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Bank of Finland
Research Unit

PO Box 160
FIN-00101 Helsinki

Phone: +358 9 1831

Email: research@bof.fi
Website: www.bof.fi/en/research

Measuring the effects of conventional and unconventional monetary policy in the euro area

Juho Anttila *

May 21, 2018

Abstract

I estimate the effects of conventional and unconventional monetary policy in the euro area by using a factor-augmented vector autoregression. I complement the standard monetary policy analysis using the short rate with models where the shadow rates by Kortela (2016) and Wu and Xia (2017) are used as proxies for unconventional monetary policy. I quantify the effects of unanticipated monetary policy shocks using impulse response functions, forecast-error variance decompositions, and counterfactual simulations. The results indicate that unconventional monetary policy shocks have similar, expansionary effects on the economy as conventional monetary policy shocks.

Keywords: monetary policy, output, inflation, employment, zero lower bound

JEL classification codes: E43, E44, E52, E58

*I wrote most of this paper while I was working at the Research Unit of the Bank of Finland. My current affliation is with the Research Institute of the Finnish Economy (ETLA). I am grateful to Mika Meitz, Miika Päällysaho and the seminar participants at the Bank of Finland for their helpful comments and suggestions. This paper is based on my Master's thesis which I submitted in December 2017 at the University of Helsinki. All the views and errors presented in this paper are my own. For enquiries, please contact me under juhojmanttila@gmail.com.

1 Introduction

Before the financial crisis in 2008 central banks conducted monetary policy mainly by targeting the short-term nominal interest rate. However, following the crisis the short-term interest rates were pushed down close to zero, leaving them impotent as policy variables and forcing central banks to adopt various unconventional policy measures, such as direct asset purchases. In contrast to conventional monetary policy, where a consensus on its effects emerged among researchers and policymakers, the effects of unconventional monetary policy (UMP) are less studied and well known, and identifying the effects of UMP has proven to be a difficult challenge. Moreover, the bulk of the studies focus on UMP's impact on the financial markets and, in particular, the yield curve (see, for example, Krishnamurthy and Vissing-Jorgensen (2011) or Joyce et al. (2012)), while the broader macroeconomic impacts of UMP have received less attention.

In this paper I contribute to this topic by studying the impact of ECB's unconventional monetary policy on macroeconomic variables such as GDP, inflation, and employment. Following Wu and Xia (2016), I estimate impulse response functions from a factor-augmented vector autoregression (FAVAR) for the euro area and identify the effects of unconventional monetary policy by using the shadow rates by Wu and Xia (2017) and Kortela (2016). Expansionary UMP shocks are followed by small-but-significant and persistent output responses, whereas the responses of prices are more subdued. Comparisons to models with the standard nominal rate as the policy variable suggest that unconventional monetary policy shocks have similar macroeconomic effects to conventional monetary policy shocks. Finally, I complement the impulse response analysis with forecast-error variance decompositions and counterfactual simulations. Overall, my results suggest that monetary policy shocks have had fairly small effects on the overall euro area economy with monetary policy likely influencing the economy through its anticipated part.

My study is part of the vast literature on monetary policy VARs.[1] Bernanke

[1]Overall, this literature is far too large to be summarized concisely here. Influential studies include, but are not limited to, Bernanke and Mihov (1998), Christiano et al. (1999),

et al. (2005) introduced the FAVAR methodology in monetary policy analysis, and it has been previously applied to the euro area by Soares (2013). Finally, Wu and Xia (2016) use a FAVAR with a shadow rate to study the effects of unconventional monetary policy in the US.

Several studies have used various different approaches to study the macroeconomic effects of unconventional monetary policy. Chung et al. (2012) and Kapetanios et al. (2012) take the reductions in yields from previous event-studies as given and then simulate their effects with a structural model. Their results suggest that the unconventional monetary policy measures had a large impact on the economy both in the US and the UK. Gambacorta et al. (2014) use cross-country data and a panel VAR to study the effects of unconventional monetary policy. They identify UMP shocks as unexpected changes in the central bank's balance sheet. Their results suggest that the monetary policy has been mainly driven by the endogenous responses of the central bank rather than unanticipated shocks. Finally, Meinusch and Tillmann (2016) model the central bank's policy as a latent variable, in the same spirit as Wu and Xia (2016). They also find positive output and inflation responses.

Finally, studies focusing on monetary policy in the euro area include Peersman and Smets (2003), Soares (2013), Rafiq and Mallick (2008), Gambetti and Musso (2017) and Puonti (2016). The evidence from the euro area is mostly in line with studies using data from different geographical regions, with the exception of Puonti (2016), who documents differences in the shapes of impulse responses to monetary policy shocks between US, Japan and the euro area. Furthermore, there is some evidence of heterogeneity in the transmission of monetary policy within different euro area countries (see Peersman and Smets (2005) and Rafiq and Mallick (2008)).

The rest of the paper is organized as follows. The second section discusses the econometric framework used in this paper. The third section describes the data, and fourth section presents and discusses the results. Finally, the fifth section concludes.

Uhlig (2005) and Primiceri (2005).

2 Econometric Framework

This section provides a brief summarization of the shadow rate term-structure model (SRTSM) used to create the shadow rate variables. The idea is to model the yields as affine functions of some underlying macroeconomic factors. However, rather than estimating the rates by myself I use directly the estimates from Kortela (2016) and Wu and Xia (2017). Therefore, I do not discuss the details of the models and, refer the reader to the original papers.

In addition, I will present the FAVAR and its estimation. Bernanke et al. (2005) provide two alternatives for estimating a factor-augmented vector autoregression: 1. Bayesian likelihood based inference using Gibbs sampling 2. Two-stage estimation using principal components estimator for the faCTORS I use the latter alternative as it is more commonly used in the literature (see, for example, Soares (2013) and Wu and Xia (2016)) and more straightforward to implement. Bernanke et al. (2005) did not find strong preference for either alternative.

When using VARs the number of extra parameters to be estimated increases rapidly with each new variable added to the model. In contrast, dynamic factor structure is relatively parsimonious as only k factor loadings need to be estimated for each extra variable and indeed, when using non-parametric least squares methodology, there is no strict upper bound for the number of series to be included. This has made dynamic factor models a popular way of modeling time-series data with large cross-sections (Stock et al., 2010).

I follow closely Bernanke et al. (2005) in the implementation of my empirical strategy. More specifically, I extract common factors from a large panel of macroeconomic indicators and then use these indicators along with the the central bank's policy rate in a VAR. I use the two-step estimation process by Bernanke et al. (2005) where the estimated factors from the first-step are used as endogenous variables in a VAR in the second step. In order to identify the monetary policy shocks I use the standard scheme which is based on timing restrictions and recursive ordering of the variables.

2.1 Shadow rate

In the shadow rate models the short-term interest rate r_t equals either the shadow rate s_t or some (possibly time-varying) lower bound $\underline{r_t}$:

$$r_t = \max(s_t, \underline{r_t}).$$

The shadow rate, in turn, is an affine function of three latent macroeconomic factors X_t, commonly called *level*, *slope* and *curvature*:

$$s_t = \delta_0 + \delta_1' X_t. \tag{1}$$

The dynamics of these factors can be described by a first-order vector autoregression both under physical and risk-neutral probability measures:

$$X_{t+1} = c + \rho X_t + \Sigma u_{t+1}, \quad u_t \sim N(0, I_M). \tag{2}$$

$$X_{t+1} = c^{\mathbb{Q}} + \rho^{\mathbb{Q}} X_t + \Sigma u_{t+1}^{\mathbb{Q}}, \quad u_t^{\mathbb{Q}} \sim N(0, I_M). \tag{3}$$

Finally, the no-arbitrage condition implies that the price $P_{n,t}$ of a pure discount asset with maturity n at date t is the given by the expression

$$P_{n,t} = \mathbb{E}_t^{\mathbb{Q}}[\exp(-r_t) P_{n-1,t+1}]. \tag{4}$$

The system is then typically estimated with the help of analytical approximations derived by Krippner (2012), Wu and Xia (2016) and Wu and Xia (2017). The shadow rate models by Kortela (2016) and Wu and Xia (2017) differ in the way the time-variation in the lower-bound is modeled. Kortela (2016) considers various exogenous schemes for the time-variation; the one used in the shadow rate that I use treats the lower bound simply as an extra parameter to be estimated. Wu and Xia (2017), in turn, argue for endogenizing the time-variation as exogenous changes in the lower-bound imply that investors in the model are myopic rather than forward-looking. They model the time-variation as a discrete regime-switching process and also include a non-constant spread between the policy rate and the short-term government bond yield.

There are some concerns that have been raised regarding the use of shadow rates. As discussed by Christensen and Rudebusch (2015) and Bauer and Rudebusch (2016) the shadow rates produced by the SRTSMs can be sensitive to the modeling choices such as the value of a (fixed) lower bound. Since both Kortela (2016) and Wu and Xia (2017) shadow rate use a time-varying lower bound it is possible that this problem is less severe in the rates that I use. Nonetheless, more work is likely to be needed to study the robustness of the estimated shadow rates to different modeling choices.

2.2 Common factors and factor-augmented VAR

Let y_t and f_t denote $n \times 1$ and $k \times 1$ vectors of observed variables and unobserved common components at time t, respectively. *A (dynamic) factor model* has the following structure[2]:

$$y_t = \Lambda f_t + \nu_t, \tag{5}$$

where Λ is a $n \times k$ matrix of factor loadings and ν_t is the $n \times 1$ vector of idiosyncratic components. Intuitively, (5) states that the evolution of y_t can be explained by a small subset of common factors f_t which are often assumed to follow an autoregressive process. Typically, it is required that $k \ll n$, that is, the number of factors is a lot smaller than the number of observables.

The principal component estimator is obtained as a solution to the following least squares problem:

$$\min_{f_1,\dots,f_T,\Lambda} V(\Lambda, f) = \frac{1}{NT} \sum_{t=1}^{T} (y_t - \Lambda f_t)'(y_t - \Lambda f_t). \tag{6}$$

Since both common factors and loadings are unobserved the normalization $N^{-1}\Lambda'\Lambda = I_r$ is needed for the solution. Using this normalization, the solution to (6) is given by $\hat{f}_t = N^{-1}\hat{\Lambda}' y_t$ where $\hat{\Lambda}$ is the matrix of the eigenvectors

[2]Strictly speaking, the model 5 is an approximate rather than dynamic factor model as it only includes current and not lagged values of f_t. Nevertheless, this distinction is somewhat arbitrary as f_t can be a vector that stacks both current and lagged values of the factors. The principal components estimator that I use is non-parametric and thus the factor dynamics are not modeled explicitly.

corresponding to the k largest eigenvalues of the sample covariance matrix $T^{-1} \sum_{t=1}^{T} y_t y_t'$.

The factor-augmented vector autoregression (FAVAR) is then defined as simply a VAR consisting of unobserved factors f_t and observed factors r_t:

$$\begin{pmatrix} f_t \\ r_t \end{pmatrix} = \boldsymbol{\mu} + \boldsymbol{B_1} \begin{pmatrix} f_{t-1} \\ r_{t-1} \end{pmatrix} + \boldsymbol{...} + \boldsymbol{B_p} \begin{pmatrix} f_{t-p} \\ r_{t-p} \end{pmatrix} + \boldsymbol{u_t}. \tag{7}$$

In my application, r_t contains only the policy variable which is either the nominal short-term interest rate or the shadow rate. I estimate equation (7) using OLS and impose structural restrictions by using the Cholesky decomposition of the residual covariance matrix. This identification corresponds to the standard recursive VAR where the policy rate is ordered last.

It is important to note that the principal components estimator recovers the whole vector space spanned by the common factors. Moreover, this space also contains the observed macroeconomic factors. To deal with this, I follow Bernanke et al. (2005) and divide the indicators y_t into slow-moving and fast-moving variables and assume that only the fast-moving variables react to monetary policy shocks on impact. More precisely, denote $\widehat{C(f_t, r_t)}$ as the first k principal components estimate of the space spanned by both unobserved and observed factors and $\widehat{C(f_t)}^*$ as the k principal components estimated from the slow-moving variables only. In order to obtain the estimate for the factors used in the VAR I run the regression $\widehat{C(f_t, r_t)} = \beta_{C^*} \widehat{C(f_t)}^* + \beta_r r_t + \zeta_t$ and construct the factors as $\hat{f}_t = \widehat{C(f_t, r_t)} - \hat{\beta}_r r_t$.

Finally, the impulse response functions can be calculated by regressing the variables of interest on the common factors and the policy rate:

$$y_{i,t} = \beta_{i,0} + \beta_{i,f} f_t + \beta_{i,r} r_t + \eta_t.$$

For the slow-moving variables the restriction $\beta_{i,r} = 0$ is imposed. In order to construct confidence intervals for the impulse response functions I use the same bootstrap-within-bootstrap algorithm as Bernanke et al. (2005) which takes into account uncertainty associated with both factor and VAR estimation.

3 Data

I mainly follow Soares (2013) in picking the indicator series that I use to extract the factors. In total, my data consist of 155 monthly series from different categories including real output, employment, prices, exchange rates, interest rates, stock indices, money and credit aggregates, industrial and business turnover, construction, balance of payments, confidence indicators, and foreign variables. Most of the series come from European Central Bank's Statistical Data Warehouse (SDW), Eurostat and Bloomberg. In addition, individual series have been downloaded from the St. Louis Fed's Federal Reserve Economic Data (FRED) database and the statistical agencies and central banks of the corresponding foreign countries. The time period considered is from March 1999 to December 2016. A detailed list of data and their sources is given in Appendix A. 51 series, mainly stock markets indices , exchange rates and interest rates, are assumed to be fast-moving.

In order to ensure stationarity, I transform the series by (log-)differencing them when needed. Instead of having a strict rule for transforming, I use some discretion, guided by unit root tests, the previous study by Soares (2013) and the interpretability of the variables. Furthermore, I apply the same transformation to all variables within a certain class (e.g. HICP). Finally, I standardize the data by subtracting the mean from each series and then dividing them by their corresponding standard deviations in order to make the series suitable for principal components estimation.

Similarly to Soares (2013) but in contrast to Bernanke et al. (2005) and Wu and Xia (2016) my dataset includes variables from national accounts. Since these variables are reported in quarterly frequency, they need to be disaggregated to monthly frequency in order to create a balanced panel.[3] I use the standard Chow and Lin (1971) method for temporal disaggregation which uses

[3]Another approach would be to modify the principal components estimator to take into account missing data and mixed frequencies. However, in this case no closed-form solution is available to the problem and numerical approximations are needed (see, for example, Stock et al. (2010)). Replicating the analysis using this method would be an interesting pursuit. However, it is computationally more burdensome and beyond the scope of this paper.

related variables to estimate the missing monthly values for variables.[4] The variables I use for the disaggregation are the first seven principal components extracted from the monthly series.

There are clearly some concerns related to the use of disaggregated series. Since the true monthly variables are not observed it is hard to assess how close these estimates are to the true values. I deal with these concerns by estimating a model that uses only the monthly variables (see Appendix C).

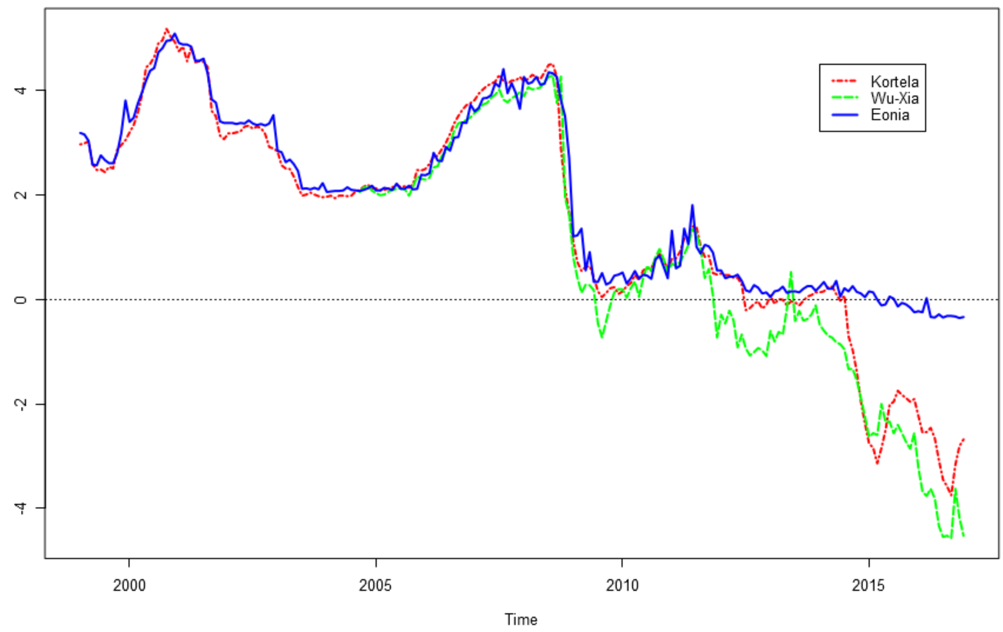
Another possible concern related to the data is the fact that I use the most recently available series. Monetary policy is exercised in real time and the data that the central bank uses is typically subject to significant ex post revisions. Because of this, the information set that the central bank faces is not the same as the one used by the econometrician using revised data. As shown by Orphanides (2001), using real-time data, as opposed to revised, can considerably change the fit of estimated policy rules and using the latest vintage could thus lead to spurious results. However, building a dataset consisting of vintage data would be far too cumbersome a project even if all the data were available. Moreover, using a large information set is likely to lessen the problem with revisions as the variables in the system represent cross-sectional weighted averages of a large panel of series.

I estimate the VARs with three different policy variables. First, like Soares (2013) I analyze conventional monetary policy using the euro area overnight index average (Eonia) as a proxy for the policy rate. EONIA is the weighted average of unsecured overnight interbank rates. It follows closely the policy rate yet it is continuous instead of changing in discrete increments. Because of this it is the most often used proxy for monetary policy in the euro area. Second, Tomi Kortela shared his estimate of the shadow rate with me. This rate starts from January 1999 so it can be used for the whole period. Third, I use the shadow rate for the euro area by Wu and Xia (2017) which can be downloaded from Cynthia Wu's website. This shadow rate is only available

[4]Soares (2013), in contrast, uses a related but slightly different method by Litterman (1983). However, with my data the Chow and Lin (1971) method tended to work better in the sense that the fitted values from the model were closer to the observed ones for most of the series.

from September 2004 onwards so I will use Eonia instead for the values before that date.

Figure 1: Shadow rates for the euro area and EONIA



Notes: This figure plots the interest rate series used as a proxy for the policy rate.

Figure 1 plots the three different rates. As can be seen, the shadow rates by Kortela (2016) and Wu and Xia (2017) follow closely Eonia for the pre-ZLB period. Indeed, the correlations between three series are over 0.9 for the whole sample period. For the post-crisis period the three series diverge, with Eonia sticking near the zero lower bound and the two shadow rates dropping sharply in 2014 when the expectations about ECB's quantitative easing were growing. The correlations remain relatively high in the final years of the sample with the correlation coefficient between Kortela's and Wu's rates being 0.83 and between Wu's rate and Eonia being 0.84 for the period starting in June 2014; the correlation between Kortela's rate and Eonia, however, is 0.64 for this subsample. The high correlations between different rates indicates that the impulse responses drawn from the different sources are likely to be close to each other.

3.1 Common factors and reduced-form VAR

Before choosing the correct specification for the VAR it is necessary to determine the number of common factors included in the system. Including more factors will ensure that the impulse response functions will capture all the effects of monetary policy shocks. On the other hand, a larger number of factors will make the model less parsimonious which makes the estimation of the VARs difficult and can lead to overfitting the data. Bai and Ng (2002) provide an $IC_k(2)$ information criterion that can be used to determine the number of factors in the model.[5] Similarly to Soares (2013), this criterion picks seven macroeconomic factors for the data. Additionally, the relative importance of different factors in explaining the data can be illustrated by plotting the cumulative amount of variation in the data explained by the principal components.

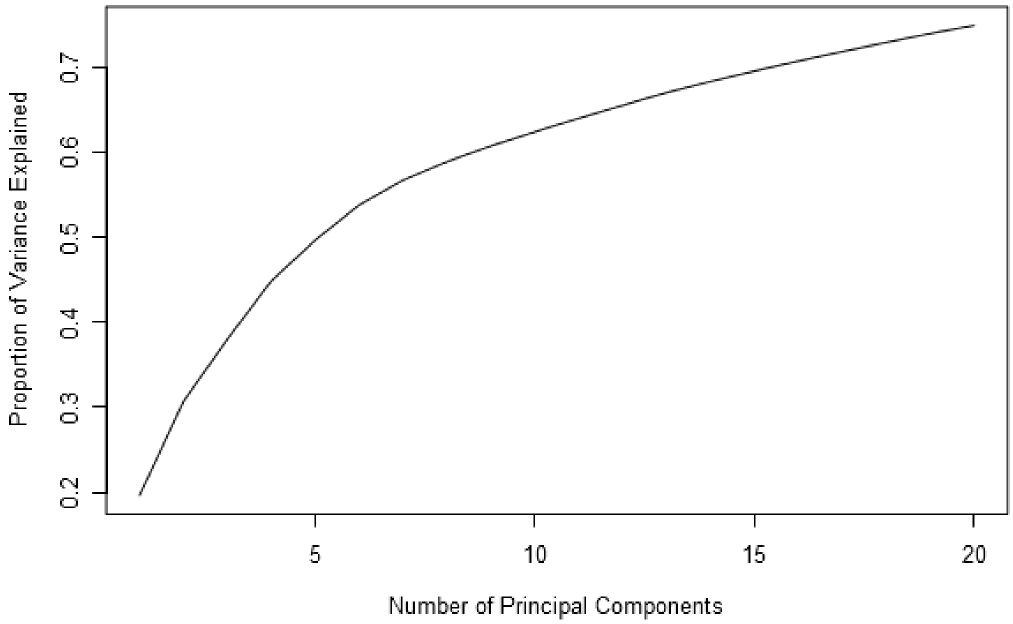
As can be seen in Figure 2, the first three principal components explain 38 percent of the variation in the data and the first five roughly half. The gain after that is relatively small: increasing the number of factors to seven will only increase the fit to 58 percent. Overall, most of the variation in the euro area macroeconomic series can be accounted by a relatively low number of common components, a finding that is consistent with results for the US data (Stock et al., 2010).

In order to ensure parsimony and to avoid overfitting the data I choose a three factor model, as is also used by Bernanke et al. (2005) and Wu and Xia (2016), as the benchmark case. Furthermore, even though the $IC_2(k)$-criterion and Figure 2 indicate that more common factors could be needed to explain the overall variation in the data, Bernanke et al. (2005) argue that this does not necessarily mean that these factors should be included in the VAR as the aim of the VAR is to explain the effects of monetary policy and not just find the best fit for the data. Nevertheless, as a robustness check I estimate a VAR with seven common factors; the impulse responses (see Subsection ??)

[5] The criterion is defined as $\min_k IC_2(k) = \log V_k(\Lambda, F) + k(\frac{N+T}{NT})$ where $V_k(\cdot)$ is the objective function for the principal components estimator from (6), k is the number of factors, N the number of series and T the length of the data. Asymptotically this criterion will recover the correct number of factors from the data.

are close to those from the benchmark model.

Figure 2: Variance of the data explained by factors



As was discussed in Section 2.2, the principal components estimator recovers the factor space and therefore the estimated factors do not necessarily correspond to true macroeconomic factors. Nonetheless, using factor loadings.[6] we can give a tentative interpretation to the three factors. Table 1 lists the factors and variables with the largest loadings for each factor[7] The first factor seems to correspond to real economic activity as it is highly correlated with value added, GDP, and volume of production. The second factor mostly captures changes in prices, and the third factor is correlated with stock market indices.

After choosing the number of factors, a key challenge in the model specification is finding the correct lag-length for the VAR. Several statistical procedures have been devised for this, including the Akaike and Bayesian information cri-

[6]Since the data is standardized the factor loadings are also correlation coefficients between factors and variables

[7]It is worth noting that the factors in Table 1 are not the principal component estimates *per se* but the ones where the influence of policy rate has been removed using the fast-slow identification scheme.

Table 1: Correlations of factors and macroeconomic variables

	Variable	Correlation
Factor 1	Value added	-0.925
	GDP	-0.911
	Manufacturing turnover	-0.894
	Volume of production, manufacturing goods	-0.870
	Employment, professional and scientific activity	-0.863
Factor 2	Industrial employment	-0.685
	HICP, All items	-0.609
	Deflator, fixed capital formation	-0.577
	HICP, Housing	-0.575
	HICP, Overall index	-0.556
Factor 3	EURO STOXX Broad	-0.879
	EURO STOXX 50	-0.876
	CAC Index	-0.872
	EURO STOXX Industrial Goods & Services	-0.803
	EURO STOXX Financial Services	-0.784

Notes: the correlations between each factor and five variables for which the correlation is highest. The factors listed are the same ones used in the VAR, that is, the influence of the policy rate has been removed using the fast-slow identification scheme.

teria and sequential likelihood ratio tests (Lütkepohl, 2005). Table 2 lists the lag-orders for the three VARs picked by the information criteria and the sequential testing.

Table 2: Results for information criteria and sequential testing

	Akaike IC	Bayesian IC	Sequential testing
Eonia	4	1	13
Kortela	4	1	14
Wu & Xia	4	1	13

Notes: the lag orders picked by Akaike information criterion, Bayesian information criterion and sequential testing. Sequential model selection is based on the likelihood ratio test starting with 15 lags. The significance level used is 5 %.

AIC and BIC pick relatively parsimonious models with 4 and 1 lags, respectively. Sequential testing, in turn, chooses a higher order model with 13 lags for VARs with Eonia and Wu and Xia's rate and 14 lags with Kortela's rate. Considering the fact that the data is monthly one lag could be too little yet the short length of the sample makes the use of higher order models inconvenient. Therefore, I choose the model with 4 lags as a middle point between the parsimonious model picked by the BIC and the high order model from the sequential testing. As a robustness check, I also estimate a higher order model with 13 lags. Unlike with the number of factors, the results are somewhat sensitive to the lag-order of the model (see Subsection C). I include an intercept in all the models that I estimate.

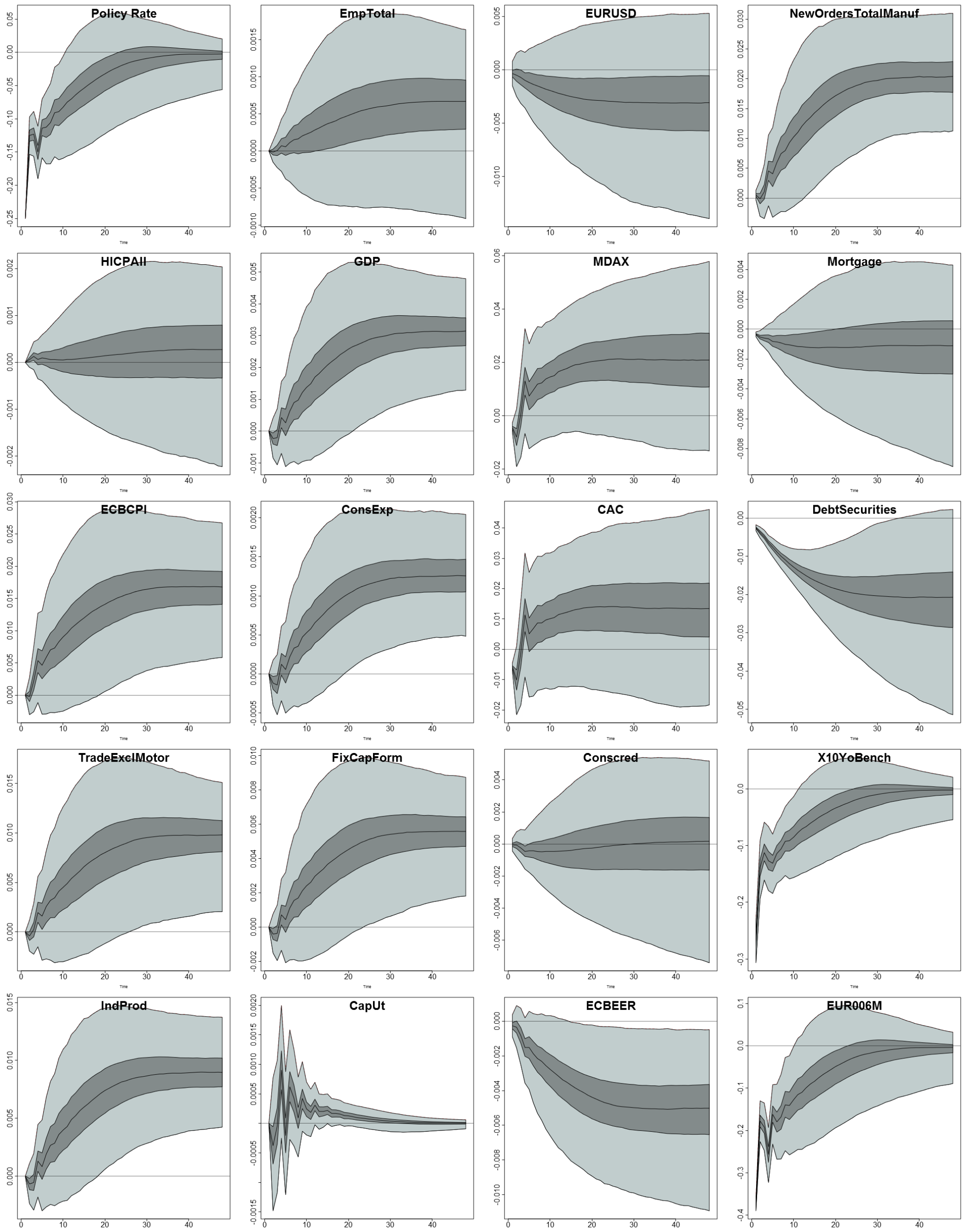
4 Results

To study the impact of monetary policy shocks on the macroeconomy, I estimate impulse response functions for 20 variables along with the 90 and 68 percent bootstrapped confidence bands. It is worth noting that the bootstrap procedure treats the shadow rates as observed variables and the uncertainty associated with their estimation is not reflected in the confidence bands. I supplement the impulse response analysis with forecast-error variance decompositions and counterfactual simulations.

4.1 Eonia

The first case that I consider is a full-sample VAR that uses Eonia as a proxy for the monetary policy. Figure 3 plots the impulse response functions following a 25 basis point expansion in monetary policy for twenty macroeconomic variables. First, the responses of consumption, investment, trade, industrial production, and GDP, have a positive hump shape known from the literature (Bernanke et al., 2005; Christiano et al., 1999), according to which monetary policy contractions lead to lagged expansions in economic activity. The effect on GDP is persistent yet rather small with the estimated increase being roughly 0.3 percentages compared to a baseline without a shock. Consumption, investment and industrial production portray highly similar patterns to GDP yet the magnitude of the responses varies: expansionary monetary policy is associated with up to 0.5 and 0.8 percent increases in the levels of investment and industrial production, respectively, whereas the response of consumption is much more subdued. Total new orders of the manufacturing industry rise by

Figure 3: Impulse response functions for a monetary policy shock with Eonia as the policy instrument



Notes: the impulse responses to a 25 basis point expansionary monetary policy shock along with the 90 and 68 percent bootstrap confidence intervals for 20 macroeconomic variables. For all variables that were log-differenced (i.e. everything except capacity utilization and the two interest rate variables) the impulse response functions are cumulative, indicating a percentage difference in level compared to the baseline of no shock. The confidence intervals are based on 2500 bootstrap samples.

almost a percentage following a monetary policy shock. All the responses are statistically significant at 68 percentage level for virtually the whole horizon and at 90 percent level 20 months after the shock.

The responses of price level variables show more heterogeneity as the results depend on the price index used. Monetary policy shocks have practically no effect on prices as measured by the HICP yet they are associated with a statistically significant, one and a half percentage point rise in the price level when using ECB's CPI as the measure. This rise in prices is immediate and the response does not show signs of the "the price puzzle" that often plagues recursively identified monetary policy VARs (see Christiano et al. (1999)). Moreover, monetary policy shocks are associated with a rise in employment that is extremely small in magnitude and statistically insignificant at 90 percent level.

As with output and inflation financial market variables respond to monetary policy shocks in a way that is consistent with previous literature. When the euro-dollar exchange rate (EURUSD) is used as a measure, monetary policy expansions are associated with an exchange rate depreciation that is persistent yet small and statistically insignificant at 90 percent level. The CAC and MDAX stock indices rise in response to monetary policy expansion, effects that both are significant at 68th percent level. The magnitude of this increase is between 1 and 2 percentages. Consumer credit and mortgages show little reaction whereas debt security holdings decrease by two percentages after a monetary policy shock. Finally, the 6-month Euribor and 10-year Government Benchmark bond yields react strongly to monetary policy shock with the interest rate reduction passing through to longer maturities.

4.2 Shadow rates

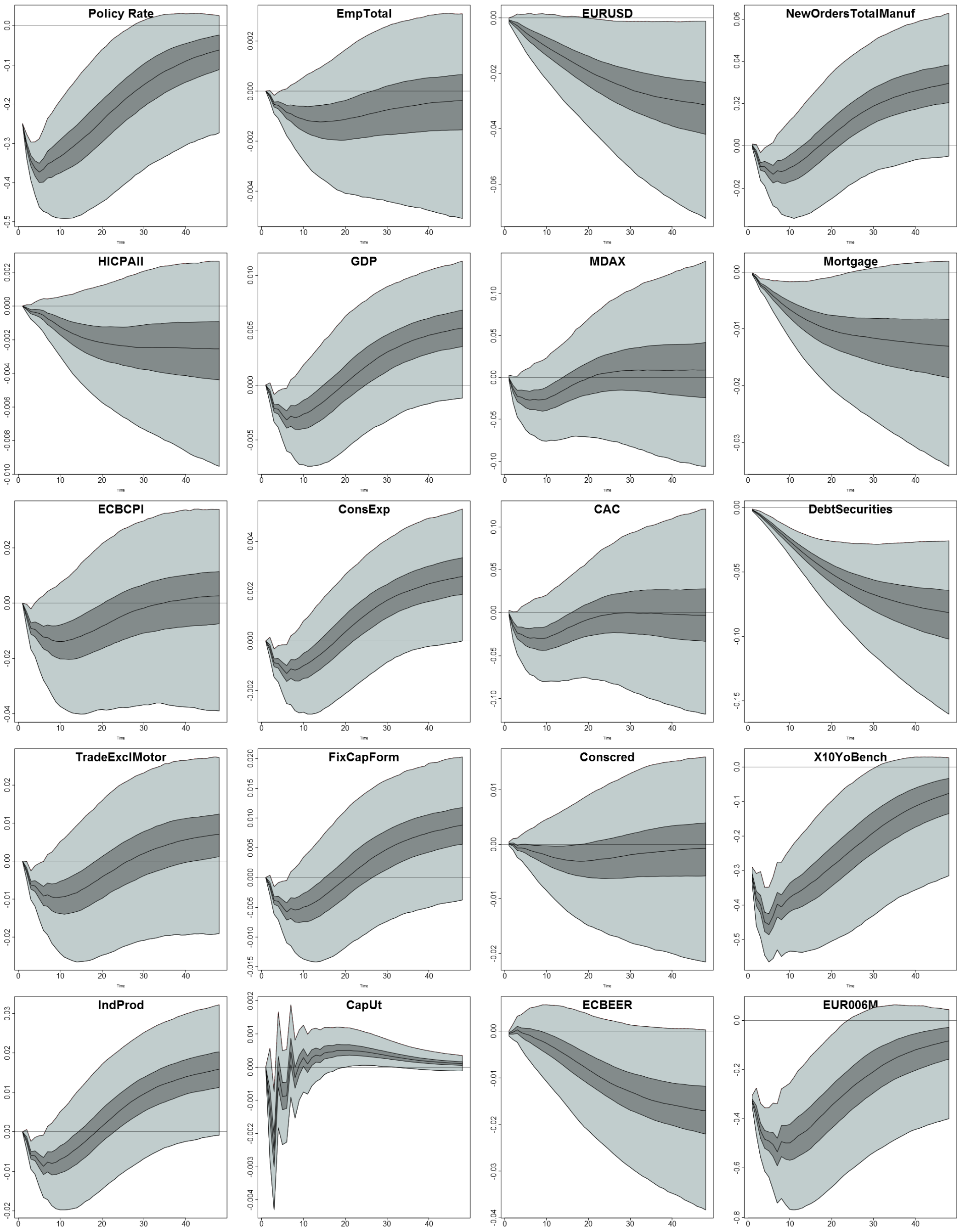
The results from a VAR with Kortela (2016) shadow rate, plotted in Figure 4, are somewhat more puzzling. Expansionary monetary policy shocks are associated with an initial decline in real economic activity. Nevertheless, this effect is transitory and mostly insignificant at 90 percent level, and GDP, industrial production, consumption, and investment all start to increase roughly ten months after the shock. The variables eventually settle at a higher level compared to the baseline. The long-run increase is roughly the same or even a bit larger than with, Eonia with GDP increasing roughly by half a percentage, investment by 0.8 percentages, and industrial production by 1.5 percentages compared to the baseline.

In contrast to the Eonia VAR, the consumer prices in the Kortela VAR exhibit a prize puzzle. The response of the Eurostat's HICP is, strikingly, negative and persistent even though it is statistically insignificant at 90 percent level for the whole time horizon. ECB's CPI produces similar pattern to the output variables, with a monetary policy expansion being associated with an initially falling price level. The effect dies out at 20 lags; yet even after that there is no rise in prices. Employment is associated with a similar counterintuitive initial decrease even though the effect is statistically insignificant at 90 percent level.

The stock prices respond fairly little to monetary policy shocks: even though there is a small initial decrease in the price indices, the effect dies out in less than twenty months. The exchange rate variables, in contrast, react more strongly to monetary policy shocks with the Euro-USD rate depreciating almost by two and a half percentages and the EER by over one and a half percentages. The confidence bands, nevertheless, are rather wide in both cases, leaving the results insignificant at 90 percent level. Finally, mortgages and consumer credit portray a highly similar lack of response as with the Eonia VAR whereas debt security holdings and longer maturity interest rates react strongly to a monetary policy shock.

Finally, Figure 5 plots the impulse response functions for Wu and Xia's shadow rate. The results lie somewhere in between the impulse response functions from the Eonia and Kortela's shadow rate. The impulse response functions measuring real economic activity portray a lagged and persistent yet rather small increase following an expansionary monetary policy shock. Quantitatively the estimated effects are highly similar to the two other VARs. The reaction of prices is similar to the VAR with Eonia with HICP showing practically no response at all and ECB's CPI showing a small yet statistically significant and persistent increase. Again, employment reacts little to monetary policy shocks.

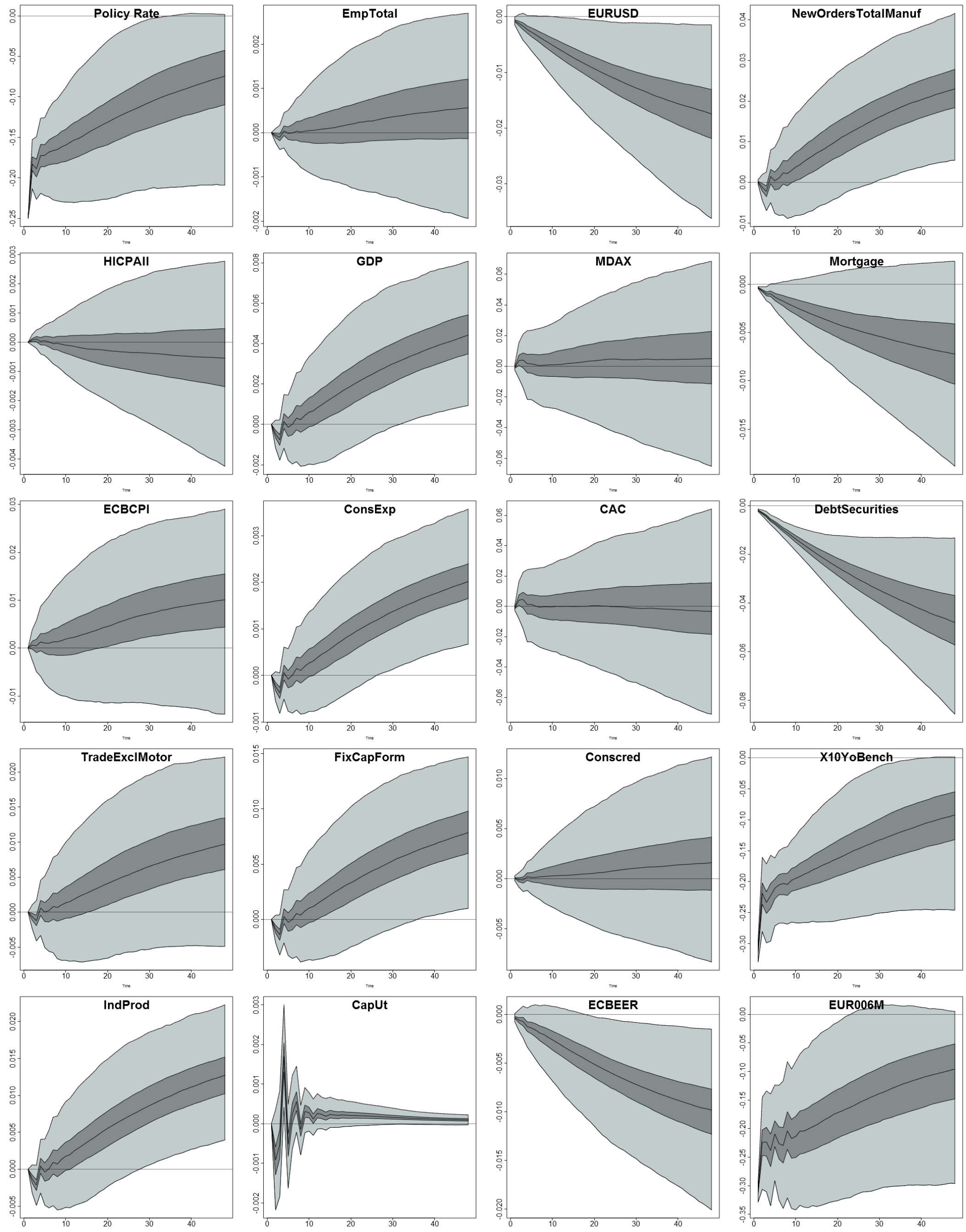
Figure 4: Impulse response functions for a monetary policy shock with Kortela's shadow rate as the policy instrument



Notes: the impulse responses to a 25 basis point expansionary monetary policy shock along with the 90 and 68 percent bootstrap confidence intervals for 20 macroeconomic variables. For all variables that were log-differenced (i.e. everything except capacity utilization and the two interest rate variables) the impulse response functions are cumulative, indicating a percentage difference in level compared to the baseline of no shock. The confidence intervals are based on 2500 bootstrap samples.

The responses of exchange rates are both quantitatively and qualitatively extremely similar to those that use Kortela's shadow rate as the policy instru-

Figure 5: Impulse response functions for a monetary policy shock with Wu and Xia's shadow rate as the policy instrument



Notes: the impulse responses to 25 basis point expansionary monetary policy shock along with the 90 and 68 percent bootstrap confidence intervals for 20 macroeconomic variables. For all variables that were log-differenced (i.e. everything except capacity utilization and the two interest rate variables) the impulse response functions are cumulative, indicating a percentage difference in level compared to the baseline of no shock. The confidence intervals are based on 2500 bootstrap samples.

ment: there is a persistent depreciation of the exchange rate after an expansionary monetary policy shock. The responses of stock indices and consumer credit are basically zero whereas, as with Kortela's rate, debt security holdings and, interestingly, mortgages decrease following a monetary policy shock; the latter effect, nevertheless, is insignificant at the 90 percent level. As with other specifications the shocks to the short-term interest rate pass through to the six month Euribor and 10-year Benchmark Government bond yields.

The results from the three VARs are largely consistent with the existing literature, as well as with each other. The differences come up mainly in shorter horizons with the Kortela VAR having slightly puzzling impulse response functions and the Eonia and Wu and Xia VARs being more in line with theory and existing evidence. Nevertheless, the long-run dynamics from the three models are both qualitatively and quantitatively fairly similar.

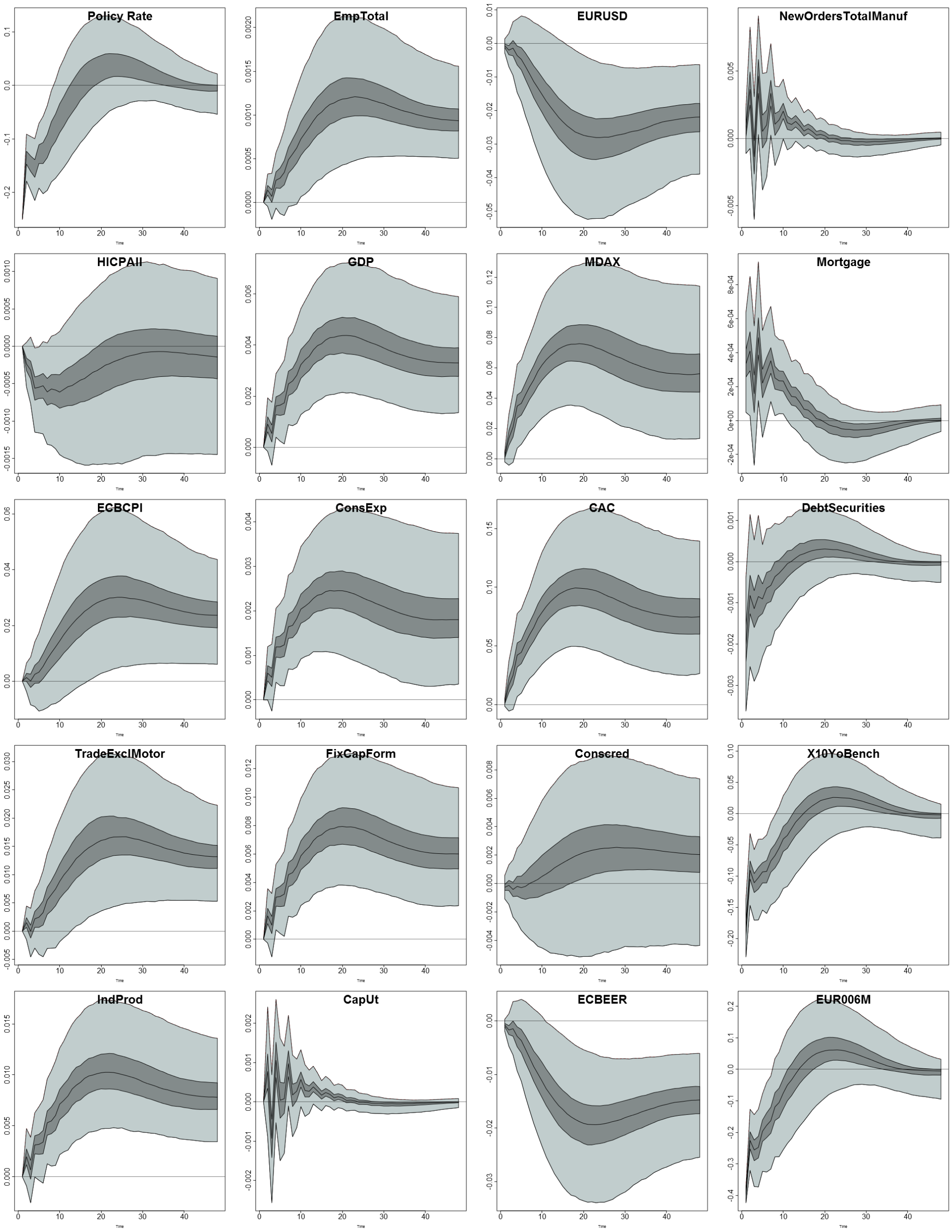
Overall, my results are in line with the view from the existing literature that associates monetary policy expansions with rising real output, an increase in the price level, and a decrease in the interest rates of different maturities (see, for example, Christiano et al. (1999) or Bernanke et al. (2005)). There is fairly little evidence for strong effects on employment whereas the evidence for stock market reaction is mixed. Unsurprisingly, the interest rate variables show the most pronounced reaction to monetary policy shocks. One caveat of these three VARs is the fact that the sample that I use to estimate them covers periods of both conventional and unconventional monetary policy. If these policies impact the economy differently, the impulse response functions could be biased. To investigate this matter I now turn to VARs estimated with subsamples of the data.

4.3 VAR for the conventional monetary policy

The fourth VAR that I estimate is a VAR(4) using a subsample from March 1999 to August 2008 (the month before the Lehman Brothers collapse). Using this subsample, I can cut out the effects that financial crisis, unconventional monetary policy measures and the zero-lower bound had on monetary policy. It also allows me to cross-check my results with those of Soares (2013) who estimates a VAR with a similar sample that includes mainly pre-crisis years.

The impulse response functions in Figure 6 are extremely close to those of

Figure 6: Impulse response functions for a pre-crisis subsample VAR with Eonia as the policy instrument.



Notes: the impulse responses to 25 basis point expansionary monetary policy shock along with the 90 and 68 percent bootstrap confidence intervals for 20 macroeconomic variables. The subsample used in the VAR ends in August 2008. For all variables that were log-differenced (i.e. everything except capacity utilization and the two interest rate variables) the impulse response functions are cumulative, indicating a percentage difference in level compared to the baseline of no shock. The VAR is estimated with four lags. The confidence intervals are based on 2500 bootstrap samples.

Soares (2013), as well as to the ones I estimated using the full sample. GDP, consumption, industrial production, investment, ECB's CPI and employment react all positively to monetary policy expansions whereas the reaction of HICP is insignificant at the 90 percent level. Moreover, a rising policy rate is also associated with an appreciation of the euro.

The reaction of financial market variables is also consistent with previous literature: stock prices rise in response to monetary policy expansion and mortgage lending increases whereas credit for consumption remains largely unchanged. Strikingly, debt security holdings react fairly little to monetary policy, contrasting the results from the full-sample VARs. Finally, the monetary policy shock again passes through to both interbank rate and government bond yields.

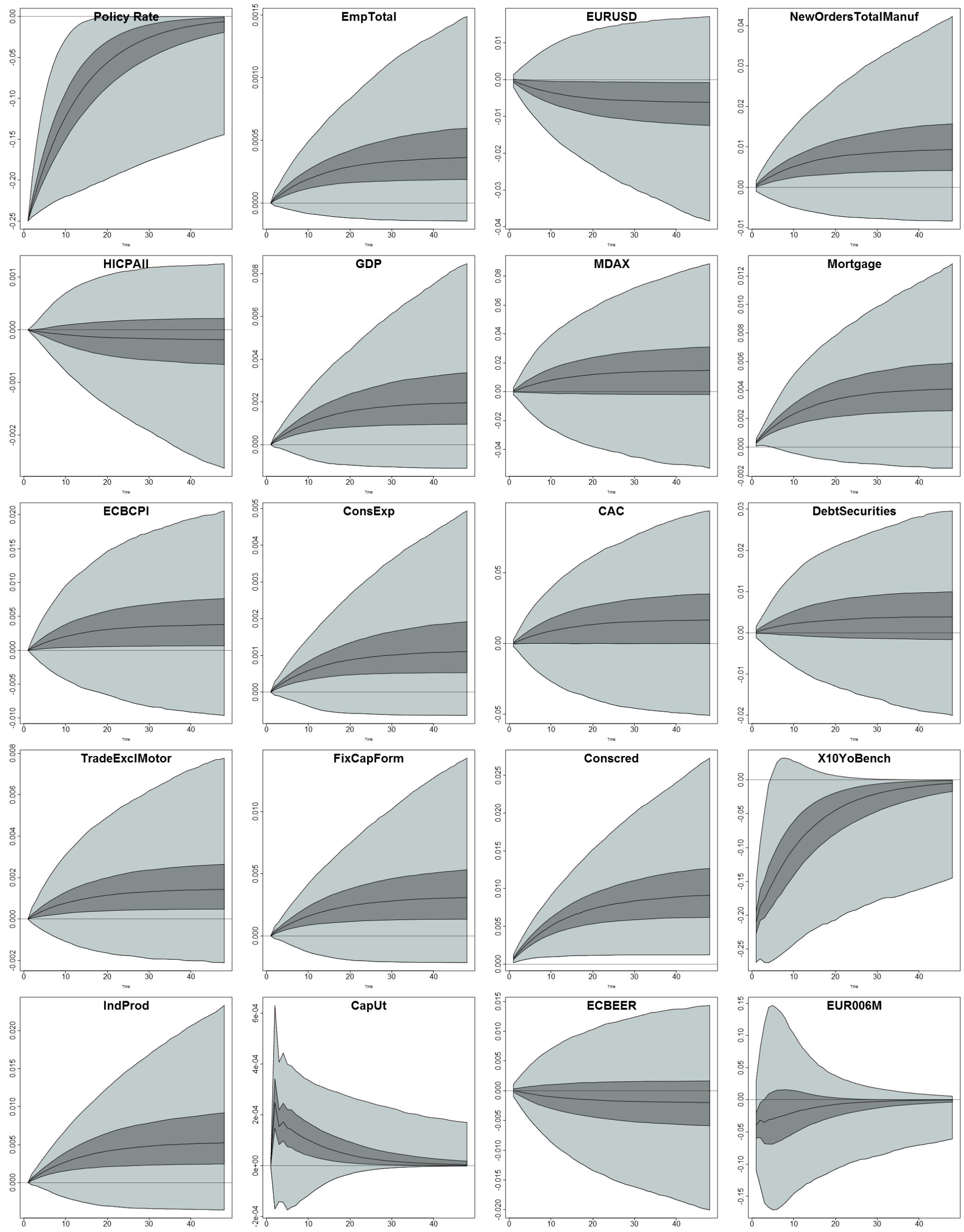
Overall, the results from the pre-crisis VAR are in line with those estimated using the full sample. This seems to indicate that monetary policy, whether conventional or unconventional, has similar effects on the macroeconomy. However, it also casts doubt on the extent that the results in the full-sample VARs have been driven by the pre-crisis period. In order to capture the unconventional monetary policy shocks it is then useful to consider a subsample consisting mainly of times of unconventional monetary policy.

4.4 VAR(1) for the unconventional monetary policy

To study the effects of unconventional monetary policy I estimate VARs with shadow rates using only the last observations of the sample. For this exercise I start the sample from June 2011 as this is the point where Wu and Xia's shadow rate first diverges from Eonia. Due to the short length of the sample I include only one lag in the VAR.

Figure 7 plots the impulse response functions from a VAR(1) that uses Kortela's shadow rate. As can be seen, the results qualitatively match those from the full-sample VAR even though the dynamics are now less rich and the confidence bands wider, yielding most of the responses insignificant at the 90 percent level. A monetary policy expansion is associated with roughly 0.2 and 0.3 percent persistent increases in the level of GDP and investment,

Figure 7: Impulse response functions for a post-crisis subsample VAR with Kortela's shadow rate as the policy instrument.



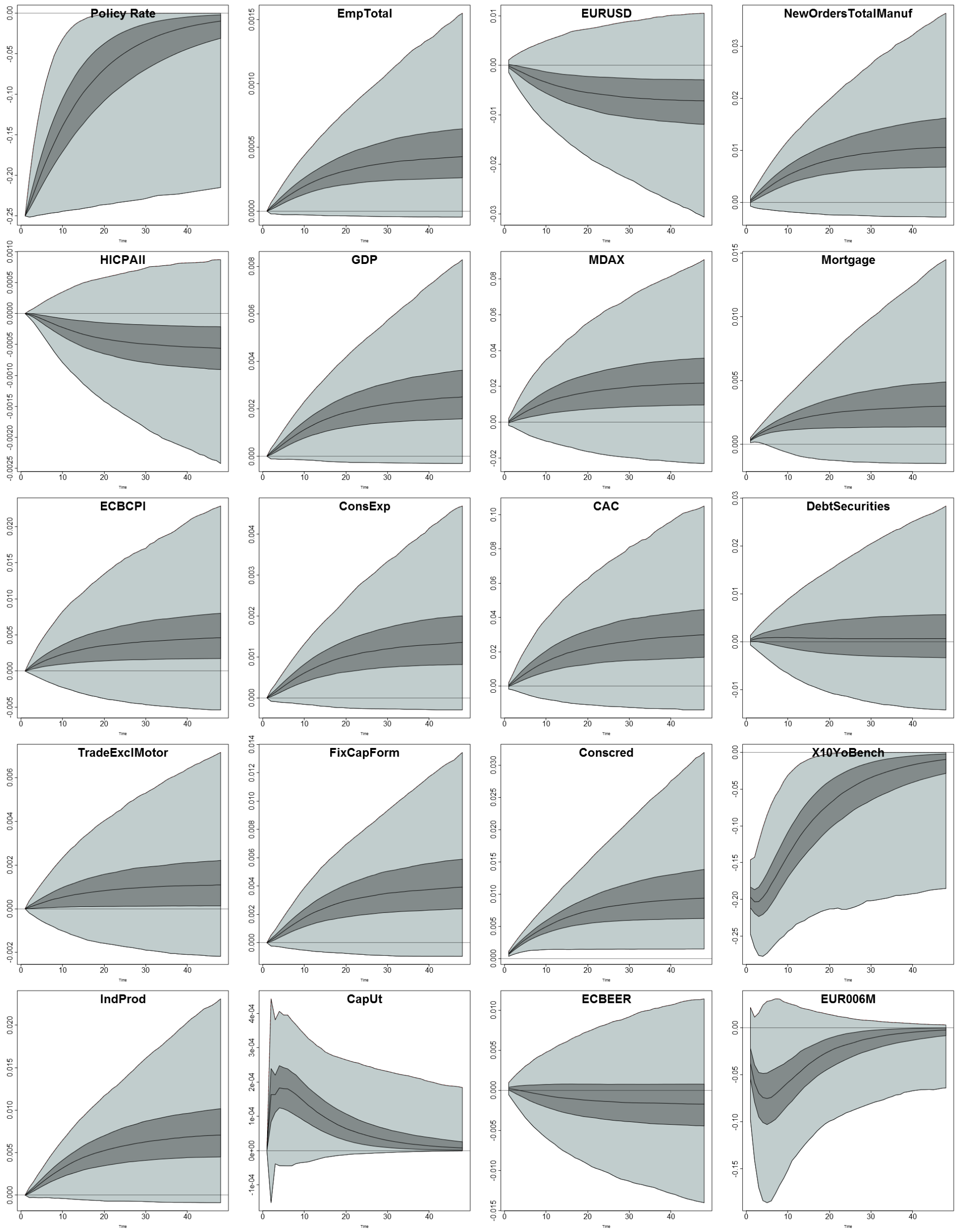
Notes: the impulse responses to a 25 basis point expansionary monetary policy shock along with the 90 and 68 percent bootstrap confidence intervals for 20 macroeconomic variables. The subsample used in the VAR starts from June 2011. For all variables that were log-differenced (i.e. everything except capacity utilization and the two interest rate variables) the impulse response functions are cumulative, indicating a percentage difference in level compared to the baseline of no shock. The VAR is estimated with one lag. The confidence intervals are based on 2500 bootstrap samples.

respectively. Strikingly, industrial production, that reacts relatively strongly in the full-sample exercises, now shows only a muted response. Price variables, stock indices, and exchange rates all show practically no response to monetary policy shocks. In contrast to full-sample VARs, the debt security holdings do not have any statistically significant responses whereas mortgage lending and consumer credit are associated with increases that are statistically significant at the 68 and 90 percent levels, respectively. The response of the 10-year Government Benchmark bond yield is similar to the results from the full-sample VARs whereas 6-month Euribor responds fairly little, likely reflecting the fact that the ZLB is constraining the shorter maturities during the sample period.

Finally, the estimated responses for an end-of-sample VAR with Wu and Xia's shadow rate are plotted in Figure 8. Overall, the results are quite similar to those from Kortela VAR yet they give a slightly more optimistic outlook on the effectiveness of unconventional monetary policy. GDP and investment increase by roughly 0.2 and 0.3 percentages following an expansionary monetary policy shock, and ECB's CPI increases by 0.4 percentages. Stock indices now portray a persistent increase and the Euro-USD exchange rate a persistent decrease, all of which are significant at the 68 percent level. The 6-month Euribor shows a clearer response whereas the shape and size of the impulse response function of the 10-year Government Benchmark yield is roughly the same as in Kortela's VAR.

The results from the post-crisis VARs are consistent with each other, as well as with the full sample VARs. The estimated responses for the real economic variables are qualitatively similar in both cases, with expansionary monetary policy being associated with a persistent rise in output. The prices show a more muted response in both cases. This indicates that unconventional monetary policy, at least as captured by the shadow rates, has highly similar macroeconomic effects as conventional monetary policy. Nevertheless, the responses of exchange rates, stock prices, and debt variables seem to be more sensitive to the choice of sample period and policy rate. This might indicate that unconventional monetary policy differs from the conventional interest rate policy by

Figure 8: Impulse response functions for a post-crisis subsample VAR with Wu and Xia's shadow rate as the policy instrument.



Notes: the impulse responses to 25 basis point expansionary monetary policy shock along with the 90 and 68 percent bootstrap confidence intervals for 20 macroeconomic variables. The subsample used in the VAR starts from June 2011. For all variables that were log-differenced (i.e. everything except capacity utilization and the two interest rate variables) the impulse response functions are cumulative, indicating a percentage difference in level compared to the baseline of no shock. The VAR is estimated with one lag. The confidence intervals are based on 2500 bootstrap samples.

its effects on the financial market variables.

4.5 Forecast error variance decompositions

Forecast error variance decompositions (FEVDs) are a common way of summarizing the relative importance of structural shocks in VARs. The idea is to calculate the share of mean-square error that can be accounted to a particular structural shock for a given variable at a given forecast horizon. In Table 3 I have calculated the FEVDs for numerous variables using the three full sample VARs.

As can be seen, the three VARs produce extremely similar FEVDs for most of the variables. Consistent with the existing literature, monetary policy shocks account for a fairly limited share of the variation in GDP, industrial production and employment growth. Curiously, the influence on the variation in inflation is even more muted, as is the impact on the growth rate of the CAC stock index. Unsurprisingly, monetary policy shocks account for a high proportion of variability in both 10-year Government Benchmark bond yield and the 6-month Euribor. Moreover, the FEVD for these two variables in the Eonia VAR is a lot smaller compared to the shadow rate VARs. This indicates that unconventional monetary policy, as captured by the shadow rate, has a strong influence on interest rates of different maturities. This effect is extremely persistent, as the FEVDs at 48 months of both Euribor and the benchmark yield are over 20 percent in the Wu and Xia VAR, and over 30 percent in the Kortela VAR.

In the final column of Table 3 I list the R^2-statistics for the impulse response equations of the economic indicators. As can be seen, the three factors and the policy rate capture the variation in different measures fairly well. Out of the figures listed in Table 3 only the R^2 associated with HICP inflation is less than 0.5 which likely reflects the fact that inflation was relatively low and stable during the sample period.

Table 3: Forecast error variance decompositions

Horizon	0	12	24	48	R^2
Eonia VAR					
HICP inflation	0.00	0.70	0.73	0.76	0.51
Industrial production	0.00	0.87	1.07	1.12	0.82
Total employment	0.00	0.71	0.85	0.89	0.58
GDP	0.00	1.01	1.23	1.29	0.94
Capacity utilization	0.00	0.73	0.88	0.93	0.66
CAC	0.04	0.88	0.93	0.96	0.89
10 year government benchmark yield	1.85	5.23	4.76	4.40	0.61
6 month Euribor	20.92	15.23	8.36	6.83	0.96
Kortela VAR					
HICP inflation	0.00	0.90	0.93	1.19	0.43
Industrial production	0.00	2.86	3.05	3.61	0.82
Total employment	0.00	2.30	2.39	2.88	0.66
GDP	0.00	3.27	3.47	4.09	0.93
Capacity utilization	0.00	2.20	2.37	2.82	0.63
CAC	0.03	1.88	2.61	3.41	0.84
10 year government benchmark yield	2.34	27.93	32.22	34.55	0.79
6 month Euribor	5.93	38.59	38.21	38.91	0.93
Wu and Xia VAR					
HICP inflation	0.00	0.50	0.63	0.98	0.42
Industrial production	0.00	1.19	1.25	1.41	0.82
Total employment	0.00	0.96	1.05	1.32	0.65
GDP	0.00	1.35	1.42	1.60	0.93
Capacity utilization	0.00	0.93	0.98	1.11	0.62
CAC	0.04	1.27	1.65	2.36	0.84
10 year government benchmark yield	4.50	16.12	17.73	20.07	0.81
6 month Euribor	8.60	20.88	20.18	21.63	0.92

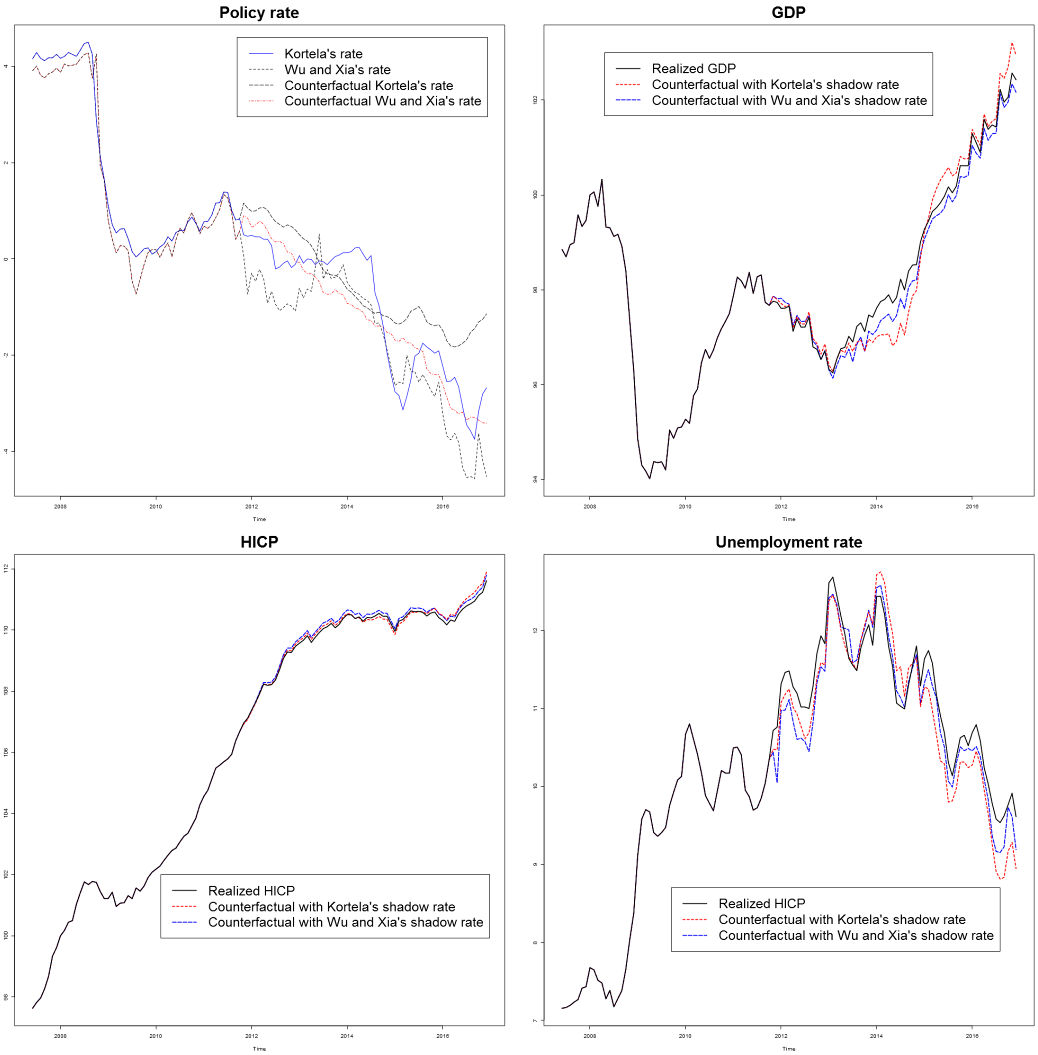
Notes: the percentage of variation explained by monetary policy shock at given lag horizons. The FEVD's have been computed using the full-sample. In contrast to impulse response functions the figures for HICP, industrial production, total employment, GDP, and CAC refer to growth rates rather than (log-)levels. The R^2 refers to the overall variation explained by the latent factor and the policy rate.

4.6 Counterfactual simulations

As a final illustration of the effects of unconventional monetary policy I produce counterfactual simulations for the VARs. I construct these counterfactuals by setting all the monetary policy shocks from June 2011 onwards equal to zero and then calculating the level of three additional variables, GDP, HICP and unemployment rate, under these conditions, assuming that all the other shocks that hit the economy are the same.

As can be seen in Figure 9, both shadow rates would have been lower dur-

Figure 9: Counterfactual simulations of economic variables.



Notes: counterfactual simulations of macroeconomic variables under the assumption that all monetary shocks from June 2011 onwards were zero. GDP and HICP are in levels (September 2009 = 100).

ing 2015-2016 than would have been implied by the simple policy rules. This time period coincides roughly with the announcement and execution of ECB's asset purchase programmes and the simulations now indicate that, given the historical policy rule, these policies have been expansionary. Somewhat more puzzling result comes from the simulated paths of macroeconomic variables: the expansionary monetary policy translates into a higher unemployment rate and, in the case of the Kortela VAR, a lower GDP whereas the HICP is virtually the same in all three scenarios. Nevertheless, it is important to keep in mind that the impulse response functions of GDP from the Kortela VAR turn positive roughly after 20 months. This would indicate that the expansionary effects from the monetary policy shocks since 2015, when ECB's QE has been carried out, do not yet show up in the data.

The counterfactuals calculated here are rather crude and, in contrast to the impulse response functions, I do not quantify uncertainty around the estimated paths. Furthermore, they might give too bleak a picture of the effectiveness unconventional monetary policy. This is because unconventional monetary policy affects the economy also through its predictable component. More precisely, unconventional monetary policy has helped ECB to conduct policy in accordance with its historical policy rule even when the ZLB stripped away the central bank's ability to conduct conventional interest rate policy. Wu and Xia (2016) investigate the anticipated effect of monetary policy by building counterfactuals where the shadow rate remains fixed at the effective lower bound. However, since the literature suggests that a time-varying effective lower bound is necessary when modeling the euro area yields (see Kortela (2016) and Wu and Xia (2017)) it is not clear what the effective lower bound used in these counterfactuals should be. Because of this I do not build here counterfactuals that take the systematic policy into account.

5 Conclusion

My results support the view that unconventional monetary policy has similar effects as conventional monetary policy. Consistent with the results of Wu and Xia (2016) for the US, I find unconventional monetary policy to be expansionary and highly similar in its effects to conventional monetary policy. I find differences mainly in the responses of financial market variables. Nevertheless, the forecast error variance decompositions and counterfactual simulations indicate that the quantitative impact is rather small.

There are, nevertheless, some limitations regarding my methodology and data. The aggregate euro area series could conceal considerable heterogeneity in responses across member states, and it is possible that this heterogeneity is also reflected in the monetary policy of the ECB. My data also ends in December 2016 and it could thus miss some lagged effects of ECB's UMP.

Moreover, even though the recursive identification used with monetary policy FAVARs is fairly standard it could also be rather limiting. Checking the results using alternative schemes, such as sign-restrictions, could help in assessing the robustness of the results. Finally, studying unconventional monetary policy shocks with alternative measures for monetary policy would yield valuable information on whether shadow rates manage to capture the effects of unconventional monetary policy well.

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Appendices

A Data

Table 4: Data used in the study

No	Code	Description	Transformation	Source
Real output and prices				
1	GDP*	Real GDP (SA)	5, D	Eurostat
2	VA*	Real value added (SA)	5, D	Eurostat
3	FinalCons*	Real government final consumption (SA)	5, D	Eurostat
4	ConsExp*	Real private consumption expenditure (SA)	5, D	Eurostat
5	FixCapForm*	Real gross fixed capital formation (SA)	5, D	Eurostat
6	CapUt*	Capacity utilization - Industry survey (% of capacity) (SA)	5, D	SDW
7	IndProd*	Industrial production index (SA)	5	SDW
8	VolProdCapital*	Volume Index of Production, Capital goods (SA)	5	Eurostat
9	VolProdInterm*	Volume Index of Production, Intermediate goods (SA)	5	Eurostat
10	VolProdConsGoods*	Volume Index of Production, Consumer goods (SA)	5	Eurostat
11	VolProdDurables*	Volume Index of Production, Durables (SA)	5	Eurostat
12	VolProdNonDur*	Volume Index of Production, Non-durables (SA)	5	Eurostat
13	VolProdConstr*	Volume Index of Production, Construction (SA)	5	Eurostat
14	VolProdManuf*	Volume Index of Production, Manufacturing (SA)	5	Eurostat
15	VolProdMinManuf*	Volume Index of Production, Mining and Manufacturing (SA)	5	Eurostat
16	VolProdElectr*	Volume Index of Production, Electricity (SA)	5	Eurostat
17	VolProdEnergy*	Volume Index of Production, Energy (SA)	5	Eurostat
Employment				
18	EmpAgric*	Employment, agriculture (persons) (SA)	5, D	SDW
19	EmpIndus*	Employment, industry excl. construction (persons) (SA)	5, D	SDW
20	EmpConstr*	Employment, construction (persons) (SA)	5, D	SDW
21	EmpTrade*	Employment, wholesale & retail trade (persons) (SA)	5, D	SDW
22	EmpFinance*	Employment, financial & real estate services (persons) (SA)	5, D	SDW
23	EmpArts*	Employment, arts, entertainment & recreation (persons) (SA)	5, D	SDW
24	EmpTotal*	Total employment (persons) (SA)	5, D	SDW
25	EmpInform*	Employment, information and communication, (persons) (SA)	5, D	SDW
26	EmpPro*	Employment, professional, scientific & technical activities, (persons) (SA)	5, D	SDW
27	Employees*	Total employees (persons) (SA)	5, D	SDW
28	SelfEmployed*	Self-employed (persons) (SA)	5, D	SDW
29	UnEmp*	Standardized unemployment rate	1	SDW
30	ProductivityAgric*	Labour productivity, agriculture	5, D	SDW
31	ProductivityArts*	Labour productivity, arts, entertainment & recreation	5, D	SDW
32	ProductivityIndus*	Labour productivity, industry excl. construction	5, D	SDW

Continued on next page

Table 4 – *Continued from previous page*

No	Code	Description	Transformation	Source
33	ProductivityConstr*	Labour productivity, construction	5, D	SDW
34	ProductivityTrade*	Labour productivity, wholesale and retail trade	5, D	SDW
35	ProductivityFinance*	Labour productivity, financial & insurance services (persons) (SA)	5, D	SDW
36	ProductivityInform*	Labour productivity, arts, entertainment and recreation (persons) (SA)	5, D	SDW
37	ProductivityRealEst*	Labour productivity, real estate activities	5, D	SDW
38	ProductivityPro*	Labour productivity, professional, scientific & technical activities	5, D	SDW
39	ProductivityTotal*	Labour productivity, total	5, D	SDW
40	ULCAgric*	Unit labour costs, deflator, agriculture (SA)	5, D	SDW
41	ULCIndus*	Unit labour costs, deflator, industry (SA)	5, D	SDW
42	ULCConstr*	Unit labour costs, deflator, construction (SA)	5, D	SDW
43	ULCTrade*	Unit labour costs, deflator, wholesale & retail trade (SA)	5, D	SDW
44	ULCInform*	Unit labour costs, deflator, financial & insurance activities (SA)	5, D	SDW
45	ULCFinance*	Unit labour costs, deflator, financial & insurance activities (SA)	5, D	SDW
46	ULCRealEst*	LabUnit labour costs, deflator, real estate activities (SA)	5, D	SDW
47	ULCPro*	Unit costs, deflator, professional, scientific & technical activities (SA)	5, D	SDW
48	ULCArts*	Unit labour costs, art, entertainment & recreation (SA)	5, D	SDW
49	ULCTotal*	Unit labour costs, deflator, total (SA)	5, D	SDW
Prices				
50	HICPALL*	HICP, All items (SA)	5	Eurostat
51	HICPAlcohol*	HICP, Alcohol (SA)	5	Eurostat
52	HICPClothing*	HICP, Clothing & footwear (SA)	5	Eurostat
53	HICPComm*	HICP, Communications (SA)	5	Eurostat
54	HICPEdu*	HICP, Education (SA)	5	Eurostat
55	HICPEnergy*	HICP, Energy (SA)	5	Eurostat
56	HICPFood*	HICP, Food & non-alcoholic beverages, (SA)	5	Eurostat
57	HICPFurnish*	HICP, Furnishings (SA)	5	Eurostat
58	HICPHealth*	HICP, Health (SA)	5	Eurostat
59	HICPHousing*	HICP, Housing	5	Eurostat
60	HICPMisc*	HICP, Miscellaneous goods and services (SA)	5	Eurostat
61	HICPTransport*	HICP, Transport (SA)	5	Eurostat
62	HICPOverall*	HICP, Overall index excl. housing, electricity & fuels, (SA)	5	Eurostat
63	ECBCPI*	ECB Commodity Price Index	5	SDW
64	OutputPriceCapital*	Output price index, capital goods	5	Eurostat
65	OutputPriceIndustr*	Output price index, industry	5	Eurostat
66	OutputPriceInterm*	Output price index, intermediate goods	5	Eurostat
67	OutputPriceManuf*	Output price index, manufacturing goods	5	Eurostat
68	Brent	Brent crude oil price, Europe	5	FRED
69	DeflGDO*	Implicit price deflator, GDP (SA)	5, D	Eurostat
70	DeflVA*	Implicit price deflator, gross value added (SA)	5, D	Eurostat
71	DeflFinalCons*	Implicit price deflator, public consumption (SA)	5, D	Eurostat
72	DeflConsExp*	Implicit price deflator, deflator, private consumption (SA)	5, D	Eurostat
73	DeflFixCapForm*	Implicit price deflator, fixed capital formation (SA)	5, D	Eurostat

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Table 4 – *Continued from previous page*

No	Code	Description	Transformation	Source
74	DeflExports*	Implicit price deflator, exports (SA)	5, D	Eurostat
75	DeflImports*	Implicit price deflator, imports (SA)	5, D	Eurostat
Exchange rates				
76	EURCHF	Euro-Switzerland franc exchange rate, average	5	Eurostat
77	EURGBP	Euro-Pound Sterling exchange rate, average	5	Eurostat
78	EURJPN	Euro-Yen exchange rate, average	5	Eurostat
79	EURUSD	Euro-US Dollar exchange rate, average	5	Eurostat
80	ECBEER	Effective exchange rate, EER-19 group against Euro	5	SDW
Interest rates				
81	EUR002V	2-week euribor	1	Bloomberg
82	EUR003M	3-month euribor	1	Bloomberg
83	EUR006M	6-month euribor	1	Bloomberg
84	EUR012M	1-year euribor	1	Bloomberg
85	3YoBench	Euro area 3-year Government Benchmark bond yield	1	SDW
86	5YoBench	Euro area 5-year Government Benchmark bond yield	1	SDW
87	10YoBench	Euro area 10-year Government Benchmark bond yield	1	SDW
88	EUR003SPRD	3-month euribor - EONIA spread	1	Bloomberg
89	10YOSPRD	10-year benchmark yield - EONIA spread	1	SDW
Stock prices				
90	CAC	CAC 40 index	5	Bloomberg
91	MDAX	MDAX index	5	Bloomberg
92	SX5E	EURO STOXX 50	5	Bloomberg
93	SXXE	EURO STOXX Broad M3	5	Bloomberg
94	SX6E	EURO STOXX Utilities	5	Bloomberg
95	SX8E	EURO STOXX Technology	5	Bloomberg
96	SXBSCE	EURO STOXX Basic Materials	5	Bloomberg
97	SXCGSE	EURO STOXX Consumer Goods	5	Bloomberg
98	SXCSVE	EURO STOXX Consumer Services	5	Bloomberg
99	SXDE	EURO STOXX Health Care	5	Bloomberg
100	SXEE	EURO STOXX Oil & Gas	5	Bloomberg
101	SXFE	EURO STOXX Financial Services	5	Bloomberg
102	SXNE	EURO STOXX Industrial Goods & Services	5	Bloomberg
103	SXKE	EURO STOXX Telecommunications	5	Bloomberg
Industrial new orders, turnover, and sales				
104	NewOrdersCapital	New orders, capital goods (SA)	5	Eurostat
105	NewOrdersDurable	New orders, durable goods (SA)	5	Eurostat
106	NewOrdersFood	New orders, food, beverages & tobacco, beer (SA)	5	Eurostat
107	NewOrdersManuf	New orders, manufacturing, domestic market (SA)	5	Eurostat
108	NewOrdersTotalManuf	New orders, manufacturing, total (SA)	5	Eurostat
109	TradeExclMotor*	Wholesale Trade excl. vehicles (SA)	5	Eurostat
110	TradeRepair*	Trade & repair of vehicles (SA)	5	Eurostat
111	TurnoverAccom*	Turnover, Accommodation & food services (SA)	5	Eurostat
112	TurnoverBasicMetal*	Turnover, manufacture of basic metal products (SA)	5	Eurostat
113	TuroverCapital*	Turnover, capital goods (SA)	5	Eurostat
114	TurnoverClothing*	Turnover, retail sale of clothing (SA)	5	Eurostat

Continued on next page

Table 4 – *Continued from previous page*

No	Code	Description	Transformation	Source
115	TurnoverFeeContr*	Turnover, wholesale on fee or contract basis (SA)	5	Eurostat
116	TurnoverMailInter*	Turnover, retail sale via mail or internet (SA)	5	Eurostat
117	TurnoverManuf*	Turnover, manufacturing (SA)	5	Eurostat
118	TurnoverPaper*	Turnover, manufacture of paper and paper products (SA)	5	Eurostat
119	TurnoverRetailSales*	Turnover, Retail sale of non-food products	5	Eurostat
120	TurnoverTobacco*	Turnover, manufacture of tobacco products (SA)	5	Eurostat
121	TurnoverTotalInd*	Turnover, total industry	5	Eurostat
122	TurnoverOther*	Turnover, wholesale of other machinery (SA)	5	Eurostat
123	TurnoverMetal*	Turnover, manufacture of fabricated metal products (SA)	5	Eurostat
124	TurnoverRepair*	Turnover, repair of vehicles (SA)	5	Eurostat
125	TurnoverRetailFuel*	Turnover, retail trade incl. fuel (SA)	5	Eurostat
126	TurnoverPlastic*	Turnover, manufacture or rubber and plastic (SA)	5	Eurostat
127	CarRegistr*	Passenger car registrations (SA)	5	Eurostat
Money and credit aggregates				
128	Conscred	Credit for consumption (SA)	5	SDW
129	DebtSecurities	Total debt securities held by non-MFIs	5	SDW
130	LoansCorp	Corporate loans	5	SDW
131	Mortgage	Lending for house purchase	5	SDW
132	M1	Monetary aggregate M1	5	SDW
133	M2	Monetary aggregate M2	5	SDW
134	M3	Monetary aggregate M3	5	SDW
Construction				
135	ConstrCost*	Construction cost index	5	Eurostat
Balance of payments and external trade				
136	CapAcc*	Capital account	2	SDW
137	CurAcc*	Current account (SA)	2	SDW
138	ImportTotal*	Import, total goods (SA)	5	Eurostat
139	ExportTotal*	Export, total goods (SA)	5	Eurostat
Confidence indicators				
140	BCI	Business climate indicator	1	Eurostat
141	ConstrConf	Construction confidence indicator (SA)	1	Eurostat
142	ConsumConf	Consumption confidence indicator (SA)	1	Eurostat
143	EconSent	Economic sentiment indicator (SA)	1	Eurostat
144	IndusConf	Industrial confidence indicator (SA)	1	Eurostat
145	RetailConf	Retail confidence indicator (SA)	1	Eurostat
146	ServConf	Service confidence indicator (SA)	1	Eurostat
Foreign variables				
147	GDPUS*	Real US GDP (SA)	5, D	BEA
148	GDPJap*	Real Japan GDP (SA)	5, D	SBJ
149	GDPUK*	Real UK GDP (SA)	5, D	ONS
150	CPIUS*	CPI US (SA)	5	OECD
151	CPIJap*	CPI Japan (SA)	5	OECD
152	CPIUK*	CPI UK (SA)	5	OECD
153	FedFunds	Effective Fed Funds rate	1	Fred
154	BoJCall	Bank of Japan Call rate	1	BoJ
155	BoEBank	Bank of England Bank rate	1	BoE
Policy variables				
156	EONIA	Eonia rate	1	Bloomberg
157	WuShadow	Shadow rate by Wu and Xia (2017)	1	Wu and Xia (2017)
158	TomiShadow	Shadow rate by Kortela (2016)	1	Kortela (2016)

Continued on next page

Table 4 – *Continued from previous page*

No	Code	Description	Transformation	Source
159	LZ	Liftoff horizon by Kortela (2016)	1	Kortela (2016)

Notes: This table lists all the series used to extract factors or as policy instruments in a VAR. The transformation codes are the same used by Bernanke et al. (2005) with 1 = no transformation, 2 = difference, 4 = log level, 5 = log difference. Additionally, D refers to quarterly series that have been disaggregated to monthly frequency. Finally, the data sources refer to Bloomberg, ECB's statistica data warehouse (SDW), Eurostat, St. Louis' Federal Reserve Economic Data (FRED), UK's Office of National Statistics (ONS), Statistical Bureau of Japan (SBJ), Bureau of Economic Analysis (BEA), Cynthia Wu's website and OECD. The shadow rate by Kortela (2016) was acquired directly from him. The asterisk behind the variable code (*) denotes slow-moving variables.

B Diagnostic checks

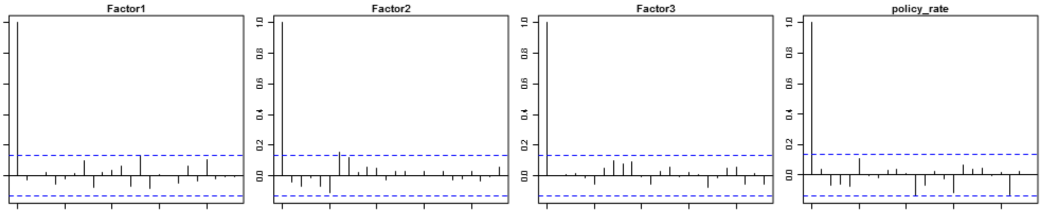
The adequacy of a VAR can be checked by inspecting the autocorrelation function of the estimated model's residuals. Presence of autocorrelation violates the white noise assumption and also implies that the model's errors contain predictive power. Therefore a model would not capture the behavior of a forward looking central bank correctly. I plot the estimated autocorrelation functions for each VAR in Figure 10. There is no presence of residual autocorrelation in the plots as virtually all the values are very close to zero. This offers reassurance that the VARs with four lags are adequate.[8]

Another possible concern is the presence of parameter instability. It is possible that the Great Recession, with the ZLB and financial distress, was associated with a structural break in the monetary policy transmission. This structural break could then manifest into parameter instability in the VAR. Compared to the US this problem might be even more severe in the eurozone, where the financial crisis was followed by a sovereign debt crisis which resulted in a "double dip" recession and a persistently slow growth and inflation. Furthermore, the deepening integration in the European economy during the sample period could also translate into shifts in the structural parameters of the economy.

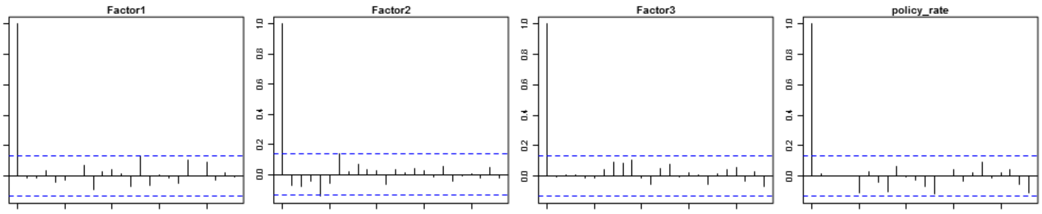
The parameter stability of a linear model can be assessed using a cumulative sum (CUSUM) test. The idea is to test whether the path of the cumulative sum of the reduced-form residuals crosses certain threshold value. The CUSUM

[8] In addition to visually inspecting the autocorrelation plots residual autocorrelation can also be tested formally. In contrast to the plotted functions autocorrelation tests consistently reject the null of no autocorrelation. This result holds regardless of the lag-length. These concerns should then be kept in mind when interpreting the results.

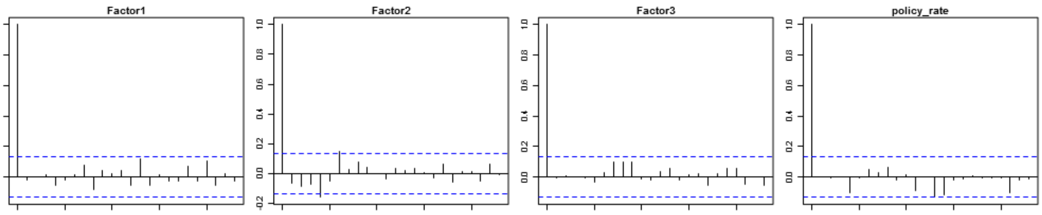
Figure 10: Empirical autocorrelation functions up to 25 lags for the VAR residuals of the three models. All VARs had four lags.



(a) Residual autocorrelation for a VAR with Eonia



(b) Residual autocorrelation for a VAR with Kortela's shadow rate



(c) Residual autocorrelation for a VAR with Wu and Xia's shadow rate

Notes: the empirical residual autocorrelation functions for three benchmark VARs along with the 95 percent confidence interval. Each VAR is estimated with four lags.

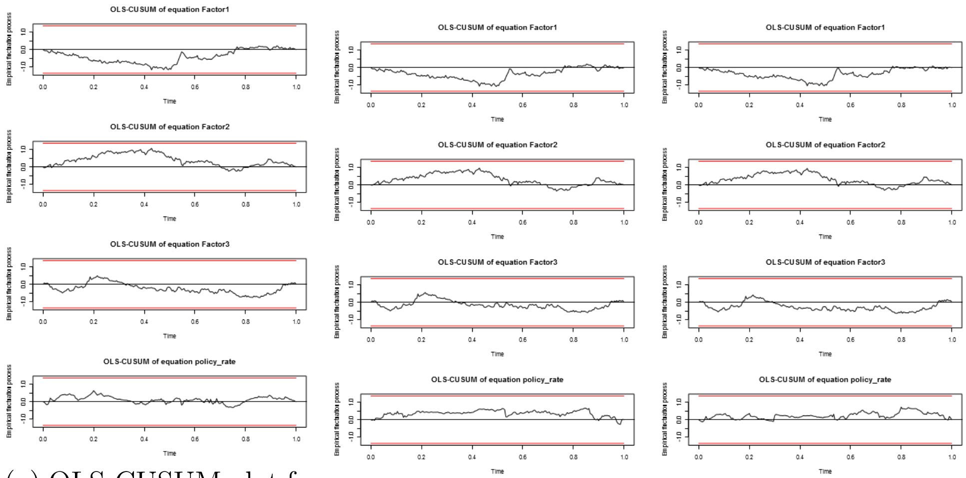
tests for the three benchmark VARs are plotted in Figure 11. As can be seen, all the values are within the 5 percent boundary. The CUSUM tests then indicate that structural instability is not a problem in the models.

Overall, the results from diagnostic checks suggest that the simple linear VARs, despite the relatively short sample length which includes exceptional macroeconomic events, provide a fairly good description of the data. As the adequacy of the reduced form model has been established, it is now time to turn the attention towards the structural analysis.

C Robustness

In order to assess the robustness of the results I consider various alternative specifications for the VAR. First, I experiment with a longer lag length and a larger number of macroeconomic factors. In order to assess the effects of data

Figure 11: Cumulative sums of the OLS residuals.



(a) OLS-CUSUM plot for the Eonia VAR

(b) OLS-CUSUM plot for the Kortela VAR

(c) OLS-CUSUM plot for the Wu and Xia VAR

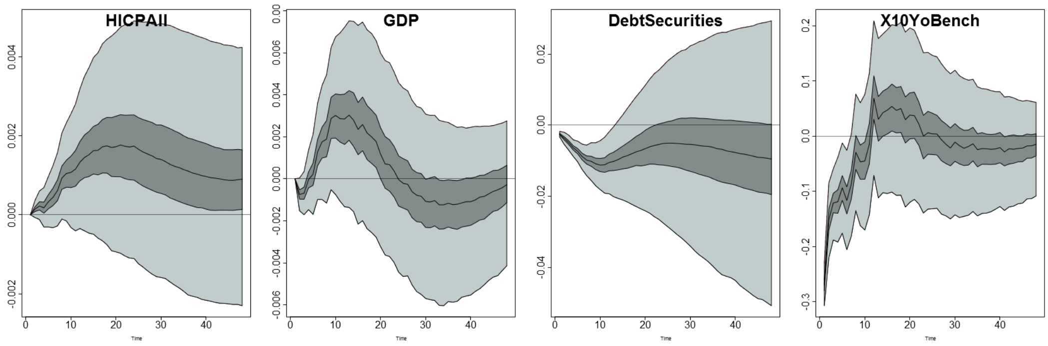
Notes: the cumulative sums of OLS residuals for each equation in the three different benchmark VAR(4)s along with the 95 percent confidence intervals corresponding to a null hypothesis of no structural change. Under the null hypothesis the empirical fluctuation process follows the standard Brownian bridge, for details see Zeileis et al. (2002).

composition and the temporal disaggregation of quarterly series I estimate VARs with monthly variables. As a final robustness check I replace the shadow rate with an alternative measure of monetary policy stance, the liftoff-horizon, derived from the shadow rate model of Kortela (2016).

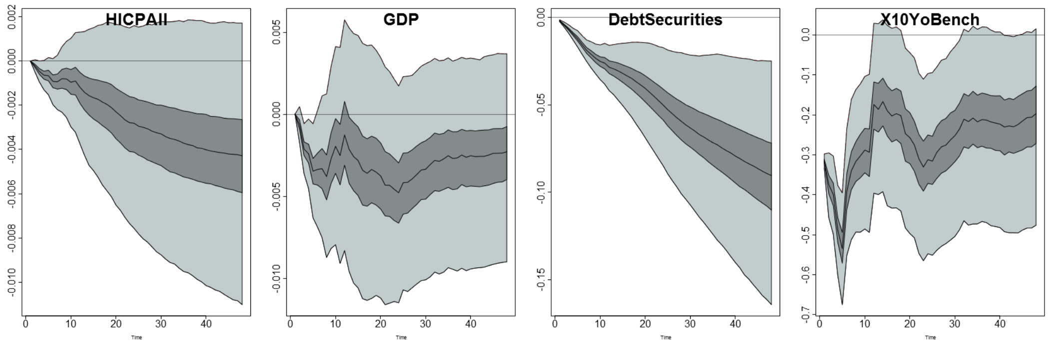
C.1 Lag length

Figure 12 features the functions for four variables, HICP, GDP, Debt securities and the 10-year Government Benchmark bond yields, estimated from a VAR(13) picked by sequential testing. The results from the higher order VARs produce impulse responses that are different from the benchmark models. For the Eonia VAR the price level rises after the policy shock whereas for the shadow rate VARs it is falling. The impulse responses of GDP are even more puzzling as there seems to be a decline in the GDP following a monetary policy shock in the shadow rate VARs. The debt security holdings and benchmark bond yields, in contrast, have responses that are qualitatively consistent with those from the benchmark models.

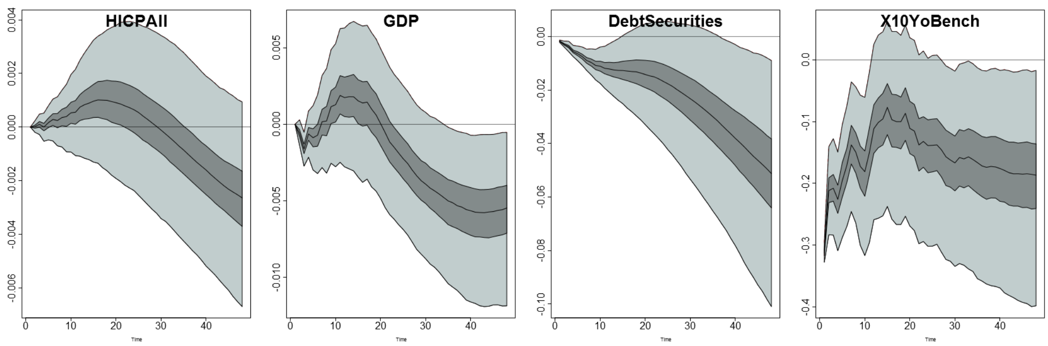
Figure 12: Impulse response functions for a FAVAR with three factors and thirteen lags.



(a) Impulse response function for a VAR(13) with three factors and Eonia



(b) Impulse response function for a VAR(13) with three factors and Kortela's shadow rate



(c) Impulse response function for a VAR(13) with three factors and Wu and Xia's shadow rate

Notes: the impulse responses along with 68 and 90 percent confidence intervals of four macroeconomic variables to an expansionary 25 basis point monetary policy shock. For HICP, GDP and debt security holdings the response measures percentage deviation from a benchmark of no shock whereas for the government benchmark bond yield it measures the absolute change in the rate. The confidence intervals are based on 2500 bootstrap samples.

Two facts should be kept in mind when interpreting the results from the higher order VARs. First, the 90 percent confidence intervals for the HICP and GDP are rather wide, leaving the puzzling effects of monetary policy shocks statistically significant. Second, since the information criteria pick shorter lag lengths and the benchmark models do not suffer from autocorrelation, the lower order models are likely to be adequate and it is then possible that the 13 lag model suffers from overfitting. Furthermore, the sample length is relatively short and therefore including lots of lags could make the parameter estimates inaccurate. Nevertheless, the results from the higher order VAR provide some caution regarding the interpretation of the VAR results.

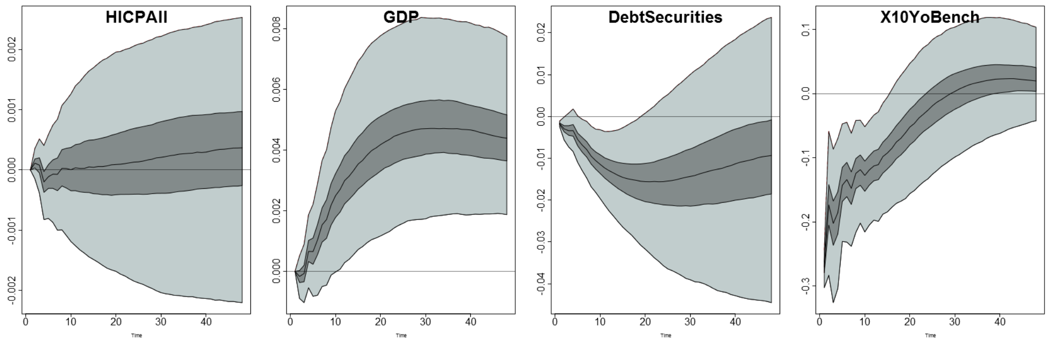
C.2 Number of factors

Next, I estimate a VAR(4) with seven macroeconomic factors, picked by the $IC_2(k)$-criterion. The results are plotted in Figure 13 for each different rate.

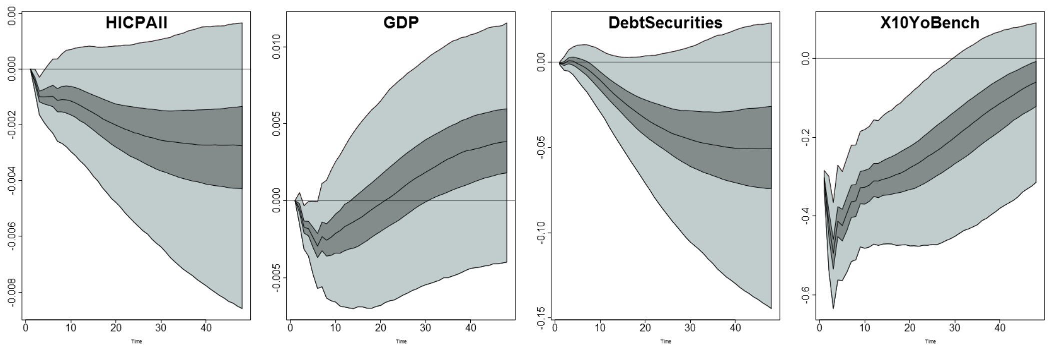
Including seven factors in the VAR does little to change the results: the impulse response functions have all extremely similar shapes to the ones from benchmark case: HICP shows little response at all whereas GDP increases following a monetary policy expansion. Additionally, debt security holdings and the Government Benchmark bond yield decrease following a negative policy rate shock.

Quantitatively, the impulse responses are also rather similar. In the Eonia VAR the increase in output is slightly larger (0.5 percent compared to the baseline) whereas with the Kortela and Wu and Xia VARs the magnitude is close or even slightly less (both models yield a rise in GDP of roughly 0.25 percent 40 months after the shock). Similarly, compared with the benchmark case the decrease in debt security holdings is smaller than in the baseline case with the size of the fall being roughly half a percentage in the shadow rate VARs and one percentage in the Eonia VAR. When the confidence bands around the impulse responses are taken into account the responses are quantitatively virtually the same as in the benchmark. Overall, the confidence bands suggest that the uncertainty around the estimates is now larger than with the benchmark models, which is hardly surprising considering that the number of shocks in the system is now eight rather than four. Overall, the results from seven factor models are consistent with the benchmark.

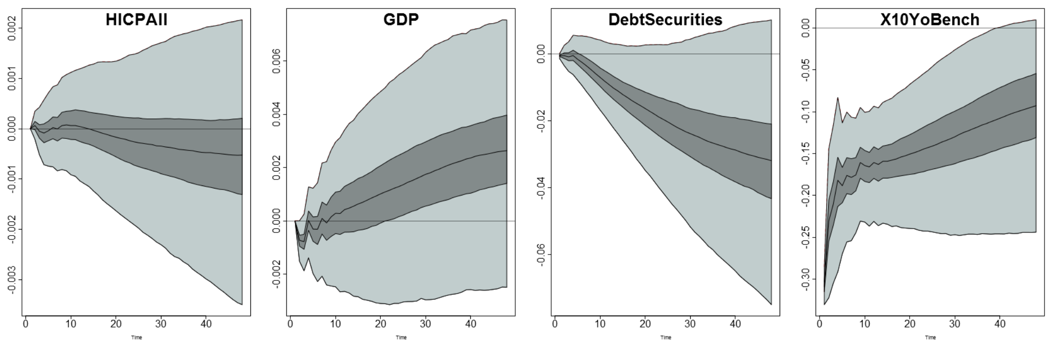
Figure 13: Impulse response functions for a FAVAR with seven factors and four lags.



(a) Impulse response function for a VAR(4) with seven factors and Eonia



(b) Impulse response function for a VAR(4) with seven factors and Kortela's shadow rate

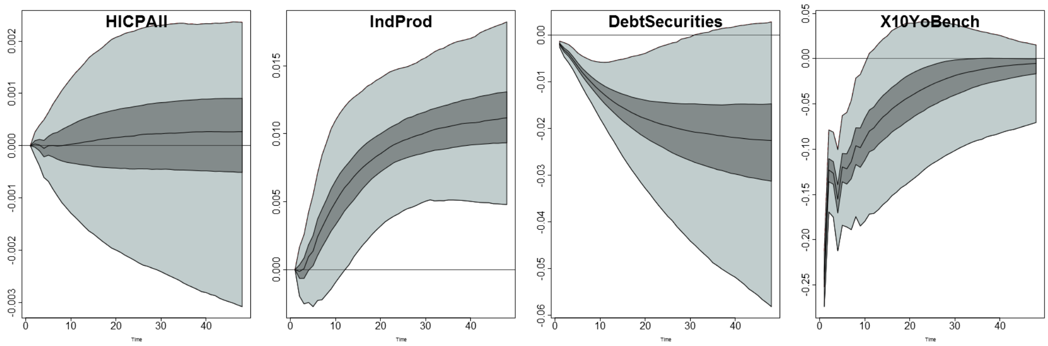


(c) Impulse response function for a VAR(4) with seven factors and Wu and Xia's shadow rate

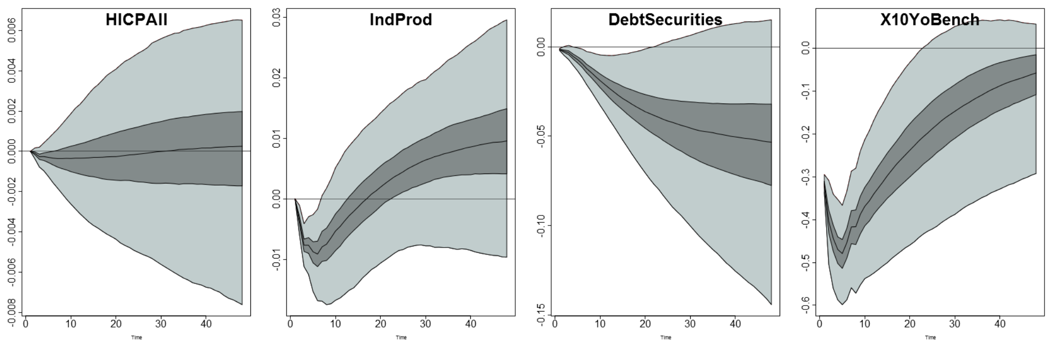
Notes: the impulse responses along with 68 and 90 percent confidence intervals of four macroeconomic variables to an expansionary 25 basis point monetary policy shock. For HICP, GDP and debt security holdings the response measures percentage deviation from a benchmark of no shock whereas for the government benchmark bond yield it measures the absolute change in the rate.

C.3 Monthly variables

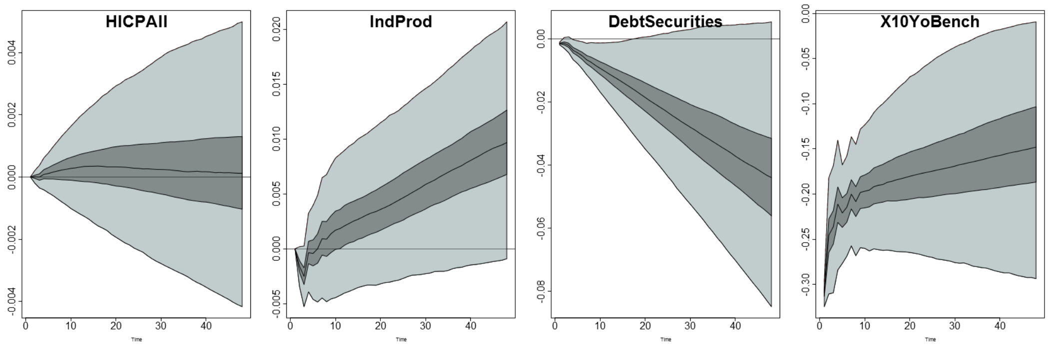
Figure 14: Impulse response functions for a FAVAR with three factors and four lags estimated using only monthly series.



(a) Impulse response functions for a VAR(4) with three factors and Eonia using only monthly variables



(b) Impulse response functions for a VAR(4) with three factors and Kortela's shadow rate using only monthly variables



(c) Impulse response functions for a VAR(4) with three factors and Wu and Xia's shadow rate using only monthly variables

Notes: the impulse responses along with 68 and 90 percent confidence intervals of four macroeconomic variables to a 25 basis point expansionary monetary policy shock. For HICP, industrial production and debt security holdings the response measures percentage deviation from a benchmark of no shock whereas for the government benchmark bond yield it measures the absolute change in the rate. The confidence intervals are based on 2500 bootstrap samples.

Figure 14 plots the impulse response functions for VARs where the factors are estimated using only monthly variables. To measure the effect of monetary policy surprises on real output I use industrial production instead of GDP.

The reaction of price level is similar to other VARs: there is hardly an effect in any of the three VARs. The effects on industrial production index are also close to the results from other specifications: expansionary monetary policy shocks are associated with a rising level in industrial production. However, the confidence bands around the shadow rate VAR responses are wide, yielding the effects statistically insignificant at the 90 percent level.

Unsurprisingly, the results for debt security holdings and government bond yield are similar to other specifications with both decreasing following an expansionary monetary policy shock. The results using only monthly variables are thus similar to those obtained from the full-sample, indicating that the exact composition of the data or the temporal disaggregation do not drive the results from benchmark VAR.

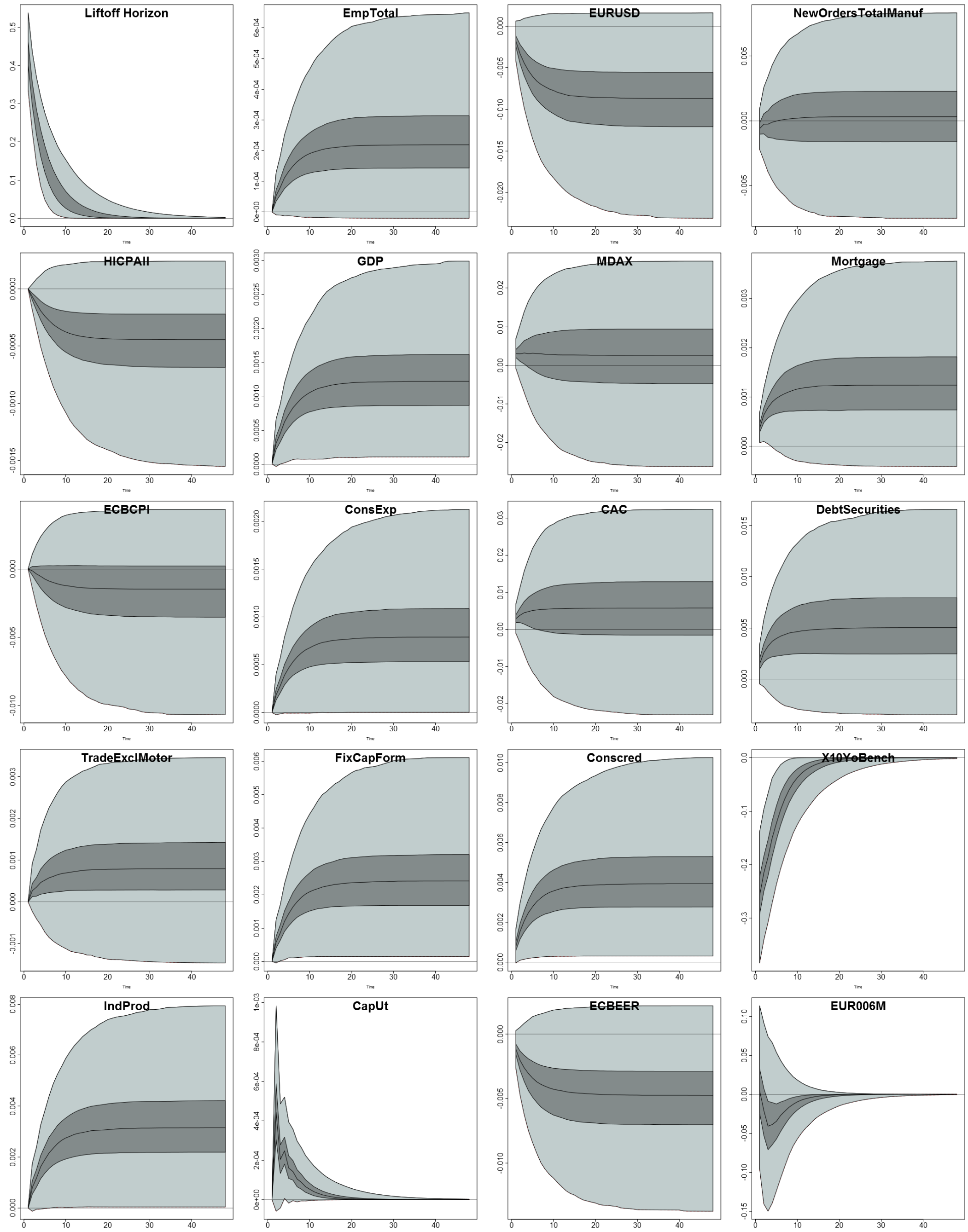
C.4 Liftoff horizon as the measure for monetary policy

The shadow rate term structure models can also be used to calculate the liftoff horizon (LOH). Liftoff horizon is the market-implied horizon after which the interest rate is expected to rise above a given threshold. Therefore, the liftoff horizon measures the expectations about future monetary policy, making it possible to use it as a measure of monetary policy stance. More precisely, higher values of LOH imply more expansionary monetary policy as interest rates are expected to stay low for a longer period. In contrast to the shadow short rate, LOH is relatively robust to different specifications of the lower bound (see Kortela (2016) and Bauer and Rudebusch (2016)). Nevertheless, LOH also has its limitations as it is available only for the periods when ZLB is binding, and it does not take into account the pace of tightening after the liftoff has taken place.

As a final robustness check I estimate a VAR(1) using the liftoff horizon from Kortela's shadow rate model.[9] I carry out the estimation only for the pe-

[9] As with the shadow rate, I obtained the LOH directly from Tomi Kortela. For details about the estimation of the LOH, see Kortela (2016). A similar exercise was also carried out by Wu and Xia (2016).

Figure 15: Impulse response functions for a post-crisis subsample VAR with market-implied liftoff-horizon from Kortela's model as the policy instrument.



Notes: the impulse responses to a one standard deviation expansionary monetary policy shock along with the 90 and 68 percent bootstrap confidence intervals for 20 macroeconomic variables. The liftoff-horizon measures the time before monetary policy is expected to tighten and it is calculated from the shadow rate term structure model (see Kortela (2016)). The subsample used in the VAR starts from November 2011. For all variables that are log-differenced (i.e. everything except capacity utilization and the two interest rate variables) the impulse response functions are cumulative, indicating a percentage difference in level compared to the baseline of no shock. The VAR is estimated with one lag. The confidence intervals are based on 2500 bootstrap samples.

riod where the lower bound is binding, starting from November 2011. Therefore, the LOH VAR should be mainly compared to the shadow rate models estimated with data from the end of the sample (see 4.4).

The impulse responses using LOH as the policy proxy are plotted in Figure 15. As with most other specifications, monetary policy shocks are associated with rising output. However, prices as measured by both HICP and ECB's CPI are now decreasing following a monetary policy expansion, even though the effect on the latter is significant neither at 90 nor 68 percent level. Nonetheless, this result is consistent with the expectations channel of unconventional monetary policy as a decrease in the liftoff horizon would be associated with higher inflation expectations. Again, the most salient effects are found from the impact on 10-year Government Benchmark bond yield.

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