiates a boom-bust cycle in the real economy that is comparable to the credit cycle. It is this finding within the literature, my papers wants to build on by constructing a Euro area level framework which allows me to study the effects of a private sector debt shock on the European economy.

Schularick and Taylor (2012) make use of a historical data set for 14 countries over the years 1870-2008 to study the behavior of money, macroeconomic indicators and credit. They find that credit growth is a powerful predictor of financial crises and report the secular upward trend of the credit-to-GDP ratio as a global phenomenon since the 1950s. This comes with clear implications for the overall macroeconomic stability due to an economy's extraordinary exposure to financial shocks compared to the pre-WWII period. Their empirical work is in line with theoretical findings by Kumhof et al. (2015), who demonstrate how very high debt levels of households, such as those observed just before the Great Depression and the Great Recession, can lead to a higher probability of a crisis happening. Even though the research by Schularick and Taylor (2012) goes into a similar direction, but with a stronger historical footing, my paper has the noteworthy advantage of capturing the full impact of private debt, an aspect that is discussed below.

The monetary perspective underlying this analysis draws upon recent publications by central banks and major international financial institutions on the functioning of the monetary system, specifically the ability of banks to create money rather than being solely intermediaries of loanable funds, such as Bundesbank (2017), the Bank of England (McLeay et al., 2014; Jakab and Kumhof, 2015, 2019), the Central Bank of Norway (Nicolaisen, 2017), the Reserve Bank of Australia (Doherty et al., 2018; Kent, 2018) or the IMF, (Benes and Kumhof, 2012).[1] Credit created by banks adds demand to the economy

[1] Bank lending creates deposits rather than they lend out deposits which have been placed with them (McLeay et al., 2014). For this, also compare Chapter 2 of Volume 1 in Keynes (2011) but also Schum-

(Turner, 2016). In this regard expansionary credit is found to drive house prices rather than higher house prices boosting credit demand; compare the discussion in Mian and Sufi (2018). This insight on banks allows to research the underlying process of the credit cycle more accurately.

Methodologically, the analysis employs a FAVAR approach going back to Bernanke et al. (2005). It represents a natural starting point to study the wide repercussions of private debt in the Euro area. Yet I follow the approach of Amir-Ahmadi and Uhlig (2012) using a Bayesian FAVAR approach with sign restrictions. However, I do not estimate monetary policy shocks but supply and demand shocks to private sector debt following Mian and Sufi (2018). This is the key difference to Amir-Ahmadi and Uhlig (2012) who look at monetary policy shocks in a sign restriction identification setting. Similar to Dees (2016) I study the interaction of the real economy and the financial sector via a VAR approach. Whereas this paper employs a global VAR setup with sign restriction, I use a Bayesian FAVAR approach with a similar identification procedure.

Hence, testing how credit has an effect on the Euro area economy is a question of far-reaching importance, as also highlighted by Benes and Kumhof's (2012) revision of the Chicago Plan for policies to reform the monetary system. In this regard, my paper lies at the intersection of three streams of literature: the literature on econometric FAVAR models to make use of the vast number of time series observed by actors like central banks as in Bernanke et al. (2005) and Amir-Ahmadi and Uhlig (2012), the literature on the importance of private debt similar to Mian and Sufi (2018) and, theoretically, by taking into account a perspective on the banking system and money as prominently discussed by McLeay et al. (2014) and others.

The IMF (2017) finds that higher growth in household debt is related to a larger probability of banking crises. These effects are more pronounced the higher household debt

peter (1983) and Turner (2016). Schumpeter specifically points to the economic function of credit creation for entrepreneurs to enable the realisation of innovations. Jakab and Kumhof (2015) introduce private debt and credit creation by banks into a DSGE model.

rises. Hence, it is a more severe problem for developed economies like the Euro area, further underlining the importance of this paper. Yet in the short-run, growing household debt has positive growth effects. Here my framework contributes to a more granular view on the short-run effects of debt expansions by estimating the reactions to supply and demand shocks. According to the IMF (2017) the growth-stability trade-off can be alleviated via a set of institutions, policies and regulations. Following this discussion, I also touch upon the implications of my finding's for macroprudential policy in the Euro area.

3 A FAVAR Model for the Euro Area

3.1 Data

The data largely follows the Euro area level data as in Corsetti et al. (2020) which cover a wide range of macroeconomic and financial variables. It has been updated until 2019 Q4. Even though data would have been available until 2020 Q1 or even 2020 Q2 for a large fraction of the series, I decide to restrict the data set due to the Covid-19 situation because of concerns about data reliability and quality. Future data revisions of the pandemic period will reveal a more reliable picture of its economic impact. For the procedure of dropping observations due to the Covid-19 shock see Lenza and Primiceri (2020). Their paper finds that dropping the extreme observations during the pandemic era is acceptable for the purpose of parameter estimation in a context of Vector Autoregression models.

Furthermore, I add time series on private sector and government debt. Dembiermont et al. (2013) from the BIS provide a rich data base with quarterly time series of private sector and government debt.[2] The debt data is expressed as percentage of GDP and captures total credit to the private sector, including credit issued by domestic and foreign banks as well as non-bank financial institutions. Dembiermont et al. (2013) define credit as debt securities, i.e. bonds and short-term paper, and loans. The specific advantage of

[2]To access the data base see: https://www.bis.org/statistics/totcredit.htm

the BIS' definition of debt is that it is wider than data which only considers bank lending, such as employed in Schularick and Taylor (2012) or Jordà et al. (2015). Hence, my paper is able to capture the full impact of private sector debt, similar to Mian et al. (2017). They also use the BIS data base to harness this broader perspective.

As Mian et al. (2017) underline, theoretically what matters is debt growth relative to the size of the economy since periods of strong real debt growth starting from a small base of debt could seem large without being actually economically meaningful. As the authors also employ a second method, the change in debt relative to a fixed base year GDP, but arrive at very similar results regardless of the normalisation procedure, this underpins using debt relative to GDP as a sufficient indicator.

All in all, the final data set is suitable to study the macroeconomic impacts of private debt shocks for the Euro area case. In addition, the underlying data contains a time series on the spread between bank interest rates for loans to households for house purchases and the ECB's official refinancing operation rate to capture the mark-up banks charge for loans relative to their funding costs from the central bank. Hereby I follow Mian et al. (2017), who also employ a variable in their data set, capturing the difference between the mortgage lending rate and the 10-year government bond yield. Unit labor cost data, the percentage of home ownership in the population and real labor productivity per hour have been added as Euro area level series as these were only present on a country level in Corsetti et al. (2020) originally. Hence Altogether, the paper gathers 106 time series.

The procedures applied when data was not available on a quarterly basis or the respective time series did range entirely from 2000 Q1 until 2019 Q4 follows Corsetti et al. (2020). Monthly series, such as HICP, one year EONIA swap rate and expectations, have been averaged over three months to make them quarterly. Annual data such as the distribution of population by tenure status to capture home ownership rates have been linearly interpolated to make them quarterly. The house price index has only been available from 2005 Q1 onwards and has been linearly interpolated backwards.

3.2 Empirical framework

The econometric setup is motivated by Bernanke et al. (2005), i.e. I employ a FAVAR model to study the effects of shocks to private debt on the Euro area. The key difference is the focus on shocks to private debt rather than monetary policy. Similarly, my paper employs the Euro area level time series as presented in Corsetti et al. (2020) but their Dynamic Factor Model approach would not allow me to research the effect of private debt on the Euro area, hence the FAVAR approach (Stock and Watson, 2016; Ramey, 2016). All time series have been transformed to induce stationarity as this is a pre-requisite to estimate FAVAR models correctly (Ramey, 2016).

Similar to Amir-Ahmadi and Uhlig (2012) I construct a Bayesian version of the FAVAR model introduced by Bernanke et al. (2005), i.e. I make use of their idea to summarise the main dynamics of a large set of time series by a small list, which consists of common factors and key variables. In the following, I analyse the response of the former to a shock in the latter.

Let X_t be a large vector of macroeconomic time series. The approach assumes that the informational time series X_t are related to the unobservable factors F_t and the observed variables Y_t by an observation equation of the form:

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t \tag{1}$$

where Λ^f is an $n \times r$ matrix of factor loadings. Λ^y is an $N \times M$ matrix of factor loadings of the observable variables and finally $e_t = (e_{1t}, ..., e_{nt})'$ denotes a vector of n disturbances. The error terms of the observables are assumed to be mutually uncorrelated.

Equation 1 indicates that Y_t and F_t represent common forces that advance the fluctuations of X_t. Subject to Y_t, the X_t are therefore noisy measures of F_t. The joint dynamics of

(F_t, Y_t) are given by the transition equation:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Psi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t \tag{2}$$

where (2) is the Factor-Augmented Vector Autoregressive model.

3.3 Identification and estimation

Following Faust (1998) as well as Uhlig (2005) this paper employs sign restriction as a shock identification method, i.e. imposing restrictions on the signs of the impulse responses. A previous example in this regard is Amir-Ahmadi and Uhlig's (2012) paper, which uses sign restriction in a Bayesian FAVAR setting. The key idea is to identify structural shocks via imposing sign restrictions on the impulse responses of certain macroeconomic variables for a specified time horizon. Regarding sign restriction, also compare the discussion in Stock and Watson (2016) and Ramey (2016). In addition, a Bayesian version of the FAVAR model has been implemented since sign restrictions are mostly only well defined from a Bayesian perspective as pointed out in Moon and Schorfheide (2012).

In line with Mian et al. (2017) I study the effects of (positive) credit supply and demand shocks, i.e. a debt expansion, by employing the spread between Bank Interest Rates (MIR) and the ECB Official Refinancing Operation Rate (REFI). As laid out in their paper, credit demand might rise due to the anticipation of higher future income; compare Aguiar and Gopinath (2007). This credit expansion, driven solely by a demand shock, should lead to higher interest rates on household credit. Similarly, an expansion in credit supply is affiliated with a decrease in credit spreads on loans to households. Excessive borrowing occurs ex-ante and a pronounced surge in household debt predicts lower successive growth in output in their analysis. I extend these assumptions on the behavior of the spread for demand and supply shocks to general private sector credit. These shocks make the case for macroprudential policy and will be discussed later in the paper, see

Section 6.

In the first case I employ positive sign restrictions on the spread and the private sector debt to estimate a positive demand shock. In the second case, I estimate a positive supply shock via a positive sign restriction on credit and a negative one on the spread. Both shocks have a magnitude of one standard deviation. My sign restrictions on the two variables hold from the point of impact until the second period of the response, i.e. for two quarters or half a year respectively. This is in line with the number of periods sign restricted in the benchmark specification of Uhlig (2005). No other variables are sign restricted for the purpose of this analysis.

Shock	*Private Sector Debt*	*Spread SMIRREFI*
Demand	>0	>0
Supply	>0	<0

Table 1: Sign restrictions for private sector debt and the interest rate spread to estimate demand and supply shocks motivated by Mian et al. (2017). These restrictions are set to hold for two periods for the baseline models.

I follow Bernanke et al. (2005) and define a set of "slow"-moving variables which are considered not to respond contemporaneously to innovations in private debt. The selection is motivated by their paper and comprises of variables associated with production, wages and spending.[3] I employ three factors in my FAVAR estimation similar to Bernanke et al. (2005) which explain cumulatively around 50 percent of the variance in my full data set. These factors have been obtained via Principal Component Analysis. Linear regressions of the individual variables on the factors and the observables show to what extent the individual series are driven by common factors or idiosyncratic forces. Compare Appendix C and for the latter especially Table C.4 and Amir-Ahmadi and Uhlig (2012) as a reference.

I estimate the Bayesian FAVAR model using a flat Normal inverted-Wishart prior. To

[3]Specifically this entails: GDP,PCON, G, CON, GFCF, IM, EX, WIN, HICP, PPI, UTIL, RENTS, U, RRENTS, EMP, OIL, IPIT, IPIM, ITIM, EMP, LABCON, BUILD, GFCFC, GFCFD, PROCO, PRD ,ULC and BUILDCOSTI.

identify structural shocks, I implement Uhlig's (2005) rejection method with 2000 draws for the posterior and 2000 subdraws for each posterior draw to compute the impulse vectors and the candidate impulse responses to which the rejection algorithm will be applied. The number of desired draws is set to 10000. My model specification does not include a constant similar to Amir-Ahmadi and Uhlig (2012).

My estimation procedure follows a four-step process. First, I extract the Principal Components from the entire data set, including the debt data. Second, I "clean" the factors from the impact of private sector debt. Third, I estimate the FAVAR via Uhlig's (2005) rejection method with three factors and the two observable time series private sector debt and the spread. Fourth, I multiply the impulse vector matrix with the loading's matrix to obtain the responds for the individual variables.

4 Empirical findings

In the following I provide an overview of my empirical findings to show how the Euro area economy is affected by shocks in private sector debt. My empirical framework allows me to present the impacts of demand and supply shocks, respectively. I report the Impulse Response Functions (IRFs), showing the median response together with the 16% and the 84% quantiles for the sample of impulse responses, following Uhlig (2005). These quantiles would correspond to a one standard deviation band if the distribution was normal. These impulse responds confidence bands are shown as read dashed lines and have been obtained from extracting the 16% and 84% quantile from the matrix consisting of the multiplication of the impulse vector matrix with the loadings matrix. As Amir-Ahmadi and Uhlig (2012) note, these bands represent posterior probability statements rather than actual confidence sets, a subject put forward in Moon and Schorfheide (2012) as well as Granziera et al. (2018). In addition, a caveat of this analysis remains: the supply and demand shocks could be capturing economic booms and busts. Given the sign restriction procedure one cannot expect tight identification, only set identification. Yet this is what is feasible, also given that the subsample analysis did not yield satisfying results as discussed below. I want to underline that my models generate impulse response functions for all times series in the data set, not only the ones presented here.

Figure 1 shows the responds of GDP and other macroeconomic and financial variables to the private sector debt demand shock. The shock impacts GDP negatively for at least up to one year and unemployment rises as an expected result. Inflation rises steadily after the shock for more than a year and private consumption falls with its median never fully recovering. House prices, investment and capacity utilization fall with a demand shock but the latter even rises higher than initially after more than five quarters. Stock prices take an instant hit and the effect does not fade away after 25 quarters. Industrial production falls but construction sees a sharp positive jump on impact which remains higher for the next year. The Economic Sentiment Indicator drops sharply. As expected for the Euro area, government expenditure increases, mirroring the gloomy development of the production and income side. Wages take a hit but the Euro strengthens against other currencies. Long-term interest rates fall initially for two quarters but rise for several quarters around a year after the shock before the impact fades away.

Interestingly, a supply-driven expansion of credit has the exact opposite effects as a demand shock as reported in Figure 2. GDP increases for more than two years, unemployment declines for a similar period and private consumption grows for a while. Investment rises to a similar extent to house prices. Stocks see an increase before coming down again. In line with this positive impact on income and employment, capacity utilization increases sharply for a few quarters together with a positive reaction in industrial production and construction investments. Wages rise for more than a year but the Euro depreciates. Economic sentiment rises but falls back shortly after. Long-term interest rates spike up first and are depressed compared to their initial level more than a year after the shock before the shock's impact fades away more than two years after.

Figures 3 and 4 report the forecast error variance decomposition for the baseline models with three lags, three factors and two periods sign restrictions for the supply and demand shock respectively. This allows me study the relevance of the shocks in explaining the dependent variables via computing the share of the variance of the forecast error of these variables which can be ascribed to these shocks. A shock to private sector debt accounts for around ten percent of the variance for Factor 2, 3 in the demand case and around ten percent for Factor 2 and nearly 15 percent for Factor 3 in the supply case for the first few periods. This grows towards twelve percent for the longer horizon. The fraction of the forecast error variance explained in Factor 1 by the demand shock remains steady at 13 to 14 percent throughout the 25 periods. For the supply shock FEVD, this fraction grows from ten percent to around twelve for the longer horizon. The private sector debt demand shock accounts for around 15 percent in the variation of private sector debt, but less so for the supply shock case where this fraction is around twelve percent. For the interest rate spread the forecast error variance explained by the debt shocks is similar for the supply and demand case.

Hence, demand shocks are more important for explaining variation in Factor 1, supply shocks are more important for explaining variation in Factor 2, and the two socks are equally important for explaining variation in factor 3. This latter finding also applies for the spread's FEVD, yet demand shocks seems to be predominant in explaining the forecast error variance of private sector debt.

The findings point to a considerable importance of private sector debt in driving the Euro area business cycle, similar to the results of Jordà et al. (2013) for their sample of 14 advanced economies between 1870 and 2008.

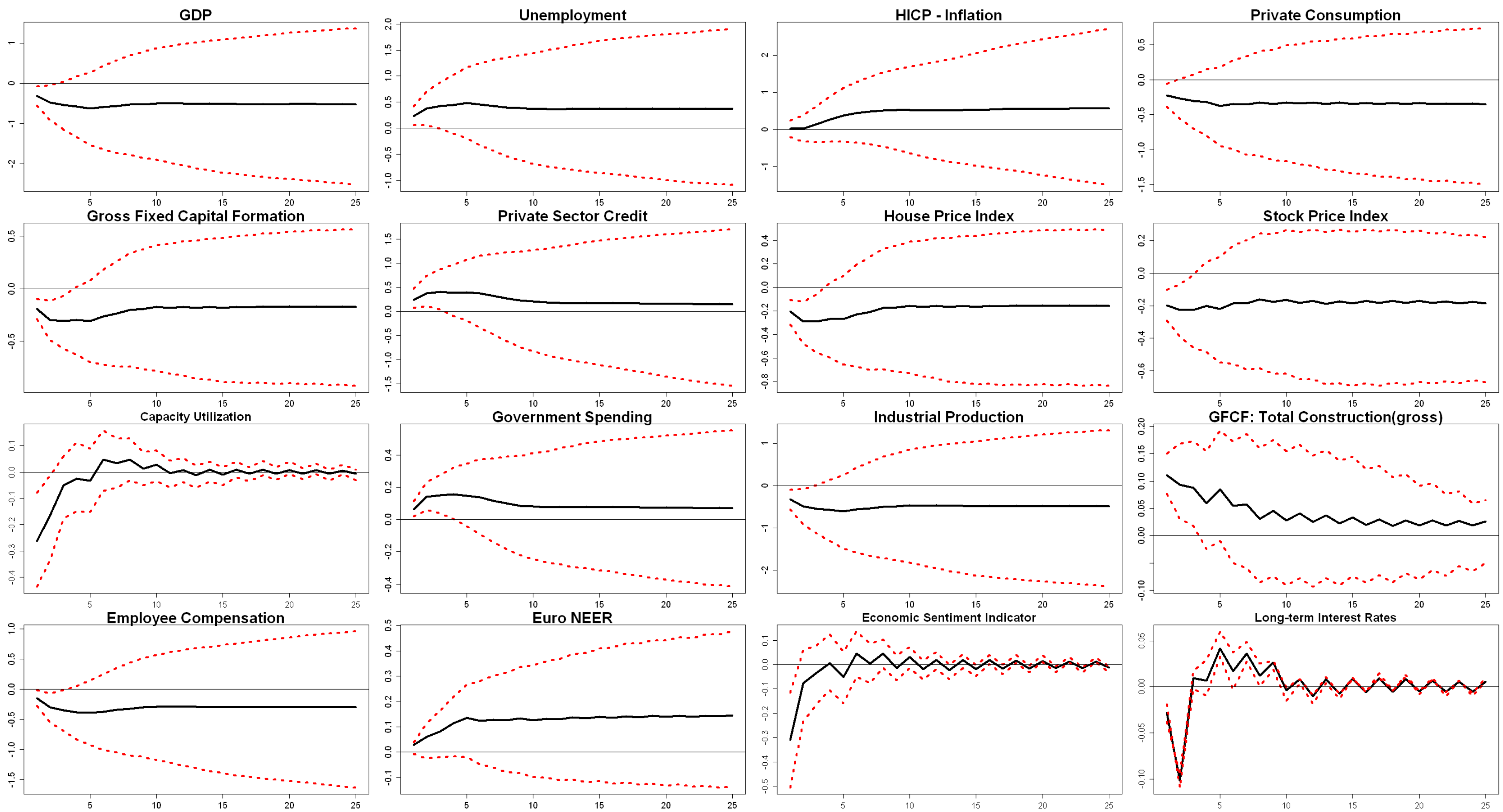

Figure 1: Impulse response functions of a one standard deviation positive demand shock in private sector debt for 25 steps. One step equals to one quarter. Black lines show the median of the simulations and the red dashed lines report the 16% and the 84% impulse responds confidence bands.

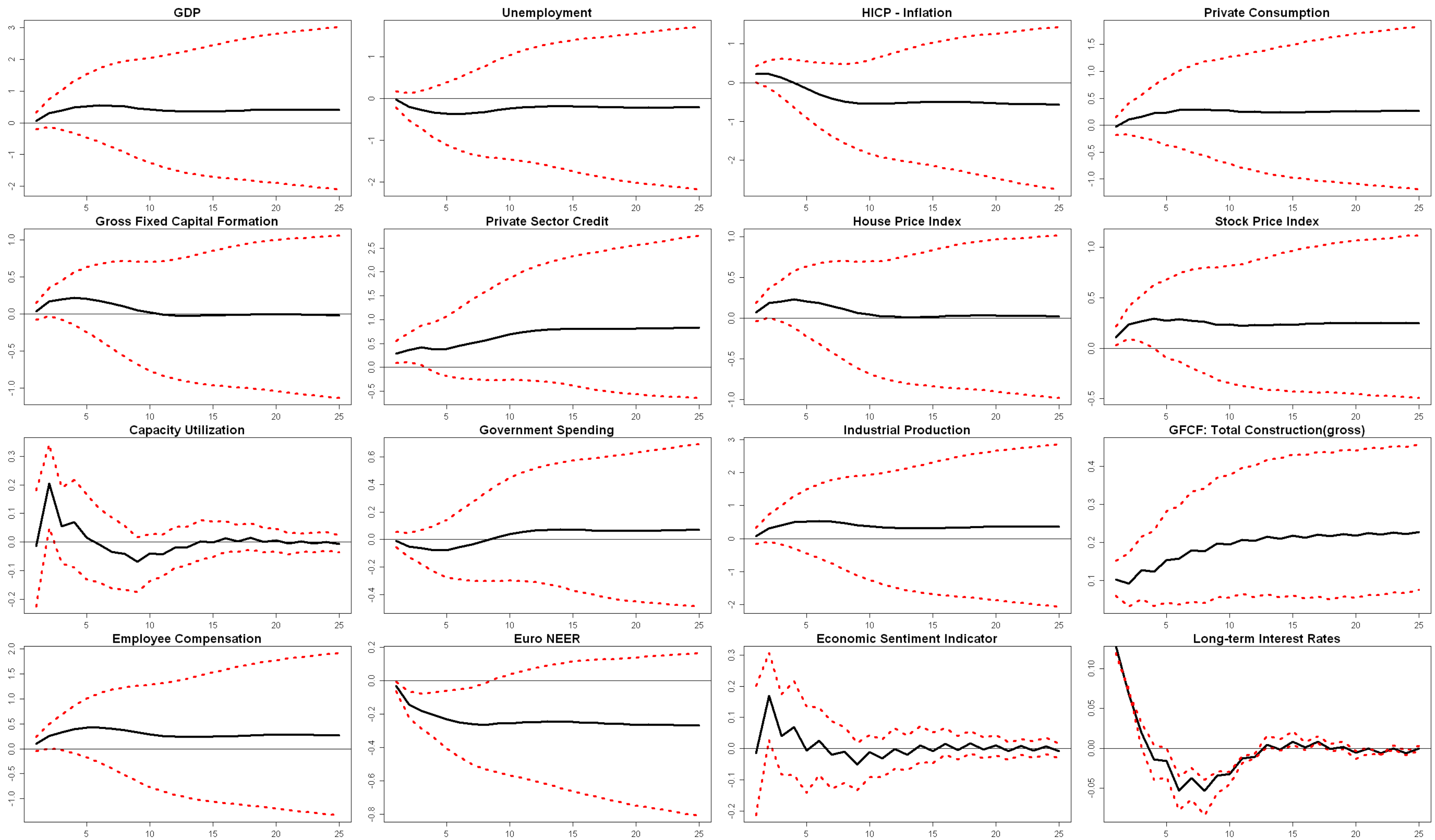

Figure 2: Impulse response functions of a one standard deviation positive supply shock in private sector debt for 25 steps. One step equals to one quarter. Black lines show the median of the simulations and the red dashed lines report the 16% and the 84% impulse responds confidence bands.

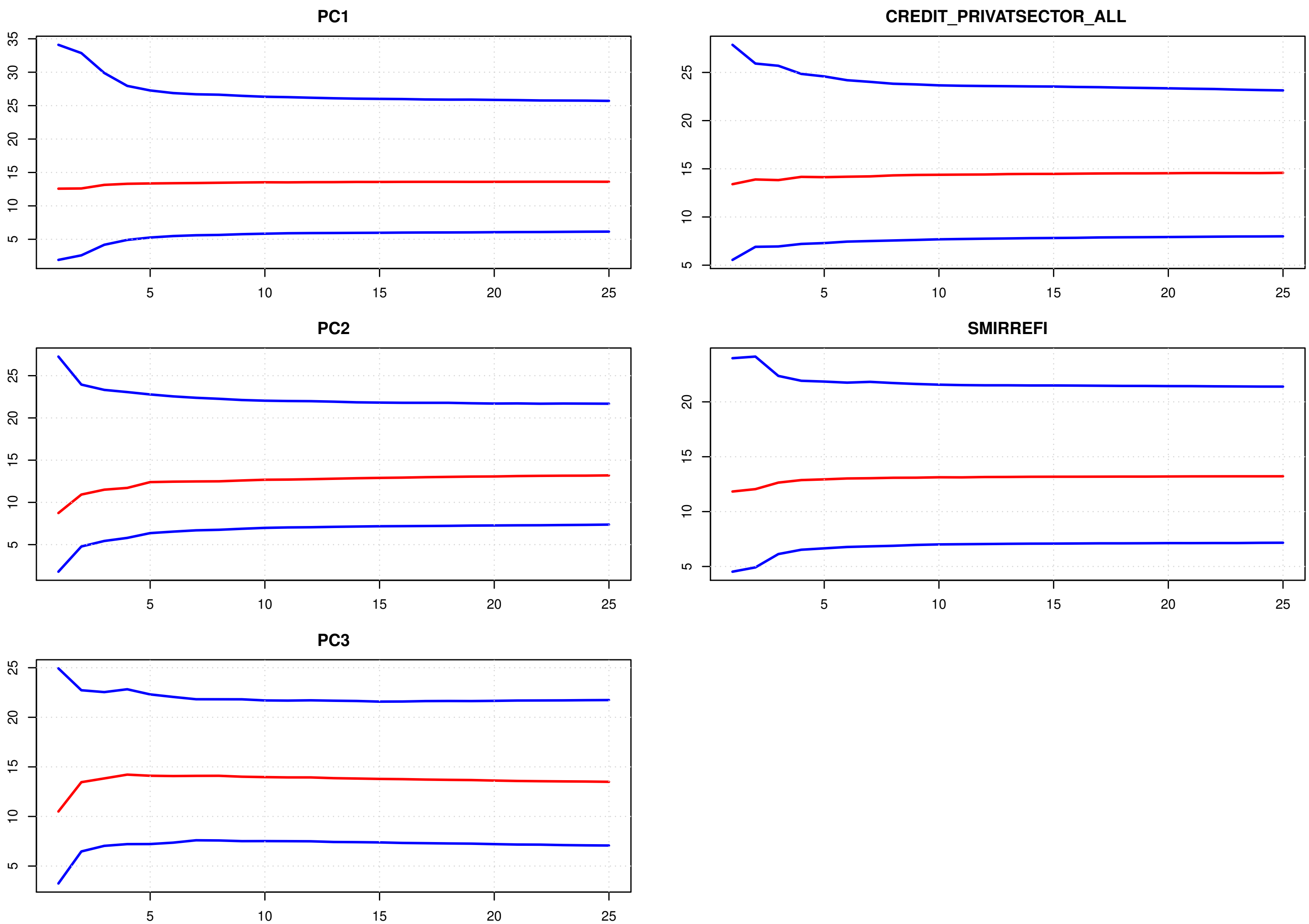

Figure 3: FEVD of the base line model for the one standard deviation positive demand shock in private sector debt. The blue lines indicate the 16% and 84% error bands of the decomposition.

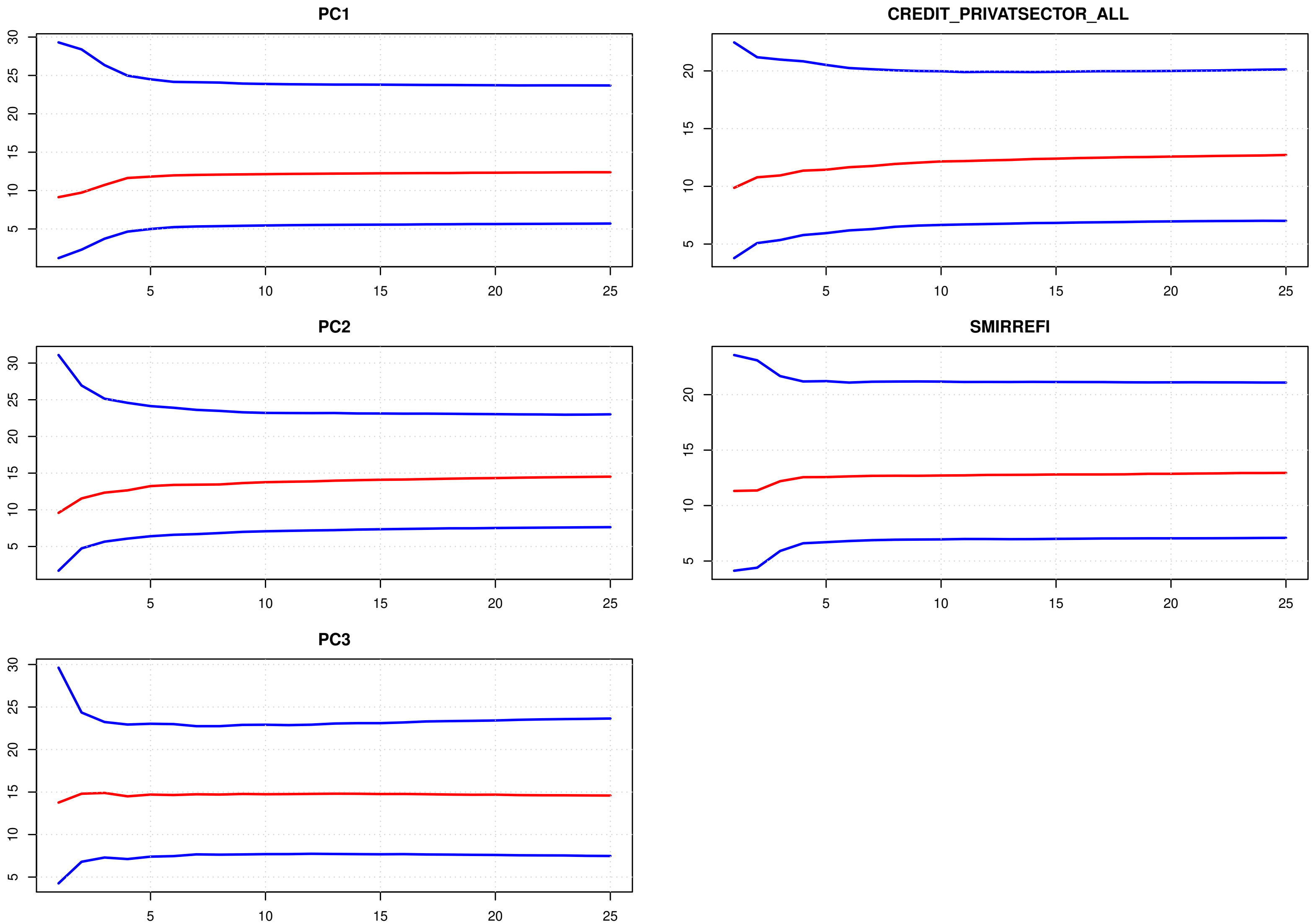

Figure 4: FEVD of the base line model for the one standard deviation positive supply shock in private sector debt. The blue lines indicate the 16% and 84% error bands of the decomposition.

5 Robustness check

Similar to Uhlig (2005) and Amir-Ahmadi and Uhlig (2012) I implement several respecifications of the base case model to understand the robustness of the outcomes to changes in the number of lags, periods the sign restrictions hold and number of factors, see Appendix B. The results are quite robust to these model adjustments.

I increase the number of lags from three to four given the quarterly data, a procedure also undertaken by Bernanke et al. (2005) and Amir-Ahmadi and Uhlig (2012), but this does not alter the results much. The direction and impact horizon of the shocks for the different variables remains similar.

In addition, I set the number of quarters the sign restrictions hold from two to three and subsequently to four, i.e. a full year. See Figures B.3, B.4, B.5 and B.6. The shocks' impacts show a stronger persistence and are more pronounced once the restriction time frame is adjusted upwards, similar to the findings of Amir-Ahmadi and Uhlig (2012) for their monetary policy shock estimations. All variables show a stretched out horizon for their reactions, the only exception may be the Euro's nominal effective exchange rate (NEER) for the demand shock case. Supply shocks have a much higher depreciation effect than demand shocks which result only in weak signs of appreciation. In general, an asymmetry in the effects of supply and demand becomes evident: demand shocks show a much longer persistence and effect in the Euro area macroeconomy than supply shocks even if the horizon for the sign restrictions to hold is the same for both shocks. Here compare especially GDP, unemployment, investment, industrial production and government spending across the four Figures. For these variables the demand shocks takes much longer to fade away than the supply shocks.

Moreover, I reestimate the models with different numbers of factors similar to Amir-Ahmadi and Uhlig (2012) and Bernanke et al. (2005). In one case I change the base case specification with three lags to only include two factors. The results are shown in Appendix B in Figure B.7 for the demand shock and in Figure B.8 for the supply shock.

Similarly, I increase the number of factors to four. Figures B.9 and B.10 present the results. The qualitative character of my results does not change with an alternative number of factors. This outcome of the robustness check is also consistent with Bernanke et al. (2005).

Hence, my overall outcomes hold for a number of specifications with respect to number of lags, time horizon the sign restrictions hold and number of factors.

5.1 Robustness check via sample splitting

Following Corsetti et al. (2020) I also envisage to present a robustness check with a subsample analysis for the periods 2001 Q1 to 2007 Q4 and 2008 Q1 until 2019 Q4. This procedure to check for subsample stability is also part of Amir-Ahmadi and Uhlig (2012), who divide their data into a before and after Volcker shock sample. This allows me to study the repercussions of the Euro area economy to a private debt shock before and after the Great Financial Crisis (GFC). As private debt has been growing significantly in many European countries prior to the crisis, this represents also an interesting analysis in itself. Unfortunately, the IRFs for the pre-2008 sample did not yield any sound results which can be attributed to a lack of data. Nevertheless, I report the past-2008 IRFs in Appendix B in Figure B.12 and B.11 and discuss the results in short.

For the subsample past-2008 I find that the impacts are similar to the full sample case but weaker. However, the impulse responds confidence bands are constantly wider and growing at further horizons for the IRFs of GDP or also unemployment and house prices. For demand I find again a negative impact for more than a year but the impact fades away. Similarly, unemployment rises for more than a year after recovering. The shock's impact on HICP is constantly negative and depresses inflation for the full 25 quarters. Investment goes down in the short-run and its median estimate never recovers fully again. Stock prices and private consumption do not show any effect. Capacity utilization deteriorates in the short-run before the shocks' impact fade away. Government spending increases for several quarters as in the full sample case. Wages go down for a year and never fully recover. The Euro depreciates and economic sentiment increases in the short-run. For the supply shock case I find that the Euro area reacts positively with short-run increases in GDP, employment, investment, industrial production, capacity utilization and a long-term positive effect for wages. The effect on economic sentiments is unclear but indicates a negative hit for more than year.

6 Macroprudential policy implications

The IMF (2017) finds short-run positive growth effects of rising household debt. For the Euro area I can only confirm these results for debt expansions driven by supply shocks similar to Kindleberger (1978) who found that asset price bubbles are mostly caused by expansionary credit supply; also see Mian and Sufi (2014). Given the results above, macroprudential policies should respond to unexpected increases in private debt conditional on the nature of the shock. A supply shock points to the build-up of a boom bust cycle with positive short-run effects for the economy. My findings point towards the need for precautionary measures to be in place for the cycle's downturn. Yet for demand-driven increases in private sector debt, the economy enters a problematic stage right away. Since the financial sector (and the overall economy) does not see stronger growth for several quarters before the downturn, buffers need to be in place *at the start of the shock*. This is a dramatic difference and, compared to supply shock effects, poses policy challenges for financial stability.

Jordà et al. (2013) find evidence that recessions are deeper and recoveries slower, the more credit has been growing prior to the downturn. For my findings regarding credit supply shocks this would imply that the magnitude of the shock plays an important role for the subsequent downturns. De Schryder and Opitz (2021) investigate the impact of macroprudential policy tightening shocks in a panel of 13 European countries. They find that the negative repercussions for the credit-to-GDP ratio are stronger in credit cycle upswings than downturns. Hence, in light of my results, this supports an active tightening of macroprudential policy in a supply-driven expansion. Yet, De Schryder and Opitz' (2021) findings do not suggest that the effects of macroprudential policy action depend on the business cycle. Tying together De Schryder and Opitz (2021) outcomes and my paper's results it appears that this kind of prudential policy is effective for debt supply and demand shocks alike. Yet the positive aspects of macroprudential policies do not apply to credit for non-financial corporations (NFCs) and De Schryder and Opitz (2021) indicate a leakage effect: firms receive their credit from non-bank or foreign lenders once conditions tighten. My study of the Euro area was designed to account for the total debt of the entire private sector (credit from banks and non-banks to households and NFCs) by using the data of Dembiermont et al. (2013) and therefore does not suffer from the drawback of this leakage effect.

On a more unconventional note, researchers have put forward policy approaches to deal with the private sector debt problem. Mian and Sufi (2014) propose direct debt forgiveness, Turner (2016) and King (2017) advocate that central banks should inject private bank accounts with fresh money and Keen (2017) considers a 'Modern Debt Jubilee': creating money by the central bank for private accounts, provided that the private sector uses these financial means to pay down debt. These policies are more targeted to cope with debt *levels* rather than policies for dealing with its *fluctuations*.

Since private debt has been growing steadily over the past decades, regulation and supervision needs to account for the growing private debt dependency of our economies. In this regard, these policies are also relevant, especially for supply shock effects, to balance macroeconomic short-run fluctuations in order to reduce the repercussions of an attempt of the private sector to deleverage altogether.

Supply shocks appear to leave time for regulators to adapt with standard regulation, e.g. increased capital buffers, to the new situation due to a (short) economic upswing. Yet the devastating repercussions of a demand shock, together with its greater persistence as reported above, might call for further consideration of these unconventional approaches as the slowdown is impending. Private sector deleveraging through classical fiscal policy does not seem to be feasible given the scale of the spending this would entail (Keen, 2017). As Fisher (1933) notes for deflationary situations and deleveraging, the debt burden rises the more debtors repay. With the view to the state of the Euro area over the past ten years, this motivates to review conventional and unconventional policy options for further analysis.

7 Concluding remarks

This paper uncovers large discrepancies in the effects of (unexpected) supply and demand shocks for the Euro area economy. Private sector debt matters for macroeconomic fluctuations with strong effects on GDP, unemployment and investment. Bank lending has been identified to be a key driver of short-run cycles in the currency union. In their responses policy makers need to account for the nature of the debt shock.

A downside of the paper's approach is the use of Euro area wide macroeconomic and financial time series. The problem lies in the fact that Germany is a vast exception to the private debt-driven cycles found for other economies. The German export surplus represents a key drawback, possibly mitigating the paper's results. For Germany, its reliance on credit growth has just been exported via its trade surplus: private credit to generate growth has been increasing in the US, UK and other European countries rather than in its domestic market (Turner, 2016). In this regard, future papers shall address this particularity by employing different data and empirical set-ups.

Departing from the outcome of this paper, I see three ways on how to take this research forward. First, a Panel VAR framework with the country-level data of Corsetti et al. (2020) would allow to establish a more granular view on how the early Euro-adopting countries are reliant on private debt dynamics. This would address the shortcomings of working with Euro area level data and further investigate the nexus between macroeconomic fluctuations and private debt in the Euro area. Second, my findings point to large differences in the effects of supply versus demand debt shocks. In this regard, research needs to disentangle whether the instantaneous negative impacts from demand shocks are mostly arising from the household or the corporate side, having in mind the recent findings of Jordà et al. (2020). Third, given that the 20 year data range includes a tremendous boom and subsequent slow recovery, this FAVAR approach to model shocks to private debt could provide further useful insights when used in combination with data spanning larger time horizons. Concretely, using US time series within a similar FAVAR model approach could provide insightful results regarding the nexus of private debt and the macroeconomy in another country setting. The paper's results provide a promising starting point.

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A Appendix - Data set

Table A contains a list of all time series in the data set, alongside detailed descriptions and information on data transformations, geographical coverage of each series as well as its respective source. The data set consists of the updated Euro area-level time series found in Corsetti et al. (2020) with minor differences and additional data from the BIS. Abbreviations and codes are as follows:

Transformation code (T)
1 - no transformation
2 - difference in levels
4 - logs
5 - difference in logs

Geography
EA - Euro area
EA12 - Euro area (12 countries)
EA19 - Euro area (19 countries)
EACC - Euro area (changing composition)

Seasonal adjustment
WDSA - working day and seasonally adjusted
SA - seasonally adjusted
NA - neither working day or seasonally adjusted

Note: The Euro are house price index HPI starts only in 2005 Q1. The home ownership series OWN has been linearly interpolated to create a quarterly data series. The HICP series, the 1-year EONIA swap rate and the seven series covering expectations have been averaged over three months to make the monthly observations quarterly. The interest rate spread SMIRREFI is the difference between the MIR and the REFI series in each given quarter.

Series	Description	T	Source	Geography	Start	End
GDP & Income						
GDP	Gross Domestic Product at market prices, Chain linked volumes, 2015=100,WDSA	5	Eurostat	EA12	2000Q1	2019 Q4
PCON	Household and NPISH final consumption expenditure, Chain linked volumes, 2015=100, WDSA	5	Eurostat	EA12	2000Q1	2019 Q4
G	Final consumption expenditure of general government, Chain linked volumes, 2015=100, WDSA	5	Eurostat	EA12	2000Q1	2019Q4
GFCF	Gross xed capital formation, Chain linked volumes, 2015=100, WDSA	5	Eurostat	EA12	2000 Q1	2019 Q4
EX	Exports of goods and services, Chain linked volumes, 2015=100, WDSA	5	Eurostat	EA12	2000 Q1	2019 Q4
IM	Imports of goods and services, Chain linked volumes, 2015=100, WDSA	5	Eurostat	EA12	2000 Q1	2019 Q4
Prices/Deflators						
GDPDEF	Gross domestic product at market prices, Price index (implicit deator), 2015=100, euro, WDSA	5	Eurostat	EA12	2000 Q1	2019 Q4
PCONDEF	Household and NPISH final consumption expenditure, Price index (implicit deator), 2010=100, euro, WDSA	5	Eurostat	EA12	2000 Q1	2019 Q4
GDEF	Final consumption expenditure of general government, Price index (implicit deator), 2015=100, euro, WDSA	5	Eurostat	EA12	2000 Q1	2019 Q4
GFCFDEF	Gross xed capital formation, Price index (implicit deator), 2015=100, euro, WDSA	5	Eurostat	EA12	2000 Q1	2019 Q4
EXDEF	Exports of goods and services, Price index (implicit deator), 2015=100, euro, WDSA	5	Eurostat	EA12	2000 Q1	2019 Q4
IMDEF	Imports of goods and services, Price index (implicit deator), 2015=100, euro, WDSA	5	Eurostat	EA12	2000 Q1	2019 Q4
PPI	Producer prices in industry, domestic market, index 2010=100, unadjusted data	5	Eurostat	EA19	2000 Q1	2019 Q4
HICP00	All-items HICP, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2019 Q4
HICP01	HICP Food and non-alcoholic beverages, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2019 Q4
HICP02	HICP Alcoholic beverages, tobacco and narcotics, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2019 Q4
HICP03	HICP Clothing and footwear, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2019 Q4
HICP05	HICP Furnishings, household equipment and routine household maintenance, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2019 Q4
HICP06	HICP Health, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2019 Q4
HICP07	HICP Transport, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2019 Q4
HICP08	HICP Communications, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2019 Q4
HICP09	HICP Recreation and culture, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2019 Q4
HICP10	HICP Education, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2019 Q4
HICP11	HICP Restaurants and hotels, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2019 Q4
HICP12	HICP Miscellaneous goods and services, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2019 Q4
HICPXFD	Overall HICP index excluding seasonal food, Index, 2015=100	5	Eurostat	EACC	2000 Q4	2019 Q4
HICPXUTIL	Overall HICP index excluding housing, water, electricity, gas and other fuels, 2015=100	5	Eurostat	EACC	2000 Q1	2019 Q4
HICPXHTH	Overall HICP index excluding education, health and social protection, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2019 Q4
HICPUTIL	HICP Housing, water electricity, gas and other fuels, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2019 Q4
PPIING	Producer Price Index, MIG - intermediate goods, unadjusted data, 2010=100	5	Eurostat	EA19	2000 Q1	2019 Q4
PPICAG	Producer Price Index, MIG - capital goods, unadjusted data, 2010=100	5	Eurostat	EA19	2000 Q1	2019 Q4
PPINDCOG	Producer Price Index, non-durable consumer goods, unadjusted data, 2010=100	5	Eurostat	EA19	2000 Q1	2019 Q4
PPIM	Producer Price Index, Manufacturing, unadjusted data, 2010=100	5	Eurostat	EA19	2000 Q1	2019 Q4
CPIIMF	IMF World Commodity Price Index, USD denominated, weights based on 2002-2004 average world export earnings, non-fuel primary commodities and energy, 2005=100	5	IMF	World	2000 Q1	2019 Q4
CPIECB	ECB Commodity Price Index, Euro denominated, Total non-energy commodity, unadjusted data, 2010=100	5	ECB SDW	EA19	2000 Q1	2019 Q4
OIL	Brent crude oil 1-month forward, fob (free on board) per barrel, Euro	5	ECB SDW	EACC	2000 Q1	2019 Q4

Series	Description	T	Source	Geography	Start	End
Industrial Production						
IPIT	Industrial Production Index, Total Industry, WDSA, 2005=100	5	ECB SDW	EA19	2000 Q1	2019 Q4
IPIING	Industrial Production Index, MIG - intermediated goods, WDSA, 2010=100	5	Eurostat	EA19	2000 Q1	2019 Q4
IPINRG	Industrial Production Index, MIG - energy, WDSA, 2010=100	5	Eurostat	EA19	2000 Q1	2019 Q4
IPICAG	Industrial Production Index, MIG - capital goods, WDSA, 2010=100	5	Eurostat	EA19	2000 Q1	2019 Q4
IPICOG	Industrial Production Index, MIG - consumer goods, WDSA, 2010=100	5	Eurostat	EA19	2000 Q1	2019 Q4
IPIDCOG	Industrial Production Index, MIG - durable consumer goods, WDSA, 2010=100	5	Eurostat	EA19	2000 Q1	2019 Q4
IPINDCOG	Industrial Production Index, MIG - non-durable consumer goods,	5	Eurostat	EA19	2000 Q1	2019 Q4
IPINDCOG	WDSA, 2010=100					
IPIMQ	Industrial Production Index, Mining and quarrying, WDSA, 2010=100	5	Eurostat	EA19	2000 Q1	2019 Q4
IPIM	Industrial Production Index, Manufacturing, WDSA, 2010=100	5	Eurostat	EA19	2000 Q1	2019 Q4
ITIING	Industrial Turnover Index, MIG Intermediate Goods (2010=100, WDSA)	5	Eurostat	EA19	2000 Q1	2019 Q4
ITINRG	Industrial Turnover Index, MIG Energy (2010=100, WDSA)	5	Eurostat	EA19	2000 Q1	2019 Q4
ITICAG	Industrial Turnover Index, MIG Capital Goods (2010=100, WDSA)	5	Eurostat	EA19	2000 Q1	2019 Q4
ITICOG	Industrial Turnover Index, MIG Consumer Goods (2010=100, WDSA)	5	Eurostat	EA19	2000 Q1	2019 Q4
ITIDCOG	Industrial Turnover Index, MIG Durable Consumer Goods (2010=100, WDSA)	5	Eurostat	EA19	2000 Q1	2019 Q4
ITINDCOG	Industrial Turnover Index, MIG Non-Durable Consumer Goods (2010=100, WDSA)	5	Eurostat	EA19	2000 Q1	2019 Q4
CAPUTIL	Current level of capacity utilization, percent	1	Eurostat	EA19	2000 Q1	2019 Q4
ITIM	Industrial Turnover Index, Manufacturing, 2010=100, SWDA	5	Eurostat	EA19	2000 Q1	2019 Q4
Employment & Unemployment						
WIN	Compensation of employees, Current prices, million euro, WDSA	5	Eurostat	EA12	2000 Q1	2019 Q4
U	Total Unemployment rate (quarterly average), WDSA	2	Eurostat	EACC	2000 Q1	2019 Q4
EMP	Total employment	5	Eurostat	EA19	2000 Q1	2019 Q4
LABCON	Labour Input in Construction, Index of Hours Worked, 2010=100, WDSA	5	Eurostat	EA19	2000 Q1	2019 Q4
Housing Starts						
BUILD	Building Permits, Residential Buildings, Index, 2010=100, WDSA	5	Eurostat	EA19	2000 Q1	2019 Q4
GFCFC	Gross fixed capital formation: Total construction (gross), chain linked volumes, Index, 2010=100	5	Eurostat	EACC	2000 Q1	2019 Q4
GFCFD	Gross fixed capital formation: Dwellings (gross), chain linked volumes, Index, 2010=100	5	Eurostat	EACC	2000 Q1	2019 Q4
PROCO	Production in Construction, Volume Index, 2010=100, WDSA	5	Eurostat	EA19	2000 Q1	2019 Q4
Inventories, Orders & Sales						
ORDING	Industrial New Orders, MIG Intermediate Goods, 2010=100, SA	5	ECB SDW	EA19	2000 Q1	2019 Q4
ORDCAG	Industrial New Orders, MIG Capital Goods, 2010=100, SA	5	ECB SDW	EA19	2000 Q1	2019 Q4
ORDCOG	Industrial New Orders, MIG Consumer Goods, 2010=100, SA	5	ECB SDW	EA19	2000 Q1	2019 Q4
ORDM	Industrial New Orders, Manufacturing, 2010=100, SA	5	ECB SDW	EA19	2000 Q1	2019 Q4
Earnings & Productivity						
PRD	Real labour productivity per hour worked, 2010=100, unadjusted data	5	Eurostat	EA11??	2000 Q1	2019 Q4
ULC	Nominal unit labour cost based on hours worked, 2010=100, unadjusted data	5	Eurostat	11 ex BEL	2000 Q1	2019 Q4

Series	Description	T	Source	Geography	Start	End
Money & Credit						
EUSWEI1	1 year EONIA swap (quarterly average)	2	Bloomberg	EA	2000 Q1	2019 Q4
STINT	3-month money market interest rate	2	Eurostat	EACC	2000 Q1	2019 Q4
LTINT	EMU convergence criterion long-term bond yields	2	Eurostat	EACC	2000 Q1	2019 Q4
MIR	Bank interest rates- loans to households for house purchases (outstanding amount business coverage), average of observations through period, percent per annum	2	ECB SDW	EACC	2000 Q1	2019 Q4
COB	Cost of borrowing for households for housepurchases (new business coverage), average of observations through period, percent per annum	2	ECB SDW	EACC	2000 Q1	2019 Q4
EURIBOR3MD	3-Month Euro Interbank Offered Rate (%, NSA)	1	ECB SDW	EA	2000 Q1	2019 Q4
EURIBOR6MD	6-Month Euro Interbank Offered Rate (%, NSA)	1	ECB SDW	EA	2000 Q1	2019 Q4
EURIBOR1YD	1-Year Euro Interbank Offered Rate (%, NSA)	1	ECB SDW	EA	2000 Q1	2019 Q4
YLD_3Y	3-Year Euro Area Government Benchmark Bondyield (%, NSA)	2	ECB SDW	EA	2000 Q1	2019 Q4
YLD_5Y	5-Year Euro Area Government Benchmark Bondyield (%, NSA)	1	ECB SDW	EA	2000 Q1	2019 Q4
YLD_10Y	10-Year Euro Area Government Benchmark Bondyield (%, NSA)	1	ECB SDW	EA	2000 Q1	2019 Q4
EONIA	Euro Overnight Index Average (%, NSA)	1	ECB SDW	EA	2000 Q1	2019 Q4
REFI	ECB Official Refinancing Operations Rate (effective, %, NSA)	1	ECB SDW	EA	2000 Q1	2019 Q4
S3MDREFI	Spread EURIBOR3MD - REFI	1	ECB SDW	EA	2000 Q1	2019 Q4
S10YYLDREFI	Spread YLD_10Y - REFI	1	ECB SDW	EA	2004 Q1	2019 Q4
SMIRREFI	Spread MIR - REFI	1	ECB SDW	EA	2000 Q1	2019 Q4
CREDIT_G	Euro area - Credit to General government from All sectors at Market value - Percentage of GDP - Adjusted for breaks	5	BIS		2000 Q1	2019 Q4
CREDIT_PRIVATESECTOR	Euro area - Credit to Private non-financial sector from All sectors at Market value - Percentage of GDP - Adjusted for breaks	5	BIS	2000 Q1	2019 Q4	
Stock Prices & Home Ownership						
SP	Share Prices, Index 2010=100	5	OECD	EA19	2000 Q1	2019 Q4
OWN	Distribution of population by tenure status: ownership, percentage	5	Eurostat	EA19	2000 Q1	2019 Q4
Housing Prices						
RENTS	HIPC Actual rents for housing, Index 2010=100	5	Eurostat	EACC	2000 Q1	2019 Q4
HPI	House Price Index, 2010=100	5	Eurostat	EACC	2005 Q1	2019 Q4
RHPI	Real House Price Index (=HPI/HICP00)	5	Eurostat	EACC	2005 Q1	2019 Q4
RENTS	HIPC Actual rents for housing, Index 2010=100	5	Eurostat	EACC	2000 Q1	2019 Q4
RRENTS	Real rents (=RENTS/HICP00)	5	Eurostat	EACC	2000 Q1	2019 Q4
BUILDCOSTI	Construction Cost Index, Residential Buildings (2010=100,WDSA)	5	Eurostat	EACC	2000 Q1	2019 Q4
Exchange Rates						
NEER	Euro Nominal Effective Exchange Rate - 42 trading partners, Index 2005=100	5	Eurostat	EA19	2000 Q1	2019 Q4
EXRUK	Foreign Exchange Rate: United Kingdom (GBP per EUR - quarterly average)	5	Eurostat	EA19	2000 Q1	2019 Q4
EXRCHF	Foreign Exchange Rate: Switzerland (CHF per EUR - quarterly average)	5	Eurostat	EA19	2000 Q1	2019 Q4
EXRJP	Foreign Exchange Rate: Japan (JPY per EUR - quarterly average)	5	Eurostat	EA19	2000 Q1	2019 Q4
EXRUS	Foreign Exchange Rate: United States of America (USD per EUR - quarterly average)	5	Eurostat	EA19	2000 Q1	2019 Q4

Series	Description	T	Source	Geography	Start	End
Expectations						
BSBCI	Euro area Business Climate Indicator (SA)	2	Eurostat	EA19	2000 Q1	2019 Q4
BSCCI	Construction Confidence Indicator (SA)	2	Eurostat	EA19	2000 Q1	2019 Q4
BSESI	Economic Sentiment Indicator Indicator (SA)	2	Eurostat	EA19	2000 Q1	2019 Q4
BSICI	Industrial Confidence Index (SA)	2	Eurostat	EA19	2000 Q1	2019 Q4
BSICI	Retail Confidence Index (SA)	2	Eurostat	EA19	2000 Q1	2019 Q4
BSICI	Consumer Confidence Index (SA)	2	Eurostat	EA19	2000 Q1	2019 Q4
BSICI	Services Confidence Index (SA)	2	Eurostat	EA19	2000 Q1	2019 Q4

B Appendix - Robustness check

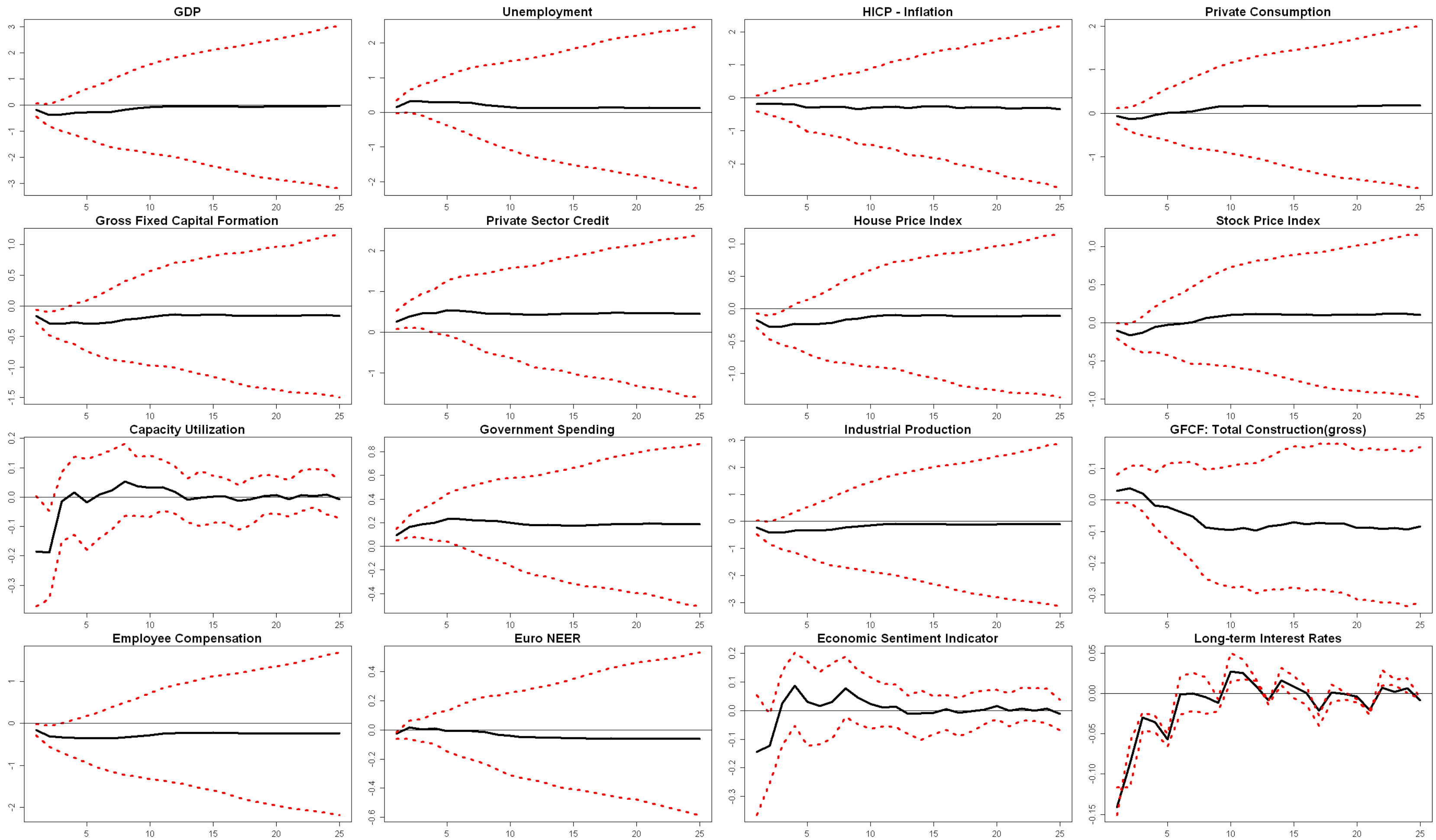

Figure B.1: Impulse response functions of a one standard deviation positive demand shock for 25 steps. Model estimated with four lags and three factors for the robustness check. Sign restrictions set to hold for two quarters. One step equals to one quarter. Black lines show the median of the simulations and the red dashed lines report the 16% and the 84% impulse responds confidence bands.

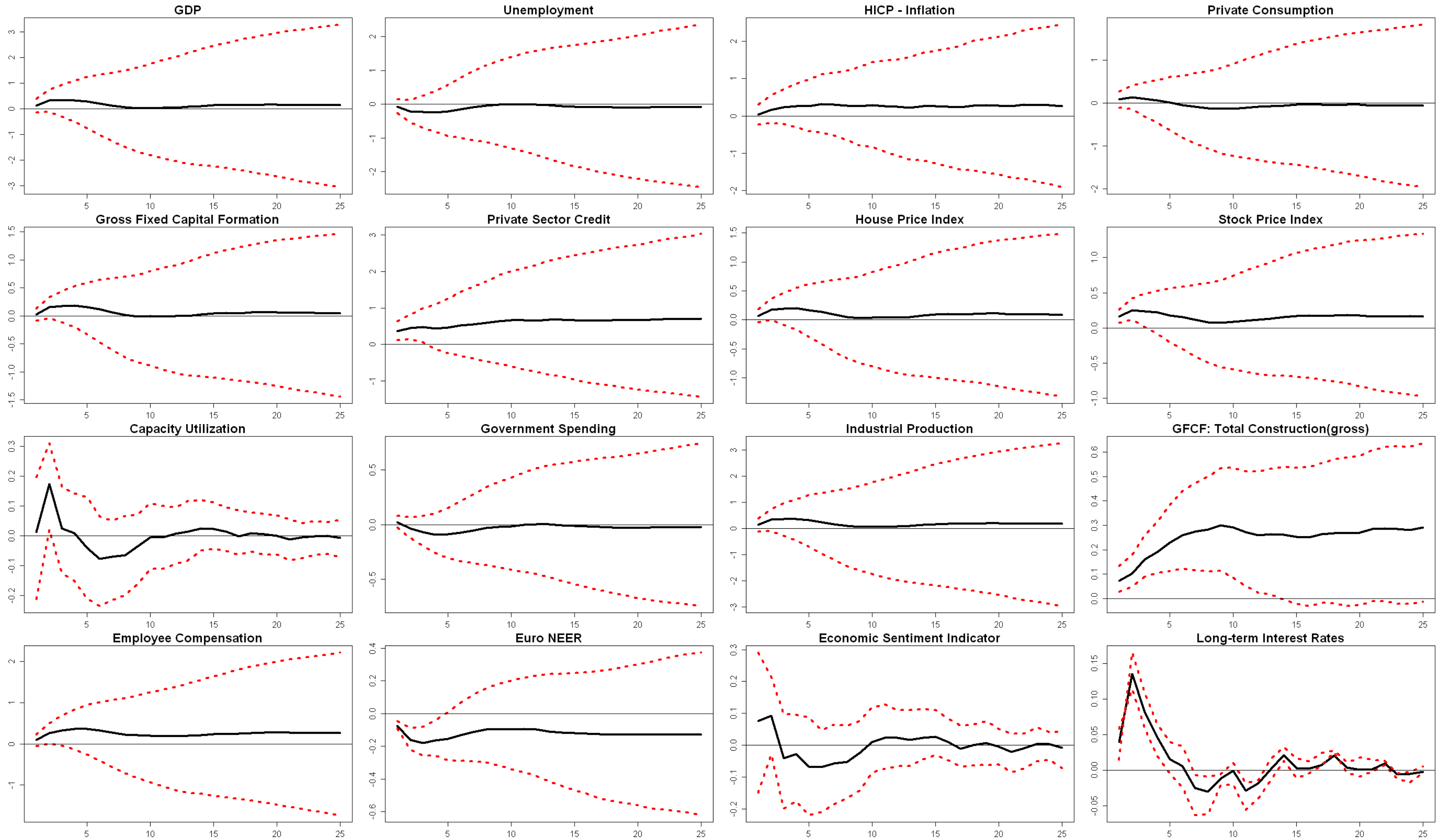

Figure B.2: Impulse response functions of a one standard deviation positive supply shock for 25 steps. Model estimated with four lags and three factors, with the sign restriction set to hold for two periods, for the robustness check. One step equals to one quarter. Black lines show the median of the simulations and the red dashed lines report the 16% and the 84% impulse responds confidence bands.

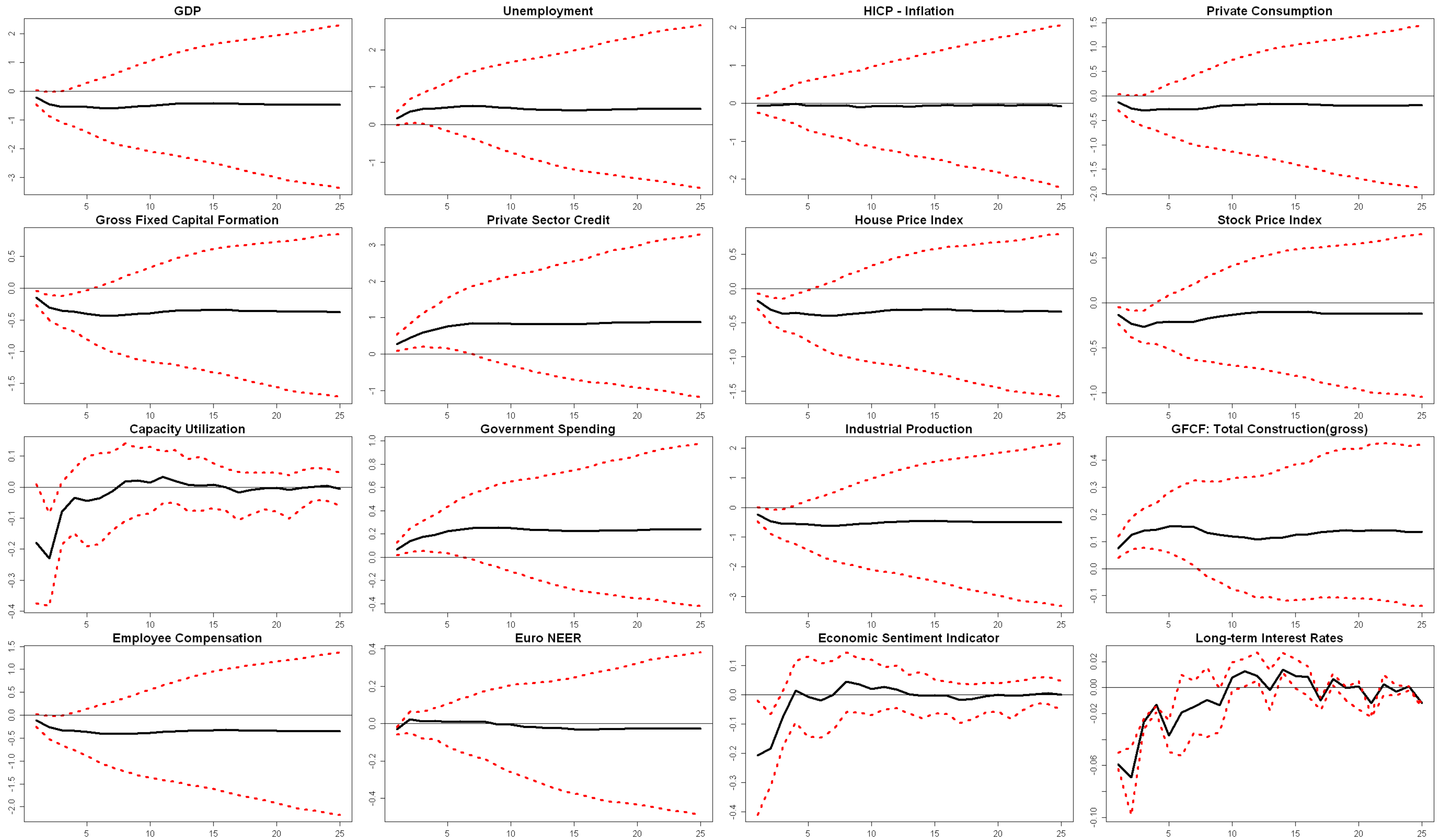

Figure B.3: Impulse response functions of a one standard deviation positive demand shock for 25 steps. Model estimated with four lags and three factors, with the sign restriction set to hold for three periods, for the robustness check. Black lines show the median of the simulations and the red dashed lines report the 16% and the 84% impulse responds confidence bands.

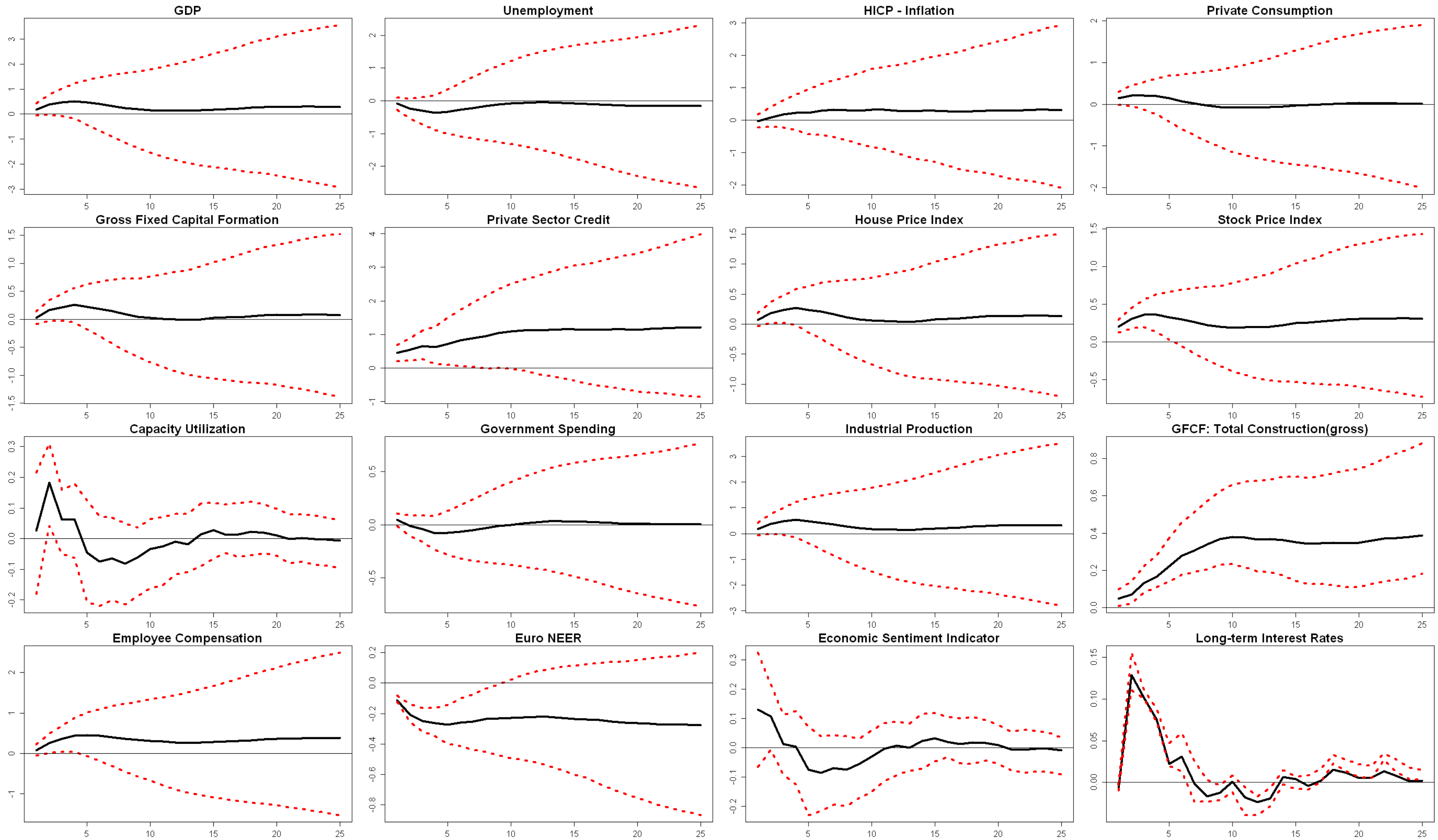

Figure B.4: Impulse response functions of a one standard deviation positive supply shock for 25 steps. Model estimated with four lags and three factors, with the sign restriction set to hold for three periods, for the robustness check. Black lines show the median of the simulations and the red dashed lines report the 16% and the 84% impulse responds confidence bands.

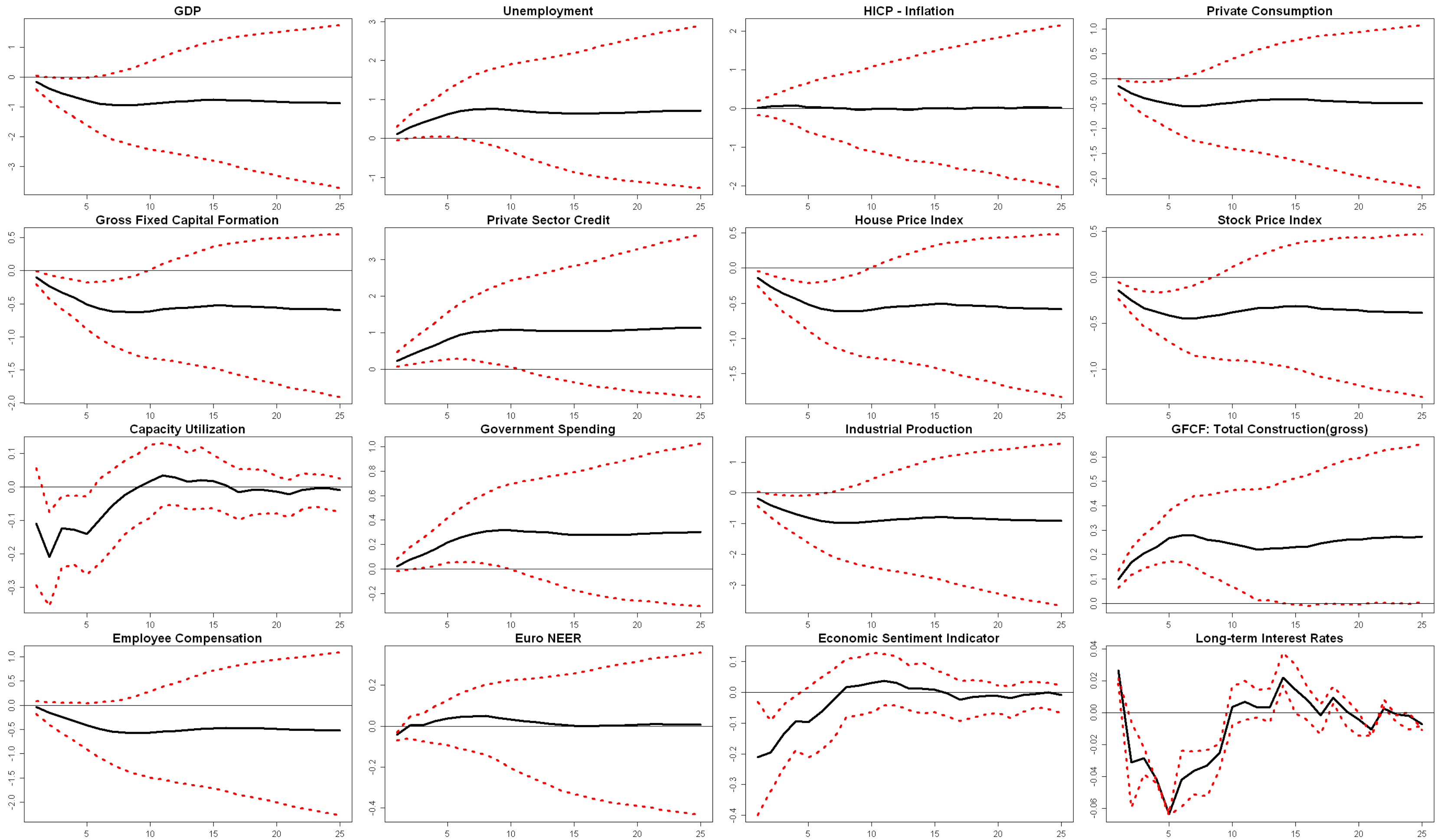

Figure B.5: Impulse response functions of a one standard deviation positive demand shock for 25 steps. Model estimated with four lags and three factors, with the sign restriction set to hold for four periods, for the robustness check. Black lines show the median of the simulations and the red dashed lines report the 16% and the 84% impulse responds confidence bands.

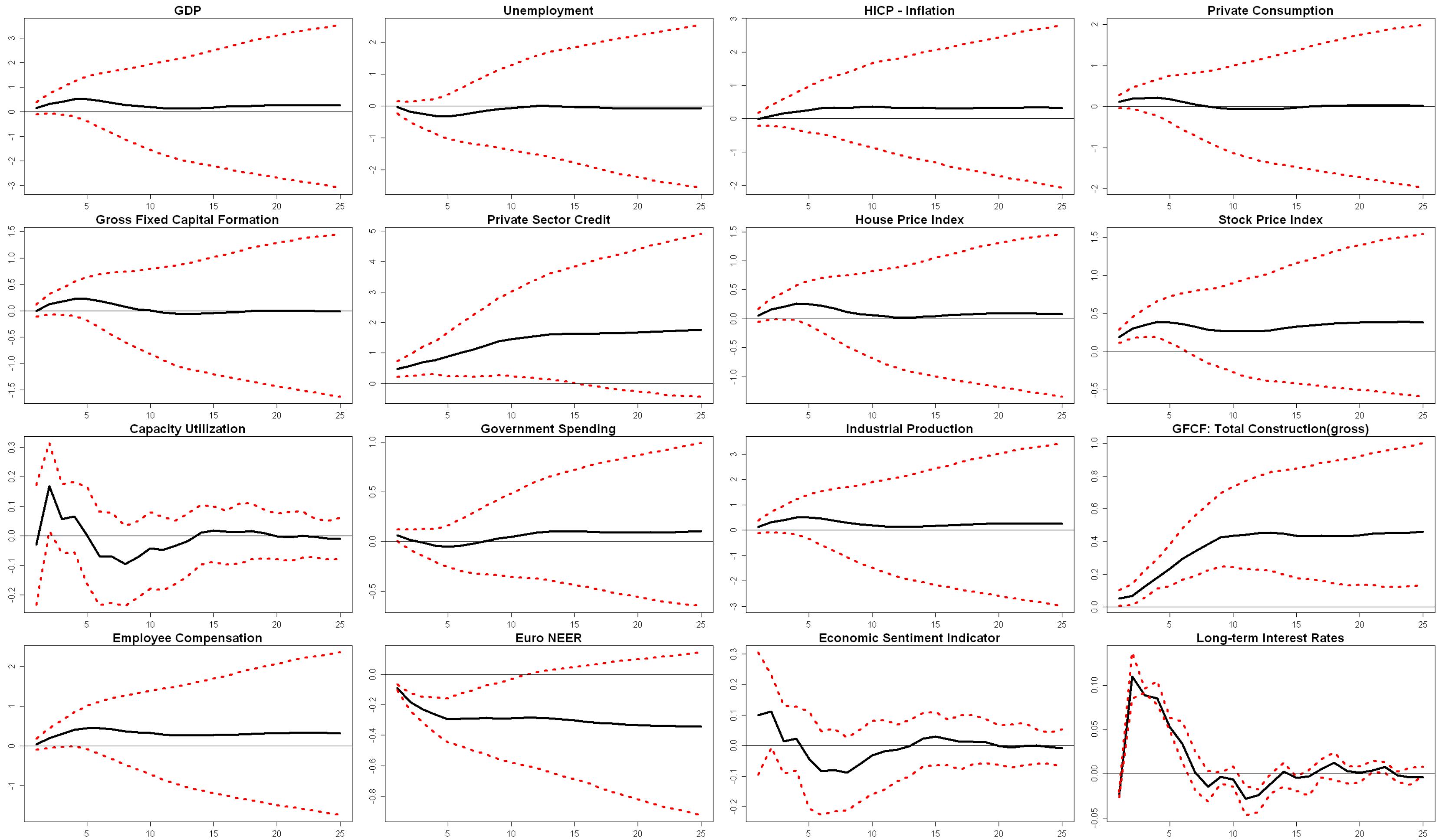

Figure B.6: Impulse response functions of a one standard deviation positive supply shock for 25 steps. Model estimated with four lags and three factors, with the sign restriction set to hold for four periods, for the robustness check. Black lines show the median of the simulations and the red dashed lines report the 16% and the 84% impulse responds confidence bands.

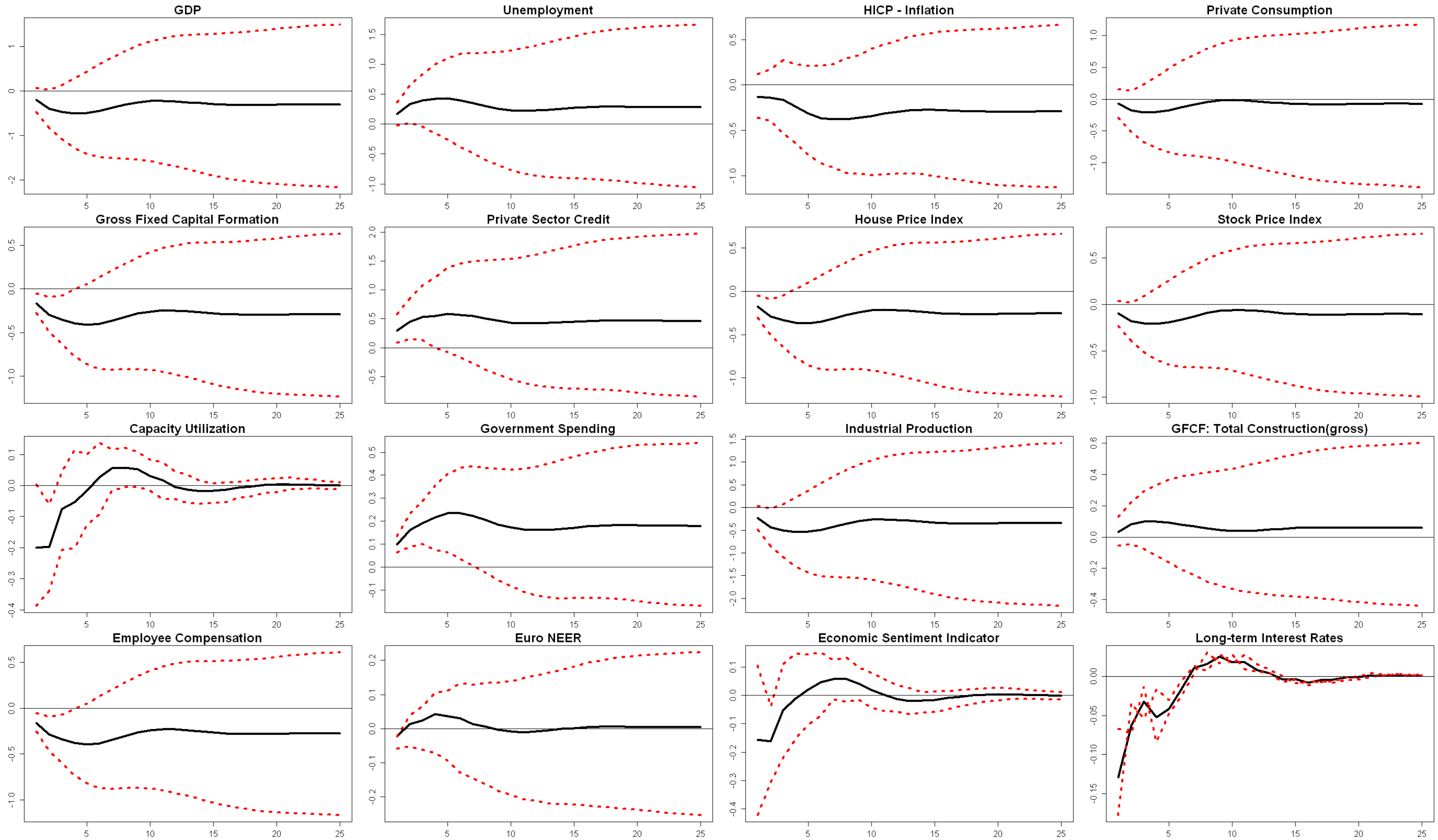

Figure B.7: Impulse response functions of a one standard deviation positive demand shock for 25 steps. Model estimated with three lags and two factors, with the sign restriction set to hold for two periods, for the robustness check. Black lines show the median of the simulations and the red dashed lines report the 16% and the 84% impulse responds confidence bands.

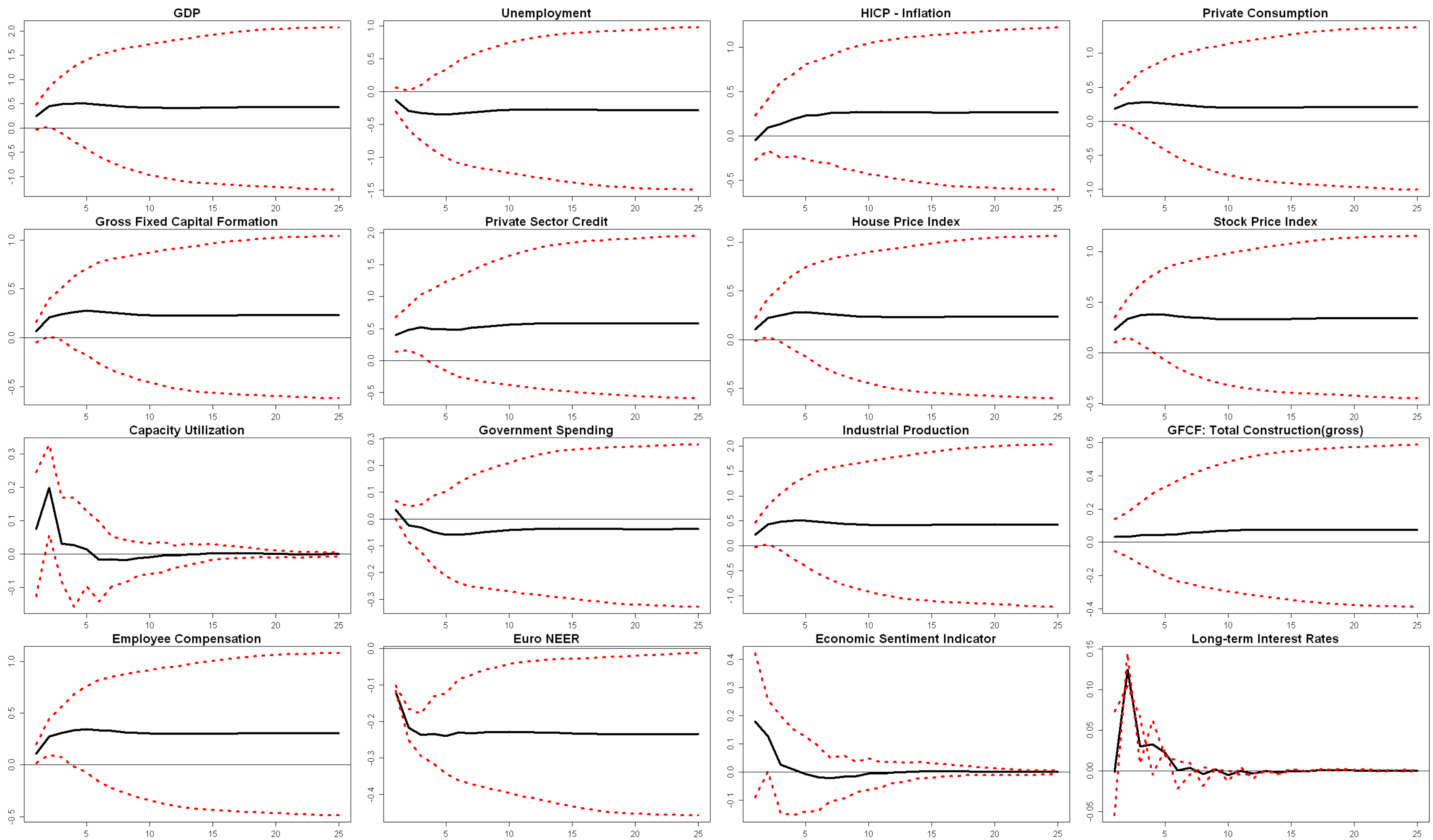

Figure B.8: Impulse response functions of a one standard deviation positive supply shock for 25 steps. Model estimated with three lags and two factors, with the sign restriction set to hold for two periods, for the robustness check. Black lines show the median of the simulations and the red dashed lines report the 16% and the 84% impulse responds confidence bands.

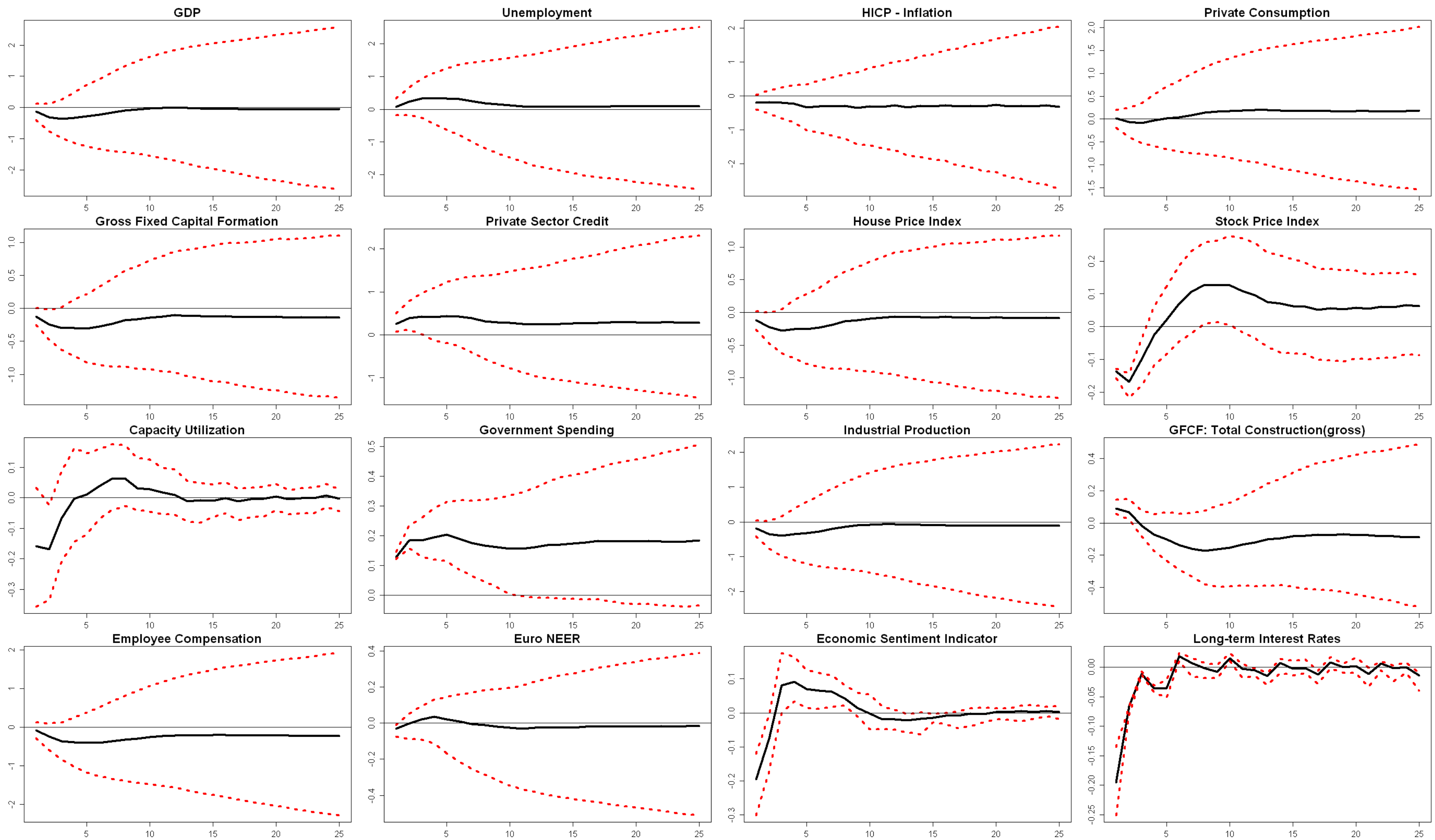

Figure B.9: Impulse response functions of a one standard deviation positive demand shock for 25 steps. Model estimated with three lags and four factors, with the sign restriction set to hold for two periods, for the robustness check. Black lines show the median of the simulations and the red dashed lines report the 16% and the 84% impulse responds confidence bands.

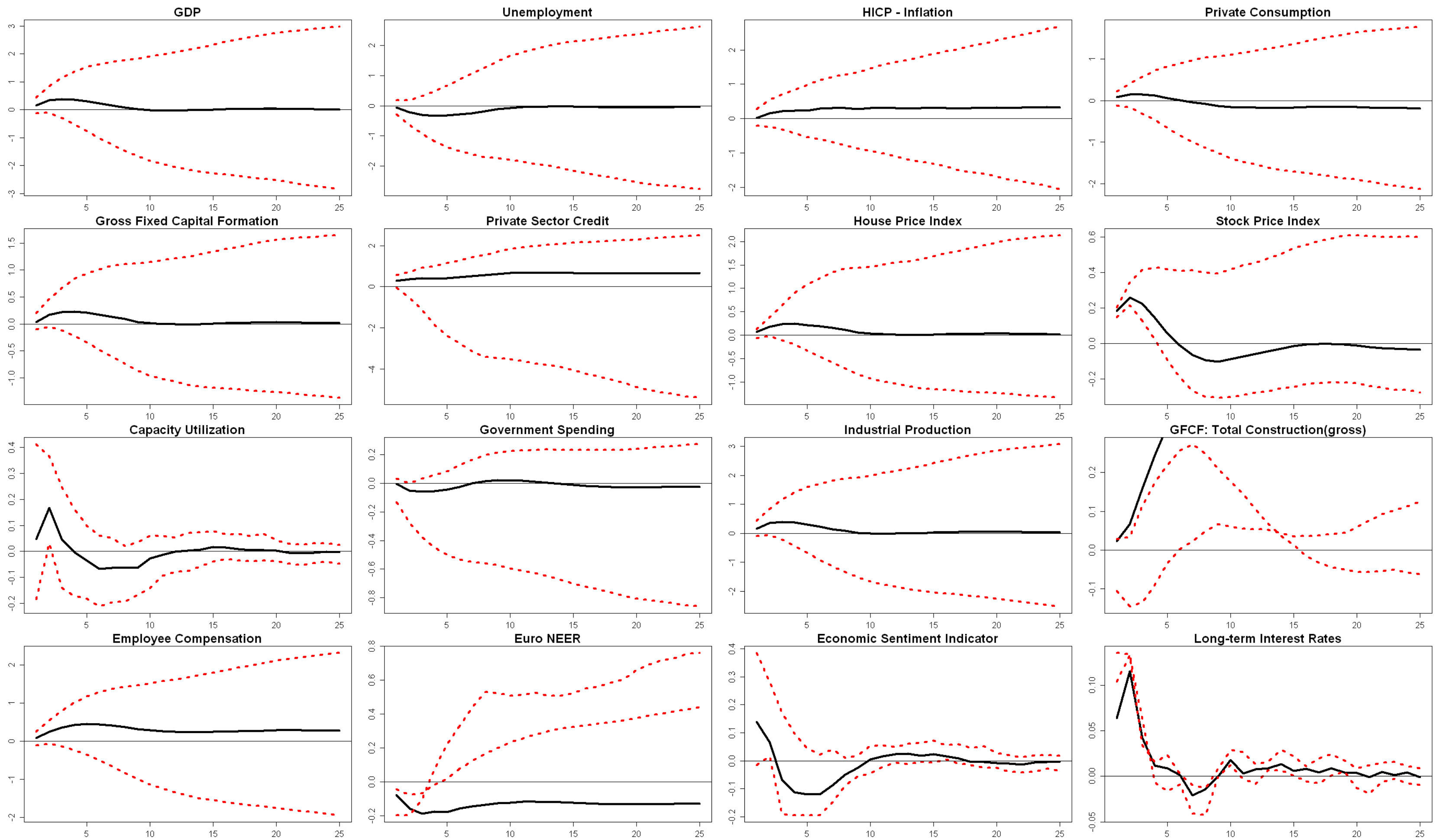

Figure B.10: Impulse response functions of a one standard deviation positive supply shock for 25 steps. Model estimated with three lags and four factors, with the sign restriction set to hold for two periods, for the robustness check. Black lines show the median of the simulations and the red dashed lines report the 16% and the 84% impulse responds confidence bands.

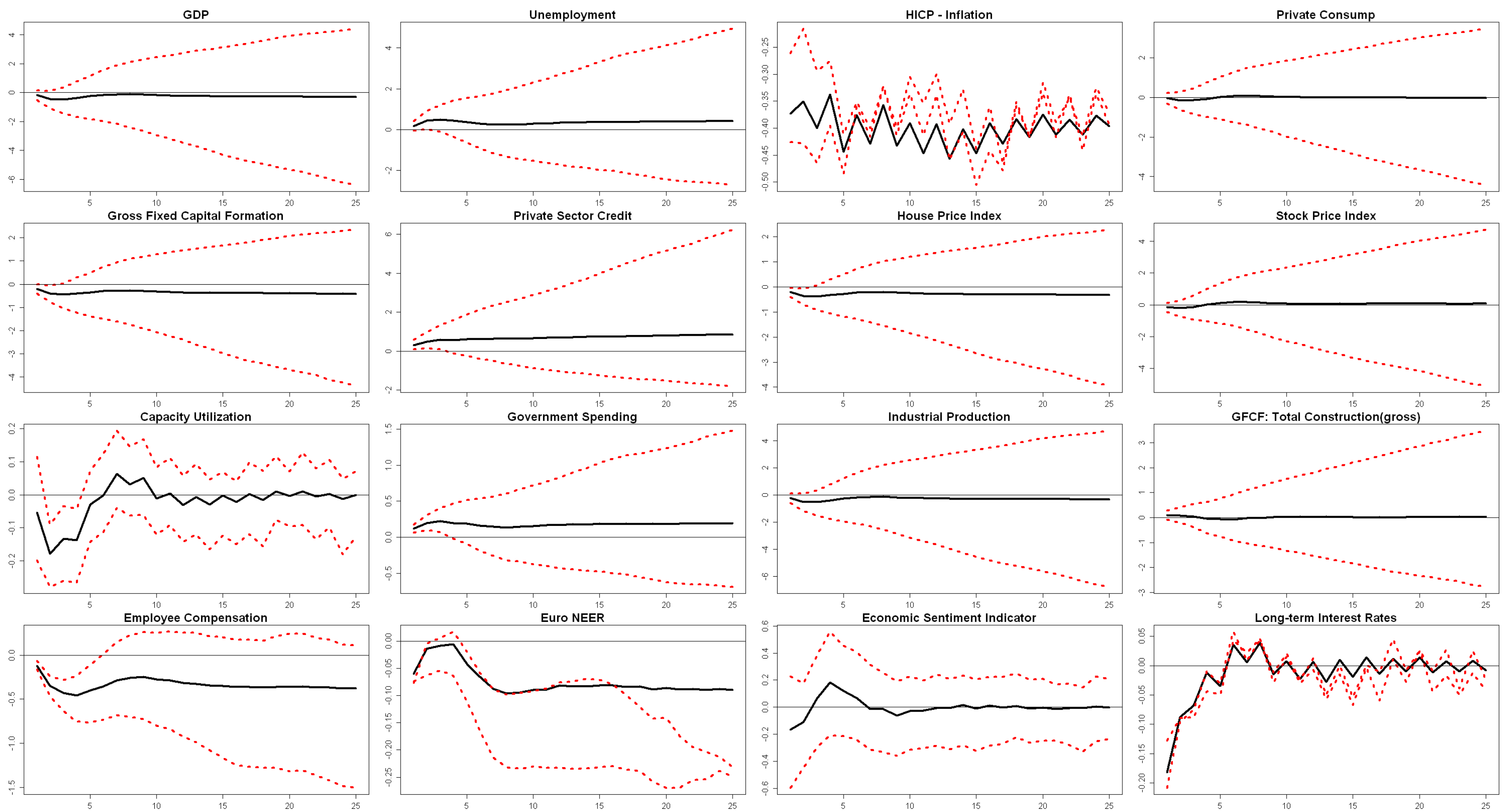

Figure B.11: Impulse response functions of a one standard deviation positive demand shock for 25 steps for the subsample 2008Q1-2019Q4. One step equals to one quarter. Black lines show the median of the simulations and the red dashed lines report the 16% and the 84% impulse responds confidence bands.

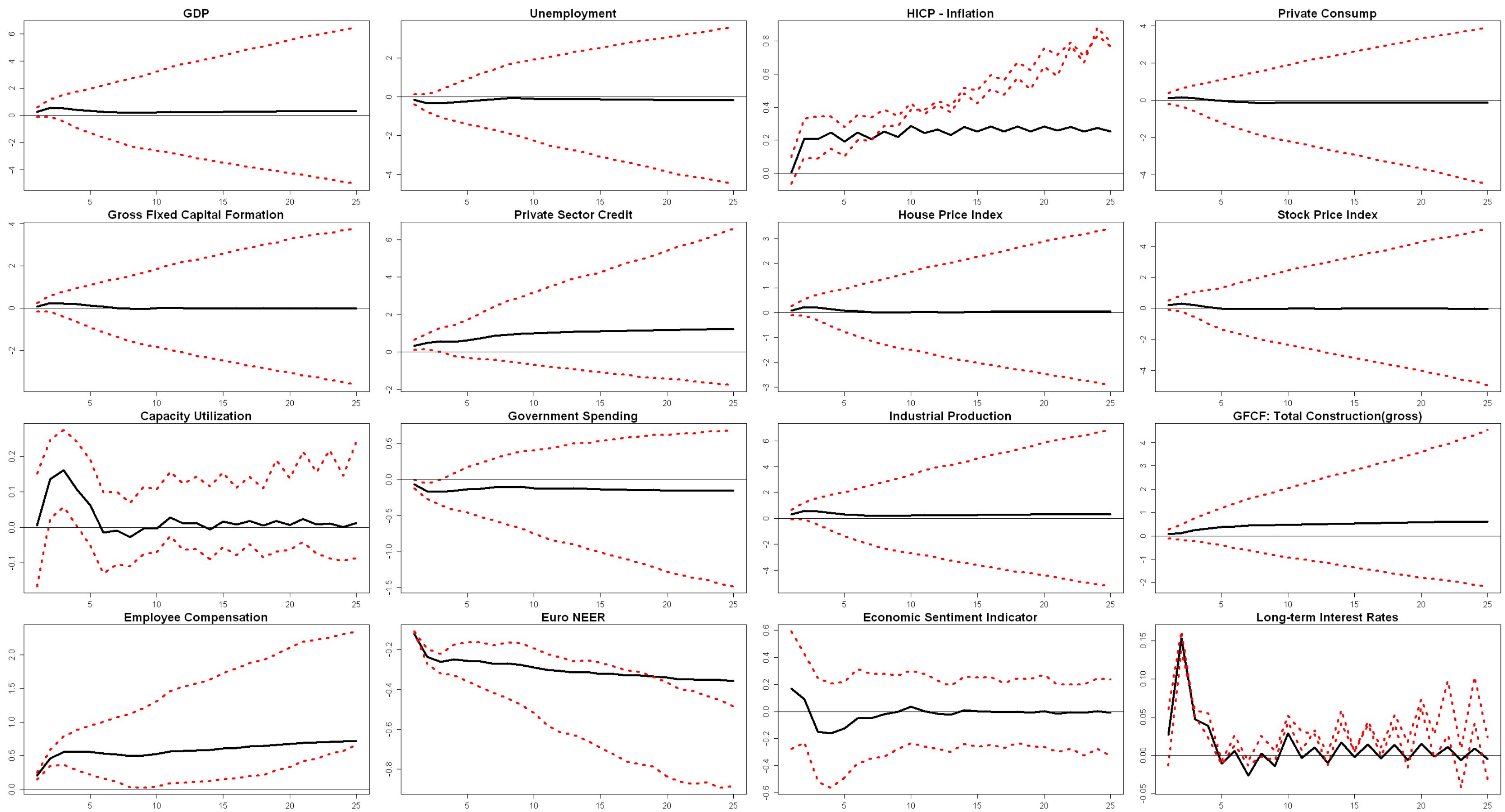

Figure B.12: Impulse response functions of a one standard deviation positive supply shock for 25 steps for the subsample 2008Q1-2019Q4. One step equals to one quarter. Black lines show the median of the simulations and the red dashed lines report the 16% and the 84% impulse responds confidence bands.

C Appendix - PCA

Appendix C reports the output of the Principal Component Analysis (PCA) for the full data set and its two subsets 2000Q2-2007Q4 and 2008Q1-2019Q4 together with the individual proportion of the variance the each of the three factors explain and the total cumulative proportion.

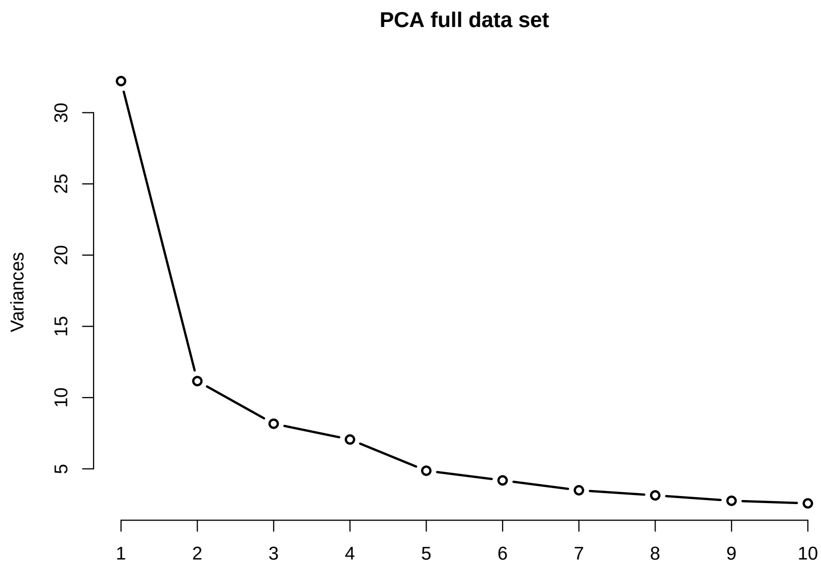

Figure C.1: PCA result for the full data set

Indicator	PC 1	PC 2	PC 3
Standard deviation	5.6760	3.3404	2.85770
Proportion of Variance	0.3068	0.1063	0.07778
Cumulative Proportion	0.3068	0.4131	0.49088

Table C.1: Importance of first k=3 (out of 79) components, full data set

Indicator	PC 1	PC 2	PC 3
Standard deviation	4.3116	3.0744	2.62860
Proportion of Variance	0.2372	0.1206	0.08816
Cumulative Proportion	0.2372	0.3578	0.44597

Table C.2: Importance of first k=3 (out of 31) components, pre-2008 subsample

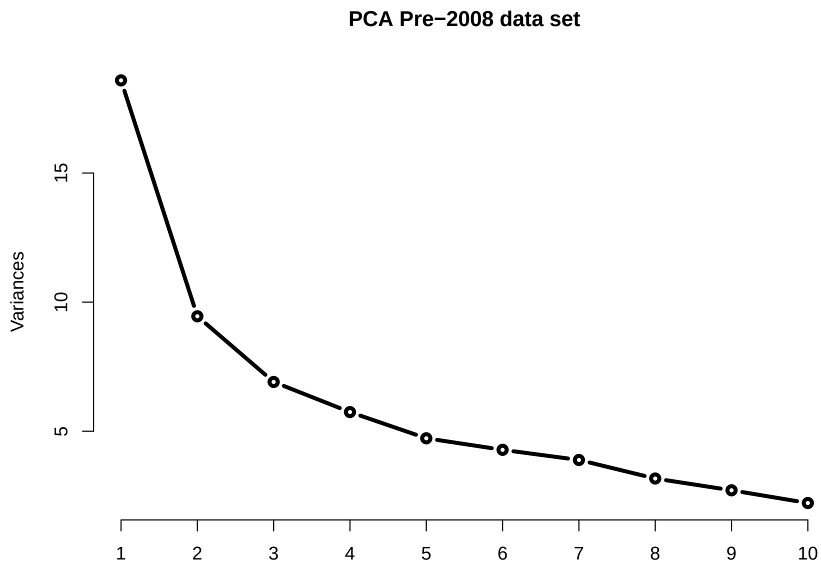

Figure C.2: PCA result for the pre-2008 sample split

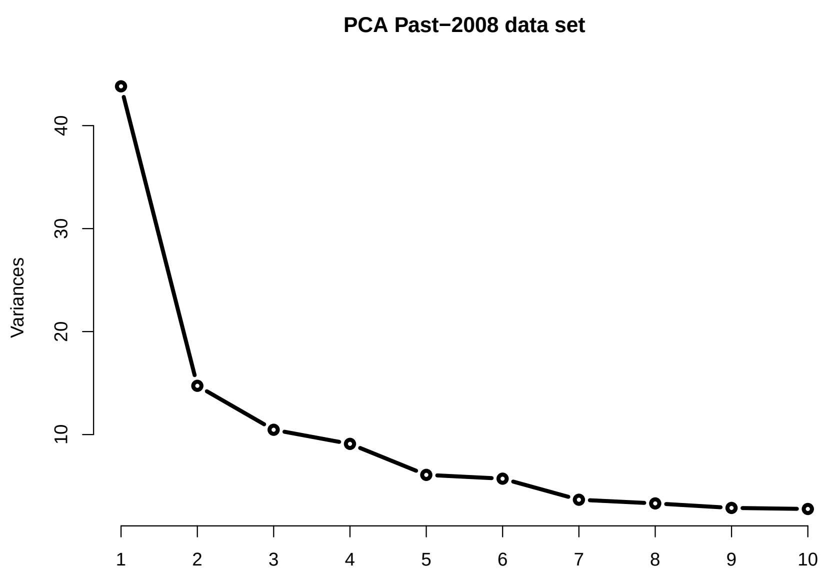

Figure C.3: PCA result for the past-2008 sample split

Indicator	PC 1	PC 2	PC 3
Standard deviation	6.6194	3.8387	3.23529
Proportion of Variance	0.3527	0.1186	0.08426
Cumulative Proportion	0.3527	0.4713	0.55557

Table C.3: Importance of first k=3 (out of 48) components, past-2008 subsample

Series	R squared	Series	R squared	Series	R squared
GDP	0,85	HICP_06	0,03	ORDM	0,85
PCON	0,36	HICP_07	0,52	SP	0,35
G	0,09	HICP_08	0,09	EONIA	0,72
CON	0,23	HICP_09	0,00	EUSWEI1	0,73
GFCF	0,38	HICP_10	0,10	CAPUTIL	0,69
IM	0,87	HICP_11	0,03	U	0,49
EX	0,61	HICP_12	0,32	EMP	0,38
WIN	0,41	HICPXFD	0,92	NEER	0,12
HICP	0,94	HICPXUTIL	0,93	GDPDEF	0,14
PPI	0,87	HICPXHTH	0,93	PCDEF	0,78
UTIL	0,75	HICPUTIL	0,75	GFCFDEF	0,10
RENTS	0,14	GFCFC	0,13	GDEF	0,14
RRENTS	0,93	GFCFD	0,77	EXDEF	0,72
HPI	0,34	STINT	0,72	IMDEF	0,74
RHPI	0,45	LTINT	0,29	CPIIMF	0,60
IPIT	0,87	MIR	0,36	CREDIT_G	0,40
IPIING	0,87	COB	0,50	CREDIT_PRIVATSECTOR	1,00
IPINRG	0,13	CPIECB	0,40		
IPICAG	0,75	OIL	0,54		
IPICOG	0,55	EXRUK	0,17		
IPIDCOG	0,76	EXRSW	0,11		
IPINDCOG	0,42	EXRJP	0,34		
IPIMQ	0,14	EXRUS	0,18		
IPIM	0,88	EURIBOR3MD	0,72		
PPIING	0,79	EURIBOR6MD	0,74		
PPICAG	0,43	EURIBOR1YD	0,73		
PPINDCOG	0,58	YLD$_{3}Y$	0,24		
PPIM	0,87	YLD$_{5}Y$	0,24		
ITIING	0,90	YLD$_{1}0Y$	0,19		
ITINRG	0,66	REFI	0,79		
ITICAG	0,74	S3MDREFI	0,52		
ITICOG	0,58	S10YYLDREFI	0,30		
ITIDCOG	0,58	SMIRREFI	1,00		
ITINDCOG	0,48	BUILD	0,18		
ITIM	0,91	BSBCI	0,71		
BUILDCOSTI	0,61	BSCCI	0,63		
PROCO	0,17	BSESI	0,60		
LABCON	0,21	BSICI	0,64		
ULC	0,68	BSRCI	0,47		
PRD	0,61	BSCSMCI	0,45		
HICP_01	0,35	BSSCI	0,47		
HICP_02	0,04	ORDING	0,83		
HICP_03	0,82	ORDCAG	0,59		
HICP_05	0,76	ORDCOG	0,51		

Table C.4: R squared of linear regression of the respective series on the three factors, the spread and private sector debt. Series with a lower R squared a more driven by idiosyncratic forces and less so by the common factors, compare Amir-Ahmadi and Uhlig (2012).