Final Paper (Writing Sample)

40257 Advanced Econometrics II

Sviatoslav Tiupin (3114906)

Abstract

This paper contributes to the literature on the monetary policy transmission and information in VARs. I apply the concept of informational sufficiency of a VAR by exploring whether the monetary policy shock identified in Gertler and Karadi (2015) is fundamental. I find that VAR in Gertler and Karadi (2015) is informationally deficient and that identification of the monetary policy shock using the same set of external instruments in a FAVAR yields a more pronounced reaction of output and interest rates of longer maturities. While the puzzles are still present, a monetary policy shock from a FAVAR explains much larger share of output fluctuations.

Introduction

The usage of external instruments to that allow to measure structural monetary policy disturbances directly has been adopted recently in the empirical literature. Most notable contributions include the narrative approach of Romer and Romer (2004) and the market-based approach of Gürkaynak et al. (2005). The latter approach is applied in Gertler and Karadi (2015), who use the surprises in Federal Funds Futures as an (external) instrument to identify the monetary policy shock in a small-scale VAR.

GK2015 shock, however, is known to be sensitive to the sample choice and the estimation method. Both Ramey (2016) and Stock and Watson (2018) show that using direct identification of causal effects via Jordà (2005) local projections yields results that are significantly different from those of GK2015. Besides, the monetary policy shock of Gertler and Karadi (2015) is predictable using the lag of the structural series itself or Greenbook forecasts, as documented by Ramey (2016).

All of these properties are not desirable for a structural shock that is fundamental. I argue that GK2015 VAR is not informationally sufficient and is not fundamental for the purposes of identification of a monetary policy shock. To test these facts, I apply the test of fundamentalness (or, more precisely, an orthogonality test) proposed by Forni and Gambetti (2014) that adds up to testing the predictability of the identified structural shock by the factors than span a much larger information set. Using this approach I largely follow Forni et al. (2014) who apply the tests of fundamentalness to news shocks[1] and using a FAVAR that is fundamental find that news shock produce the reaction of output that is much more modest than was considered initially.

I proceed in steps: section 1 describes the external instruments approach (see Mertens and Ravn (2013)) that I use to identify the original GK2015 shock. Section 2 describes the data treatment and the approach to factor estimation when there is a threat of cointegration. Section 3 provides the description of the procedure and the results of the fundamentalness/informational sufficiency tests as in Forni et al. (2014). Section 4 provides a comparison of the impulse-response functions from the original VAR and from the FAVAR. Section 5 concludes.

1 Identification using external instruments

In this section, I describe the procedure that allows to identify a structural shock using the external instruments approach. Presented in Stock and Watson (2012), this approach has been successfully used in empirical literature to identify monetary policy (Gertler and Karadi, 2015; Miranda-Agrippino

[1] The literature that followed the seminal paper by Beaudry and Portier (2006)

and Ricco, 2018), fiscal policy (Mertens and Ravn, 2013) and oil supply news shocks (Känzig, 2021). First, consider a VAR(p) model:

$$\mathbf{y_t} = \mathbf{v} + \mathbf{A_1 y_{t-1}} + \mathbf{A_2 y_{t-2}} + \cdots + \mathbf{A_p y_{t-p}} + \mathbf{u_t} \tag{1}$$

where p is the lag order, $\mathbf{y_t}$ is a $n \times 1$ vector of endogenous variables, $\mathbf{u_t}$ is a $n \times 1$ vector of reduced-form residuals with covariance matrix $Var(\mathbf{u_t}) = \mathbf{\Sigma}$, $\mathbf{b}$ is a $n \times 1$ vector of constants, and $\mathbf{A_1}, ..., \mathbf{A_p}$ are $n \times n$ coefficient matrices. The structural shocks of interest, $\varepsilon_\mathbf{t}$, can be obtained linearly from the reduced-form residuals:

$$\mathbf{u_t} = \mathbf{S}\varepsilon_\mathbf{t} \tag{2}$$

where $\mathbf{S}$ is an $(n \times n)$ structural impact matrix and $Var(\varepsilon_\mathbf{t}) = \mathbf{\Omega}$ is digagonal. An identifying assumption is that the instrumental variable (or variables) not included in a VAR affects the shock of interest (is valid), but not the other shocks (exogeneous to them):

$$\begin{aligned} E[z_t \varepsilon_{1t}] &= \alpha \\ E[z_t \varepsilon_{\mathbf{2:n}}] &= \mathbf{0} \end{aligned} \tag{3}$$

where z_t is an instrumental variable, ε_{1t} is the structural shock of interest (in our case, monetary policy shock) and $\varepsilon_{2:n}$ are all the other shocks in the system. With the above assumptions, we can see that ε_{1t} is identified, starting from the reduced-form residuals:

$$E[z_t \mathbf{u_t}] = \mathbf{S}E[z_t \varepsilon_\mathbf{t}] = (\mathbf{s_1} \;\; \mathbf{S_2}) \begin{pmatrix} E[z_t \varepsilon_{1t}] \\ E[z_t \varepsilon_{\mathbf{2:n}}] \end{pmatrix} = \mathbf{s_1}\alpha. \tag{4}$$

After some algebra, we can show that

$$\tilde{\mathbf{s}}_{\mathbf{2:n,1}} = \frac{\mathbf{s_{2:n,1}}}{\mathbf{s_{1,1}}} = \frac{E[z_t \mathbf{u_{2:n,t}}]}{E[z_t u_{1,t}]} \tag{5}$$

The right-hand side term is exactly the ratio of elements of a partitioned left-hand side term in (4). Provided that the instrument is valid (meaning $E[z_t u_{1,t}] \neq 0$), the right-hand side of (5) is an IV estimator of $\mathbf{u_{2:n,t}}$ on $u_{1,t}$ using z_t as instrument. The structural impact vector is $\mathbf{s_1} = (s_{1,1}, \;\; \tilde{s}'_{2:n,1} s_{1,1})'$ where the scale of $s_{1,1}$ is identified, in our case, from $\mathbf{\Sigma} = \mathbf{S\Omega S'}$ by setting $\mathbf{\Omega} = \mathbf{I}$. The identified shock then is normalized to induce a 1 standard deviation increase on $y_{1,t}$ on impact.

2 Data treatment and factor construction

We begin by using the same data as in Gertler and Karadi (2015). As per equation (1), we set $p = 12$ and consider the same variables GK2015 used as our baseline and set $\mathbf{y_t}$

$$\mathbf{y_t} = \begin{bmatrix} R_t^1 \\ \log(CPI_t) \\ \log(IP_t) \\ EBP_t \end{bmatrix} \tag{6}$$

That is, we consider a four-variable VAR(12) that consists of a log industrial production index, log consumer price index, one-year government bond rate that is a monetary policy indicator and a measure of credit costs, specifically excess bond premium constructed and updated by Gilchrist and Zakrajšek (2012).

We obtain the updated series from the Fed's website. Our estimation sample spans from 1978M2 to 2021M6, however, we are limited by the series used by Gertler and Karadi (2015) as insturments. 4-months Federal Funds Futures series spans from 1991M1 to 2012M6. Although it has been critisized by Ramey (2016), I employ the same approach as in the original GK2015, estimating reduced-form coefficients over the whole available sample and identifying monetary policy shock using limited sample of an IV. I also construct factors from a large panel of macroeconomic series. In particular, I use FRED-MD dataset by McCracken and Ng (2016) that contains 130 series spanning from 1959M1

FRED-MD code	My code	Transformation
1	1	Levels
2	1	Levels
4	4	Log
5	4	Log
6	5	Δ Log
7	5	Δ Log

Table 1: Transformations used

to 2021M11. However, in order to avoid missing value imputation as proposed by the authors, we limit our sample to start from 1978M2, a date from which almost all of the series start without missing data.

In order to have a direct comparison to the original VAR, we have to consider the variables in log-levels. Therefore, we use a transformation scheme that is different from one proposed by McCracken and Ng (2016). In that regard, I follow the approach described by Barigozzi et al. (2016) that allows for I(1) variables from which the principal components that are a consistent estimator of factors can be constructed. In particular, we assume the following relationship between the factors and the data:

$$X_t = \alpha + \beta * t + \Lambda F_t + \xi_t \tag{7}$$

where X_t is a panel of M possibly non-stationary time-series, α is a constant t denotes a time trend F_t are R possibly non-stationary factors, whereas Λ is an $M \times R$ matrix of factor loadings and ξ_t is an innovation that can be I(1) or I(0).

That is, the factors are defined as $F_t = \Lambda'(X_t - \alpha - \beta * t)$. In practice, I detrend the series before standardizing them and estimating principal components. This approach allows us to estimate VAR in levels on the original data, augmenting it with possibly non-stationary factors without being threatend by possible information loss due to differencing.

Table 1 provided the relationship between the codes assigned by FRED-MD and the transformation performed.[2] I transform the I(2) data, taking log-differences and take either logs or levels of I(1) variables. That is, nominal variables are log-differenced, while real variables are either taken in logs or in levels.

3 Testing for fundamentalness

We start by identifying the structural shock series using the approach described in section 2 and a VAR(12) with the variables described by equation (**??**). In particular, following Stock and Watson (2018), the structural shock series, $\varepsilon_{1,t}$ can be identified as follows:

$$\begin{aligned}
\mathbf{s_1'\Sigma^{-1}u_t} &= \mathbf{s_1'(SS')^{-1}u_t} \\
&= \mathbf{s_1'S'^{-1}S^{-1}u_t} \\
&= \mathbf{s_1'S'^{-1}S^{-1}S}\boldsymbol{\varepsilon}_\mathbf{t} \\
&= \mathbf{e_1'}\boldsymbol{\varepsilon}_\mathbf{t} \\
&= \varepsilon_{1,t},
\end{aligned} \tag{8}$$

where $\mathbf{e_1}' = [1, 0, \ldots, 0]$.

Having computed the structural series, we employ the procedure described in Forni et al. (2014): we estimate 11 principal components from out data panel and regress ε_{1t} on the lags of first j of these components.

[2] There are no variables with the code 3.

	Principal components (from 1 to j)									
Lags	1	2	3	4	5	6	7	8	9	10
1	0.06	0.16	0.05	0.07	0.07	0.08	0.01	0.01	0.01	0.03
4	0.02	0.01	0.02	0.06	0.00	0.00	0.00	0.00	0.00	0.00
8	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	0.02	0.05	0.07	0.02	0.00	0.00	0.00	0.00	0.00	0.00

Table 2: The results of orthogonality test as in Forni et al. (2014)

Table 2 provides the results of the orthogonality test as in Forni et al. (2014). Each entry of the table is a p-value of a robust F-test from a regression of the idetified monetary policy shock on the lags of principal components from 1 to j. Here I report the results from a specification with all the four variables, but the result is robust to removing variables (except for the MP variable) one at a time. In all the specifications except for one, we can clearly reject the null of orthogonality on 10% level.

Next we employ the recursive procedure from Forni et al. (2014) to determine recursively the number of factors sufficient to estimate the shock of interest. The idea is as follows: although there exist information criteria for determining the number of factors spanning a particular panel of variables, adding all the factors might not be necessary to identify the shock of interest. Therefore, we proceed as follows: we let the $\mathbf{y_t}$ be a subvector of $\mathbf{X_t}$ described in equation (6) and g_{jt} be a jth principal component of $\mathbf{X_t}$. We estimate a VAR(12) for $\mathbf{w_t^h} = (\mathbf{y_t}\ g_{1t}, \ldots, g_{ht})'$ by recursively adding one principal component at a time to a VAR, then performing the orthogonality test as in table 2 on the estimated structural shock.

	Principal components (from h+1 to j)									
FAVAR with h factors	1	2	3	4	5	6	7	8	9	10
0	0.06	0.16	0.05	0.07	0.07	0.08	0.01	0.01	0.01	0.03
1	–	0.20	0.21	0.24	0.39	0.29	0.07	0.08	0.11	0.16
2	–	–	0.09	0.16	0.30	0.27	0.19	0.19	0.23	0.28
3	–	–	–	0.66	0.59	0.34	0.34	0.41	0.55	0.61
4	–	–	–	–	0.25	0.31	0.51	0.66	0.72	0.68
5	–	–	–	–	–	0.22	0.45	0.64	0.47	0.55
6	–	–	–	–	–	–	0.27	0.51	0.42	0.59
7	–	–	–	–	–	–	–	0.85	0.22	0.39
8	–	–	–	–	–	–	–	–	0.02	0.08
9	–	–	–	–	–	–	–	–	–	0.47

Table 3: The results of the test for the number of PCs included in FAVAR

Table 3 provides the result of the recursive test for the number of components to be included in FAVAR. The results of the test are not conclusive. Although we are unable to reject the null of orthogonality after adding from the first to the third components, at 8 components the null of orthogonality to the 9th and 10th components is rejected. We start by setting the number of components equal to 3, then considering all the specifications up to the 9th.

4 Impulse responses and FEVD

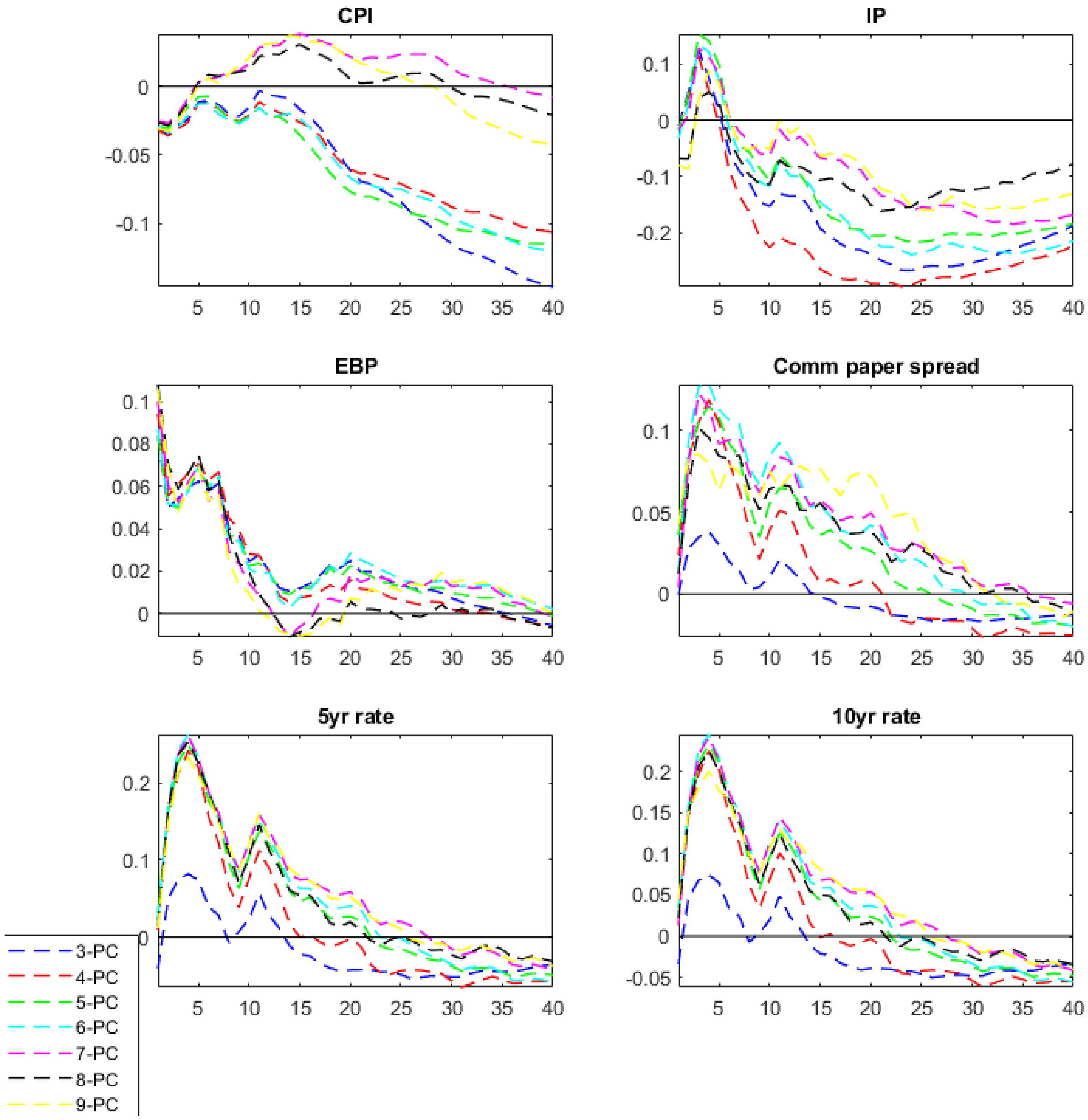

Figure 1: Impulse Response functions: FAVARs with varying number of factors. A shock is a 1 SD increase in 1-year rate (not shown)

Figure 1 provides a comparison of all the specifications from 3 factors to 9. We report all the variables except for the policy rate (since it is present on other plots). We observe that FAVARs with 3-6 PCs have extremely similar responses, whereas starting from the 7 PCs to 9, the responses change dramatically: the response of CPI turns positive 5 months after the shock, while the response of output is more muted with a greater number of factors, similarly to the original VAR.

Note that we decide to keep 4 variables that are present in the original GK2015 VAR out of the factors. The reason is that we would like to obtain a comparison that is as close as possible to the original 4-variable VAR.

An advantage of a FAVAR, however, is that we can obtain the IRFs for all the variables of interest from the original panel, simply obtaining Λ by regressing the PCs used in a FAVAR on the original variables without a constant. Therefore, we are able to obtain IRF for the financial variables without the need to add them to the original VAR one-by-one. An important note is that the responses of financial variables are much larger than in the original paper. Stronger reaction of the longer rates is consistent with the expectations hypothesis and evidence of importance of forward guidance documented by Gertler and Karadi (2015).

We choose a FAVAR with 4 PCs as our baseline, since the specification with 3 PCs has drastically different responses for commercial variables.

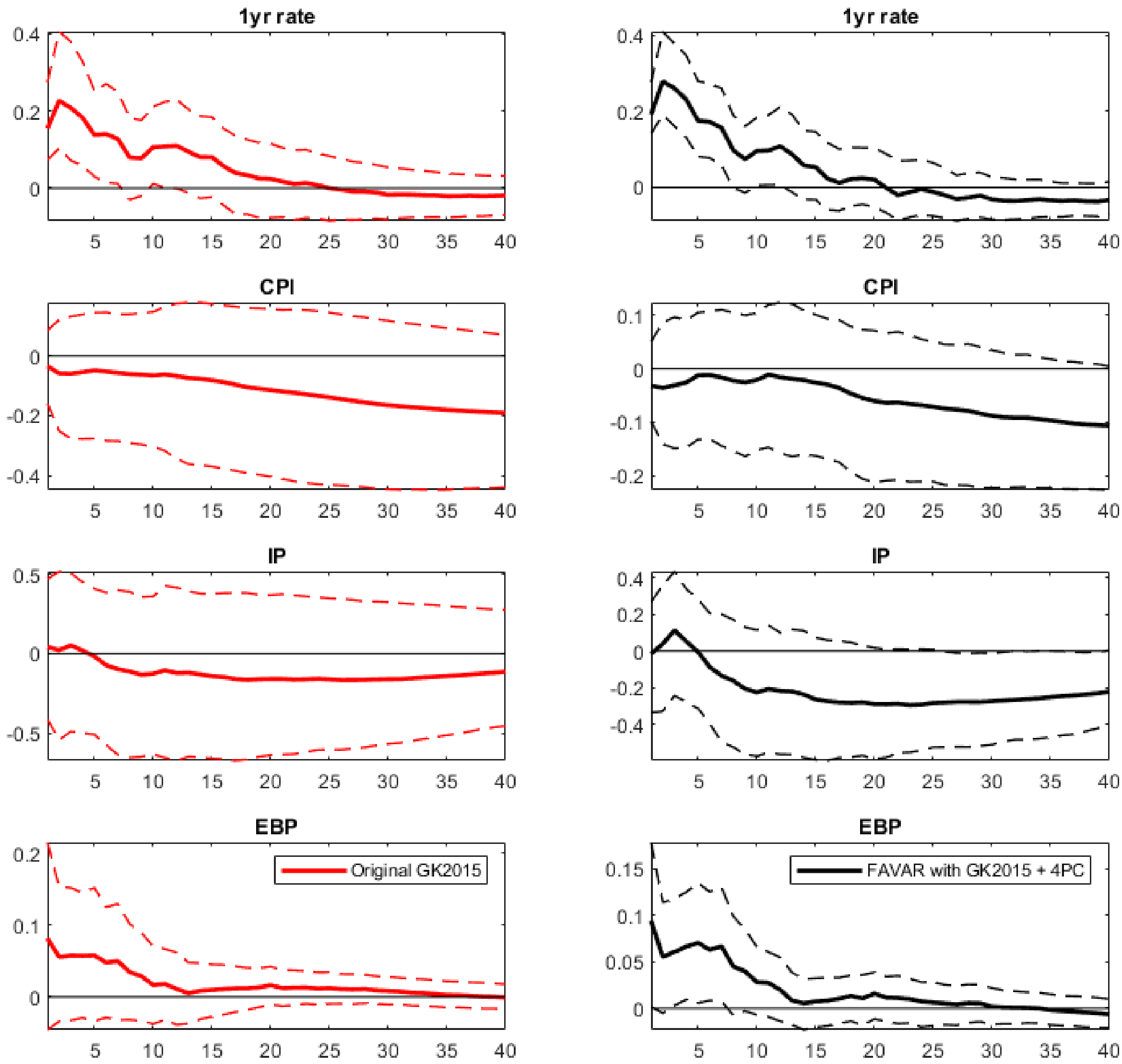

Figure 2: Impulse Response functions: Original GK2015 in red, FAVAR with 4 factors in black. Dotted lines are 90% bootstrapped confidence bands. A shock is a 1 SD increase in 1-year rate.

Figure 2 provides a comparison of the IRFs obtained for the variables present in the original baseline GK2015 VAR(12). It is clear that, although the identified shock is orthogonal now, the responses are not drastically different from the original ones. CPI declines roughly with the same magnitude following a contractionary shock, while the initial positive reaction of output that was puzzling in the original GK2015 is even more pronounced now. Note, however, that at the end of the IRF horizone the negative response of output is statistically significant and is larger that in the original VAR.

Horizon	FAVAR-4PC	VAR
10	0.02	0.01
20	0.05	0.01
30	0.07	0.02
40	0.08	0.02

Table 4: Forecast error variance decomposition: share of output variance explained by the MP shock

The effect of output fluctuations is clearer when we compare the FEVD of FAVAR-4PC and a VAR. Table 4 provides the comparison of shares of variance of output explained at horizons of 10 to

40 months. The result from FAVAR is closer to the recent literature: Bernanke et al. (2005) estimate a FAVAR on monthly data and find the effect of monetary policy shock on output of around 5% at 10 year, whereas Uhlig (2005) find the effects of around 5-10%. Our new estimate safely lies within these bands, whereas the 2% from Gertler and Karadi (2015) is significantly lower (not reported in the original paper).

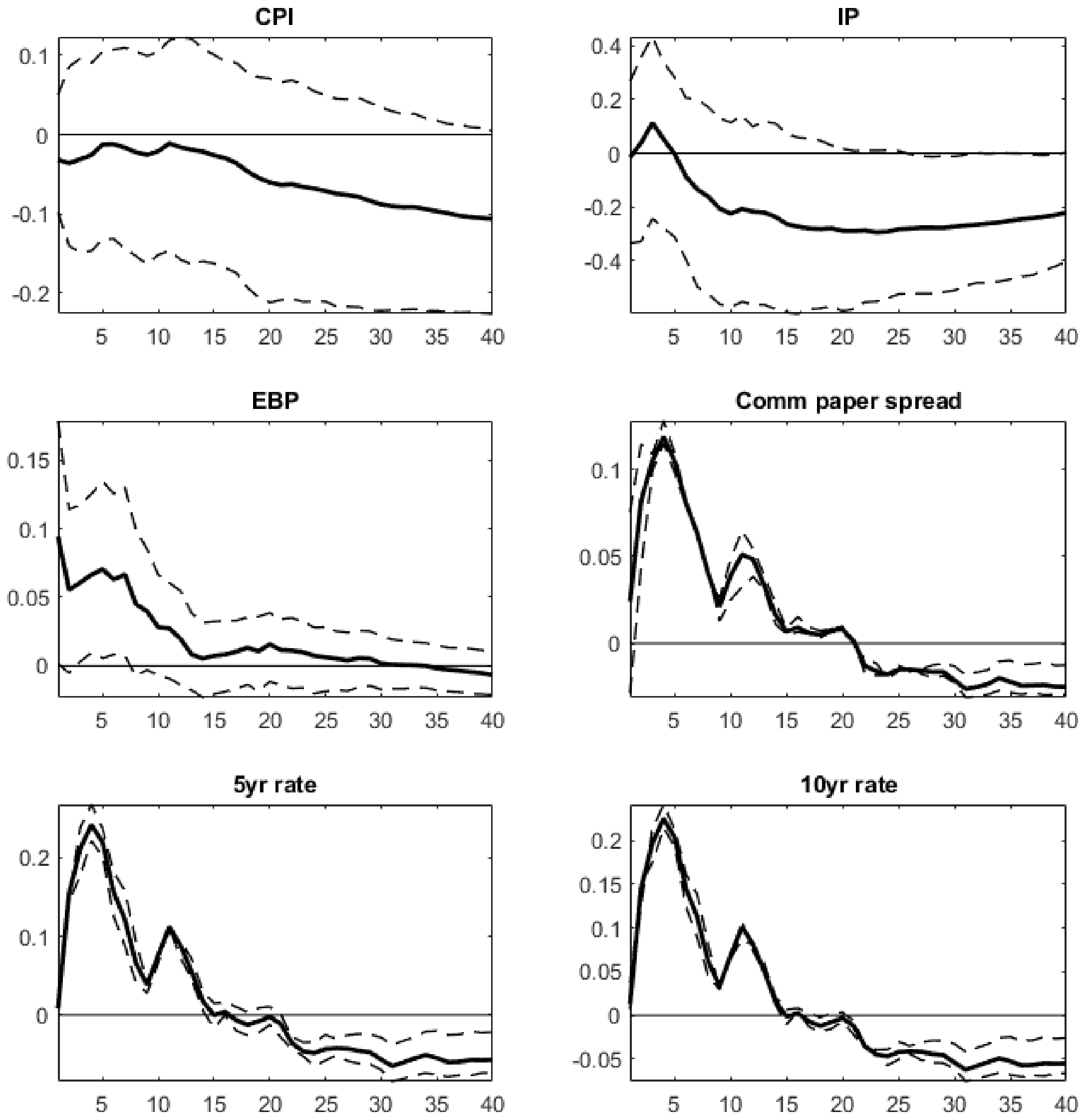

Figure 3: Impulse Response functions: FAVAR with 4 factors. Dotted lines are 90% bootstrapped confidence bands. A shock is a 1 SD increase in 1-year rate (not shown).

Finally, figure 3 provides the impulse responses of the FAVAR-4PC for all the variables of interest with 90% confidence bands. The effect on excess bond premium is comparable to the original, while the effect on interest rates of longer maturities is much stronger.

5 Conclusion

In this paper we assessed the issue of non-fundamentalness in Gertler and Karadi (2015) VAR. Using the same High frequency identification scheme with external instruments, we were able to identify the monetary policy shock and test whether it spans all available information. We clearly reject the null of orthogonality and conclude that the shock in Gertler and Karadi (2015) is indeed non-fundamental. We use a fundamental FAVAR with a baseline of 4 PCs to estimate the impulse-response functions and FEVD for output and compare them to the original.

Although they are different, this difference is not large and mostly affects the financial variables: 5-year and 10-year interest rates react stronger than in the original paper, and the effect on output is much more pronounced. The puzzles, with industrial production index having a positive reaction on impact and around the first five months after the shock, are still present. Removing the autocorrelation directly might be a path to explore in future research. For instance, Miranda-Agrippino and Ricco (2018) analyze the GK2015 shock and build a path-information robust series of monetary policy shocks, removing private information from Greenbook forecasts and autocorrelation. They show that impluse responses change drastically after using this new series as instrument and have the expected sign.

References

Barigozzi, M., Lippi, M., and Luciani, M. (2016). Non-stationary dynamic factor models for large datasets. *Available at SSRN 2741739*.

Beaudry, P. and Portier, F. (2006). Stock prices, news, and economic fluctuations. *American Economic Review*, 96(4):1293–1307.

Bernanke, B. S., Boivin, J., and Eliasz, P. (2005). Measuring the effects of monetary policy: a factor-augmented vector autoregressive (favar) approach. *The Quarterly journal of economics*, 120(1):387–422.

Forni, M. and Gambetti, L. (2014). Sufficient information in structural vars. *Journal of Monetary Economics*, 66:124–136.

Forni, M., Gambetti, L., and Sala, L. (2014). No news in business cycles. *The Economic Journal*, 124(581):1168–1191.

Gertler, M. and Karadi, P. (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, 7(1):44–76.

Gilchrist, S. and Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American economic review*, 102(4):1692–1720.

Gürkaynak, R., Sack, B., and Swanson, E. (2005). Do actions speak louder than words? the response of asset prices to monetary policy actions and statements. *International Journal of Central Banking*, 1(1).

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review*, 95(1):161–182.

Känzig, D. R. (2021). The macroeconomic effects of oil supply news: Evidence from opec announcements. *American Economic Review*, 111(4):1092–1125.

McCracken, M. W. and Ng, S. (2016). Fred-md: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics*, 34(4):574–589.

Mertens, K. and Ravn, M. O. (2013). The dynamic effects of personal and corporate income tax changes in the united states. *American economic review*, 103(4):1212–47.

Miranda-Agrippino, S. and Ricco, G. (2018). The transmission of monetary policy shocks.

Ramey, V. A. (2016). Macroeconomic shocks and their propagation. *Handbook of macroeconomics*, 2:71–162.

Romer, C. D. and Romer, D. H. (2004). A new measure of monetary shocks: Derivation and implications. *American Economic Review*, 94(4):1055–1084.

Stock, J. and Watson, M. (2012). Inference in structural vars with external instruments. Technical report, Working Paper.

Stock, J. H. and Watson, M. W. (2018). Identification and estimation of dynamic causal effects in macroeconomics using external instruments. *The Economic Journal*, 128(610):917–948.

Uhlig, H. (2005). What are the effects of monetary policy on output? results from an agnostic identification procedure. *Journal of Monetary Economics*, 52(2):381–419.