The Puzzling Effects of Monetary Policy in VARs: Invalid Identification or Missing Information?

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Abstract

Standard VAR models often find puzzling effects of monetary policy shocks. Is this due to an invalid (recursive) identification scheme, or because the underlying small-scale VAR neglects important information? I employ factor methods and external instruments to answer this question and provide evidence that the root cause is missing information. In particular, while a recursively identified dynamic factor model yields conventional monetary policy effects across the board, a small-scale VAR identified via external instruments does not. Importantly, the discrepancy between both models largely disappears once the information set of the VAR is augmented via factors. This finding is comforting news for the recent monetary literature. Two leading empirical advances with different underlying assumptions - namely external instruments (applied to a factor-augmented VAR) and dynamic factor models (identified recursively) - find very similar effects of monetary policy shocks, cross-verifying each other.

Keywords: Monetary Policy, Dynamic Factor Models, FAVAR, External Instrument, High-Frequency Identification.

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1 Introduction

Why do small-scale vector autoregressions (VARs) regularly produce puzzling results, in particular regarding the effects of monetary policy? One suspected culprit has been the common Cholesky identification scheme, which imposes zero restrictions on the contemporaneous effects of shocks that might be invalid. Fortunately, the monetary literature has developed less restrictive identification schemes, most notably the external instrument approach (see Ramey, 2016, for an overview). By exploiting high-frequency data, this approach avoids any dubious timing restrictions. Gertler and Karadi (2015) e.g. use interest rate future movements around policy announcements as instruments. They find intuitive effects of monetary policy and conclude that the recursive Cholesky scheme - which yields puzzling results - is invalid, at least within the standard VAR framework they employ.

This last qualifier is important, because the Cholesky scheme might also produce puzzling results not because it is invalid per se, but rather because of problems with the model it is applied to. One potential problem, which small-scale VARs are particularly prone to, is that of missing information. In fact, an empirical model needs to contain sufficient information to span the space of the structural shock of interest. Otherwise, the correct shocks and impulse response functions cannot be recovered from the history of observed variables. The problem is also known as "non-fundamentalness". VARs implicitly assume fundamentalness, but the assumption is not necessarily legitimate and - given the sparse number of variables they can include - quite often questionable.[1]

In principle, the problem can be addressed by expanding the information space. Conventional VARs, however, are ill-suited for this task, since they suffer from the "curse of dimensionality".[2] To overcome these shortcomings, the applied monetary literature has incorporated factor models. These models can capture the common dynamics of a vast number of macroeconomic variables, thus making the fundamentalness assumption - i.e. a direct mapping between reduced-form innovations and structural shocks - more plausible. In practice, factors are usually extracted as the principal components of a large dataset and are either added directly to the observable variables of a conventional VAR - leading to the factor-augmented VAR (FAVAR) approach by Bernanke et al. (2005) - or used as the building blocks for the more general dynamic factor model (DFM) approach.

In this paper, I combine factor methods and external instruments to answer whether the puzzling results of VARs are due to an invalid identification scheme or missing information. I focus on the effect monetary policy has on output, prices, credit costs, and real exchange rates and find the following: First, a small-scale VAR identified via external instruments resolves some of the puzzles found in recursive VARs, but others remain. Second, a large-scale factor model yields intuitive results across the board, even within a recursive identification scheme (as in Forni and Gambetti, 2010). Third, the remaining discrepancies between both models are driven by a gap in their underlying information sets. Augmenting the external instrument VAR with factors closes this gap and yields broadly similar results to those of the recursive factor model. Indeed, the two approaches cross-verify each other: They impose distinctly different assumptions to estimate monetary policy effects but still arrive at the same answer.

[1] Alessi et al. (2011) provide a review of the literature, for early contributions see Hansen and Sargent (1991); Lippi and Reichlin (1993, 1994); Fernández-Villaverde et al. (2007). A prominent empirical application of non-fundamentalness are "news shocks", i.e. foresight of economic agents about changes in future fundamentals, see Sims (2012); Forni and Gambetti (2014); Forni et al. (2014); Beaudry et al. (2016); Canova and Hamidi Sahneh (2017).

[2] Sims (1992) e.g. argues the "price puzzle" occurs because the VAR misidentifies as contractionary shocks what are in fact preemptive tightenings of the central bank to expected future inflation. His solution is to enlarge the information set by adding a commodity price index as a proxy for upcoming price pressure. Apart from its ad-hoc nature, however, this approach has clear limits, as the number of parameters proliferates quadratically with each new variable that is added to the VAR.

2 Empirical Methods

2.1 Overview of Models

To see how factor models augment the information set, it is instructive to show that conventional VARs - and FAVAR extensions thereof - are restricted versions of the more general dynamic factor model.[3] Starting point in each framework is a dataset X_t of n observable time series that is assumed to be driven by r shocks u_t:

$$\underset{n\times 1}{X_t} = \underset{n\times r}{\Lambda}\ \underset{r\times 1}{F_t} + \underset{n\times 1}{e_t} \tag{1}$$

$$\underset{r\times r}{\Phi(L)}\,\underset{r\times 1}{F_t} = \underset{r\times 1}{u_t}\,. \tag{2}$$

The standard **VAR** postulates that the factors driving the economy can be captured by a handful of observable variables, i.e. $X_t = F_t = Y_t^{\text{VAR}}$, $n = r$ and $e_t = 0$, making Equation (1) redundant, and letting Equation (2) boil down to a familiar VAR of lag length p.

The **FAVAR** model augments the simple VAR by adding factors to observable variables. In particular, latent factors F_t^* are estimated as the principal components of a large dataset X_t with $n \gg r$ variables. Equation (2) is thus again a conventional VAR equation with $F_t = (Y_t^{\text{FAVAR}}, F_t^*)$ comprising both observable macroeconomic variables and estimated factors.

The **DFM** further generalizes the FAVAR model by treating all factors as unobservable and by allowing u_t to have a singular variance-covariance matrix, see Section 2.3. In contrast to the aforementioned models, the DFM approach allows for serially and cross-sectionally correlated idiosyncratic errors e_t in all series of X_t.

2.2 Data

To ensure consistency and comparability, I estimate all aforementioned models on the same dataset X_t. The dataset contains 132 macroeconomic and financial series from April 1973 to September 2016 and is largely based on McCracken and Ng (2016), cf. online Appendix. As in Forni and Gambetti (2010), I add short-term interest rate spreads and real exchange rates (CPI based) between the US and Switzerland, Japan, the United Kingdom, and Canada. I also transform various private sector interest rates into spreads over their sovereign counterparts, as in Gertler and Karadi (2015). Since X_t is used to extract principal components for both the FAVAR and DFM, I transform some series into log-differences to ensure stationarity. The only exception pertains the industrial production and consumer price index, which I keep in log-levels when they are used as observable variables in the VAR and FAVAR models (see below).

2.3 Model Specification and Parametrization

In the VAR model, the observable variables Y_t^{VAR} include log industrial production, the log consumer price index and the one-year government bond rate. The various interest and real exchange rates whose response I want to study are added one at a time as the fourth variable, i.e. $r = 4$.[4] The FAVAR model differs in this respect, as it allows to study the response of all variables in one single model. In particular, Y_t^{FAVAR} includes the same three variables of Y_t^{VAR} mentioned above, but it adds nine latent factors to capture the common dynamics of the entire dataset at once, i.e. $r = 3 + 9$. In both cases, the lag length is set to $p = 12$ as in Gertler and Karadi (2015). For the DFM, I follow Forni and Gambetti (2010) by setting

[3] The dynamic factor model approach presented here is due to Forni et al. (2009). See Stock and Watson (2005) for a thorough treatment of the methods and Stock and Watson (2016) for an extensive literature review.

[4] This procedure is adopted from Gertler and Karadi (2015). In their benchmark specification, their fourth variable in Y_t^{VAR} is an excess bond premium. Gilchrist and Zakrajsek (2012) construct this series based on micro-level data as the residual spread of corporate over sovereign bonds after accounting for default risk.

$r = 16$ and $p = 2$ and by allowing the number of pervasive macroeconomic shocks to be smaller than the number of principal components extracted from X_t.[5] The online Appendix provides a battery of robustness checks to alternative parameter specifications and sample periods.

2.4 Identification

To obtain a structural interpretation of the shocks u_t in Equation (2), I employ two different identification schemes, see the online Appendix for details.

The well-known recursive Cholesky scheme assumes that i) a contractionary monetary policy shock increases the one-year government bond rate, ii) the shock has no contemporaneous effect on industrial production or consumer prices, and iii) the one-year government bond rate can only be affected by the first three shocks contemporaneously, but none other. Particularly the last assumption is quite ad-hoc and casts doubt on the validity of the recursive identification scheme. This is why the monetary literature has put great emphasis on finding more plausible and transparent identification strategies.

One such strategy is the use of external instruments, which does not impose any zero restrictions on the contemporaneous effects of shocks. Instead, it relies on an instrumental variable Z_t that meets the usual relevance and exogeneity conditions. Given such a variable, the monetary policy shock can be identified by running a regression of the instrument Z_t on all reduced-form shocks u_t.[6] Following Gertler and Karadi (2015), the instrument Z_t I use is constructed from high-frequency futures price data. More precisely, Z_t captures the change in the three month ahead fed funds future in a tight window around FOMC meetings (ten minutes prior and twenty minutes after the policy announcement).[7] The relevance and exogeneity conditions thus imply that, within this tight window, movements in the fed funds future should be driven by revised market expectations about Fed policy and not any other structural shock.[8]

3 Results

Roughly speaking, there are two potential reasons for the puzzling monetary policy effects conventional small-scale VARs often find: Either the (recursive) identification scheme is wrong or the identification scheme is applied to the wrong (informationally deficient) model. To shed light on this issue, I extend a basic VAR model in two directions, namely by enlarging the information set (i.e. estimating factor models) and by applying external instrument identification. In particular, the following figures compare results across four different models, ordered column-wise: i) a recursively identified small-scale VAR, ii) the same VAR identified via external instruments, iii) a recursively identified dynamic factor model, and iv) a factor-augmented VAR identified via external instruments.

For each model, I discuss three sets of responses, namely those of output and prices (Figure 1), credit spreads (Figure 2, as in Gertler and Karadi, 2015) and real exchange rates (Figure 3, as in Forni and Gambetti, 2010).

Starting with the recursive small-scale VAR (cf. **first columns**), we observe puzzling results throughout. After a contractionary shock, industrial production expands in the short-run and turns significantly negative only after two years, while consumer prices rise throughout, i.e. the familiar price puzzle is present (Figure 1). Regarding the response of credit spreads, only the three-month commercial paper spread rises significantly in the Cholesky VAR, Gilchrist and Zakrajsek (2012)'s excess bond premium barely moves and the 30-year conventional mortgage spread even narrows (Figure 2). The reaction of real

[5] Specifically, I obtain $q = 4$ "dynamic" factors as the first q principal components of the residuals one obtains by estimating a VAR on the "static" factors F_t. See Stock and Watson (2016) for an overview of formal criteria to determine r and q.

[6] Stock and Watson (2012) show that is approach is equivalent to the two-stage approach presented in Gertler and Karadi (2015).

[7] The instrument is one of five interest rate futures studied by Gürkaynak et al. (2005). As a robustness check, the online Appendix shows results when these other futures are used as external instrument.

[8] Neither the exogeneity nor the relevance condition is directly testable in the current setting, see online Appendix.

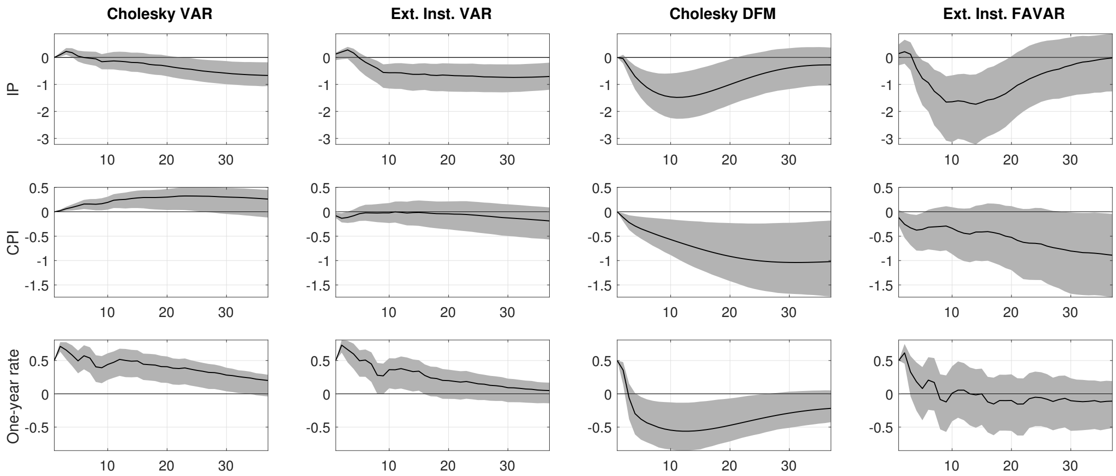


Figure 1: Macroeconomic Effects of Monetary Policy Shocks Across Models

The solid black line and shaded areas refer to point estimates and 90% confidence bands (the online Appendix describes the employed wild bootstrap procedure). All responses are in percent. The policy shock is standardized to a 50bp rise in the one-year government bond rate. Each column refers to a different empirical model and/or identification scheme. The first and second column refer to the four-variable VAR including the excess bond premium, as in Gertler and Karadi (2015)'s Figure 1.

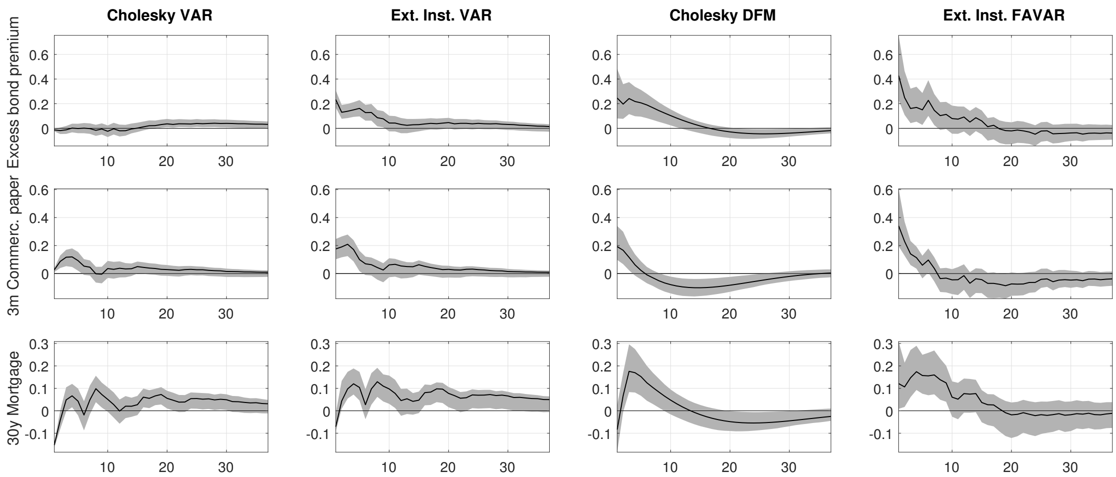


Figure 2: Credit Spread Responses

See Figure 1 for details. In the first two columns, each row refers to a separate VAR with the interest rate spread stated left as the fourth variable, cf. Section 2.3.

exchange rates to a monetary tightening is equally counter-intuitive. The sluggish hump-shaped responses - also dubbed "delayed overshooting puzzle" - are at odds with basic theory (Figure 3).

To address these puzzles, Gertler and Karadi (2015) apply the external instrument identification scheme to an otherwise identical VAR model (cf. **second columns**). In this setting many - but not all - puzzling results disappear. Output declines significantly, but the CPI response is largely muted. In fact, the tiny fall in consumer prices is out of proportion to the sizeable response of industrial production. Interest rate spreads spike after a contractionary shock - consistent with a credit channel of monetary policy - but the response of real exchange rates remains hard to square with economic theory, just like in

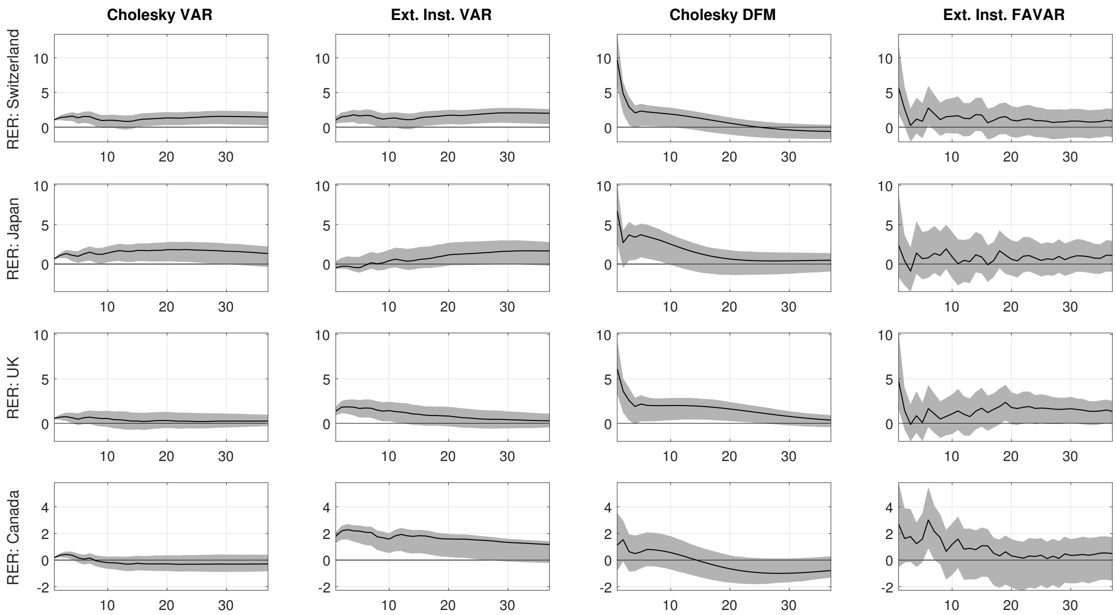


Figure 3: Real Exchange Rate Responses

See Figure 1 for details. In the first two columns, each row refers to a separate VAR with the exchange rate stated left as the fourth variable, cf. Section 2.3.

the Cholesky VAR case.

An entirely different approach to resolve the puzzling results of VARs are dynamic factor models (cf. **third columns**). In fact, the same recursive identification scheme that produces counter-intuitive results in a VAR, yields results consistent with standard theory when applied to a DFM (see also Forni and Gambetti, 2010). An unexpected monetary tightening leads to a significant decline in both industrial production and consumer prices, to rising credit spreads, and to a sharp and immediate appreciation of the domestic currency.[9]

To wrap up, the external instrument identification resolves many of the puzzling results of recursive VARs, while a recursive dynamic factor model solves all. The remaining differences are substantial but, reassuringly, this gap effectively vanishes when the information space underlying the external instrument VAR is expanded. Specifically, extending the small-scale VAR to a FAVAR (cf. **last columns**) yields results very similar to the recursive DFM. The output response is more pronounced and short-lived, a decline in consumer prices is clearly visible, the initial rise in the one-year rate is less persistent, and credit spreads spike. Most strikingly, the external instrument FAVAR finds the same sharp immediate reaction of real exchange rates, only the associated confidence bands are somewhat larger than in the DFM framework. Indeed, the two approaches cross-verify each other: They impose distinctly different assumptions to estimate monetary policy effects but still arrive at the same answer.

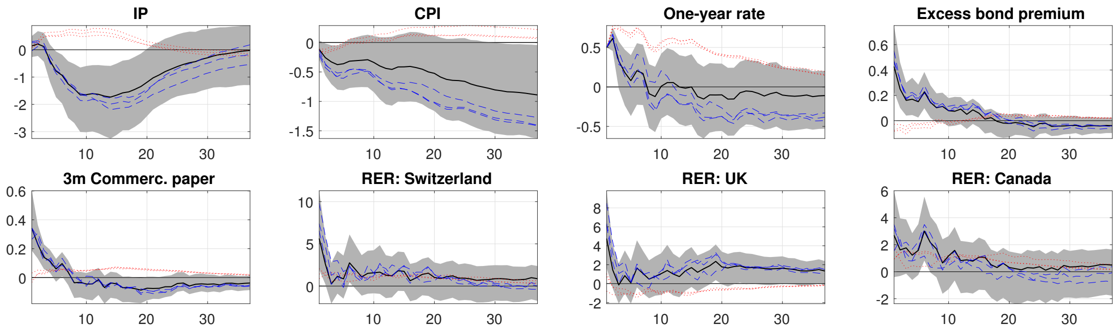
The similar results in the last two columns underscore the importance of a sufficiently large information set: while the small-scale VAR seems to require additional information (in the form of external instruments and factors) to correctly identify monetary policy shocks, a dynamic factor model apparently does not. In this sense, my results suggest that to the question raised at the beginning - i.e. whether the puzzling results of standard VARs are due to an invalid identification scheme or an insufficient information set - the answer is the latter: It is the informational deficiency of the underlying VAR that renders the

[9] Based on Euro area data, Alessi and Kerssenfischer (2016) find similar results for asset prices more generally: corporate bond yields, exchange rates, and stock and house prices all respond rapidly in the DFM framework, but only delayed and mildly in VARs.

recursive identification scheme invalid.

On a final note, consider three further pieces of evidence consistent with the claim that a deficient information set is the root cause behind the puzzling results of conventional VARs. First, the external instrument FAVAR produces intuitive and robust results, as long as sufficiently many factors are included, i.e. the information set is sufficiently large. With too few factors, on the other hand, the puzzling results of small-scale VARs reappear (see Figure 4).

Figure 4: Different Number of Factors in External Instrument FAVAR



The solid black line and shaded areas reproduce the fourth column in Figures 1-3, i.e. they refer to the external instrument FAVAR with $r = 3 + 9$ (adding nine factors to the three observable variables). The dashed blue lines refer to models with $r \in 3 + \{7, 11, 13\}$, the red dotted lines to models with $r \in 3 + \{1, 2, 3\}$.

Second, the dynamic factor model - in contrast to VARs - produces quite similar results in both identification schemes (see Figure 5). Though the point estimates in the external instrument scheme tend to be larger, the confidence bands in both identification schemes overlap for most variables.[10] The instrument, in other words, does not seem to contain information that is not already captured by the large dataset underlying the DFM. Rather, the less precise estimates in this scheme suggest the instrument introduces noise.

Third, some of the intuitive VAR results presented here and in Gertler and Karadi (2015) depend crucially on the underlying information set. If, for example, the VAR does not include a financial conditions indicator, it finds virtually no effect of monetary shocks on real activity, even within the external instrument approach (see Herbst and Caldara, 2018). Factor models, in contrast, largely avoid the inherently arbitrary variable selection process. They capture a vast number of variables in a consistent and parsimonious framework.

4 Conclusions

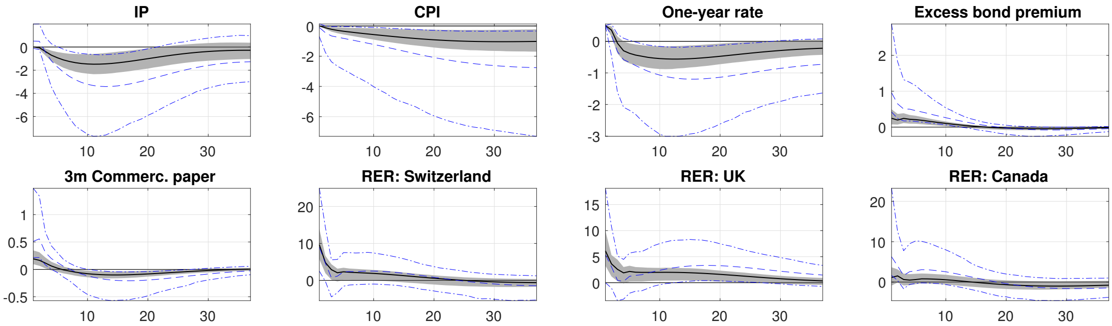
Why do conventional VARs regularly produce puzzling effects of monetary policy shocks? I explore two major competing hypotheses: Either the Cholesky identification scheme imposes invalid timing restrictions, or the handful of VAR variables are insufficient to capture the central banks' information set.

The applied literature has developed methods to address both of these alleged problems. First, high-frequency futures data around policy announcements can be used as an external instrument to identify monetary policy shocks without imposing any dubious timing restrictions (Gertler and Karadi, 2015). Second, the information set can be drastically expanded by extracting factors from virtually all macroeconomic variables the central bank considers in its decision-making. These factors can either be added

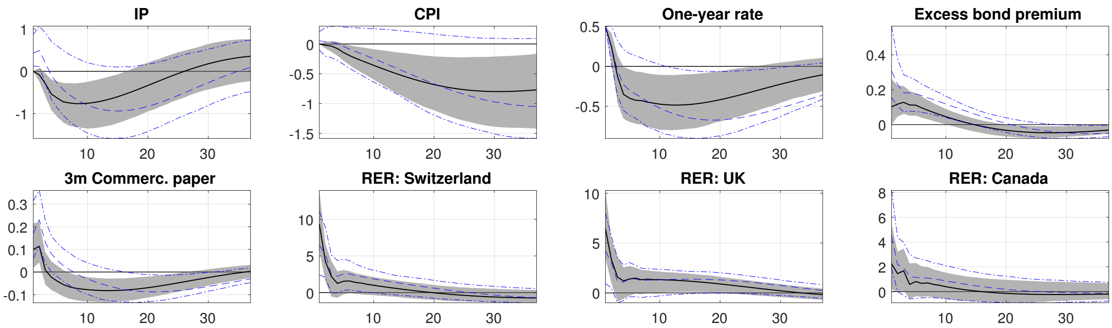
[10] As the lower panel of Figure 5 shows, most differences between the recursive Cholesky and the external instrument scheme in the DFM are due to the recent financial crisis. In the pre-crisis sample, both identification schemes yield largely similar results.

Figure 5: Dynamic Factor Model with Recursive and External Instrument Identification

(a) Full Sample



(b) Pre-Crisis Sample



The solid black line and shaded areas reproduce the third column in Figures 1-3, i.e. they refer to the recursively identified DFM. The dashed blue lines analogously refer to the DFM identified via the external instrument mentioned in Section 2.4. Panel (a) is estimated on the entire sample (April 1973 to September 2016), panel (b) on the pre-crisis sample (ending June 2008).

directly to the observable variables of a VAR - leading to the factor-augmented VAR (FAVAR) approach by Bernanke et al. (2005) - or used as the building blocks for the more general dynamic factor model (DFM) approach as e.g. in Forni and Gambetti (2010).

Starting from a basic recursive VAR that exhibits the well-known puzzles, I examine both approaches to show whether and which puzzles they are able to solve. I find that i) applying external instrument identification solves some of the puzzles but others remain; (ii) a recursively identified dynamic factor model yields intuitive results across the board; (iii) the remaining discrepancies are driven by the limited information set of the VAR and largely disappear once the information set is augmented via factors. That is, an external instrument FAVAR and a recursive dynamic factor model yield almost identical results, cross-verifying each other. The recursive identification scheme might thus not be invalid per se. Rather, it is invalid in conjunction with small-scale VARs, because these models are unable capture a sufficiently large information set.

Overall, my findings are comforting news for the recent monetary literature. Two of the leading empirical advances - external instruments and dynamic factor models - find the same monetary policy effects, despite their distinctly different underlying assumptions.

Bibliography

Alessi, L., Barigozzi, M., and Capasso, M. (2011). Non-Fundamentalness in Structural Econometric Models: A Review. *International Statistical Review*, 79(1).

Alessi, L. and Kerssenfischer, M. (2016). The response of asset prices to monetary policy shocks: stronger than thought. Working Paper Series 1967, European Central Bank.

Beaudry, P., Feve, P., Guay, A., and Portier, F. (2016). When is Nonfundamentalness in SVARs A Real Problem? TSE Working Papers 16-738, Toulouse School of Economics.

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.

Canova, F. and Hamidi Sahneh, M. (2017). Are Small-Scale SVARs Useful for Business Cycle Analysis? Revisiting Nonfundamentalness. *Journal of the European Economic Association*, jvx032.

Fernández-Villaverde, J., Rubio-Ramírez, J., Sargent, T. J., and Watson, M. W. (2007). A, B, C's (and D's) for understanding VARs. *American Economic Review*, 97(3):1021–1026.

Forni, M. and Gambetti, L. (2010). The dynamic effects of monetary policy: A structural factor model approach. *Journal of Monetary Economics*, 57(2):203–216.

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. *Economic Journal*, 124(581):1168–1191.

Forni, M., Giannone, D., Lippi, M., and Reichlin, L. (2009). Opening the black box: Structural factor models with large cross-sections. *Econometric Theory*, 25(5):1319–1347.

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 Zakrajsek, 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):55–93.

Hansen, L. P. and Sargent, T. J. (1991). Two difficulties in interpreting vector autoregressions. In Hansen, L. P. and Sargent, T. J., editors, *Rational Expectations Econometrics*, pages 77–120. Westview Press, Boulder.

Herbst, E. and Caldara, D. (2018). Monetary Policy, Credit Spreads, and Business Cycle Fluctuations: Evidence from Bayesian Proxy SVARs. Technical report.

Lippi, M. and Reichlin, L. (1993). The dynamic effects of aggregate demand and supply disturbances: Comment. *The American Economic Review*, 83(3):644–652.

Lippi, M. and Reichlin, L. (1994). VAR analysis, nonfundamental representations, Blaschke matrices. *Journal of Econometrics*, 63(1):307–325.

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

Ramey, V. (2016). Macroeconomic Shocks and Their Propagation. Handbook of Macroeconomics 2, pages 71 – 162.

Sims, C. A. (1992). Interpreting the macroeconomic time series facts: The effects of monetary policy. *European Economic Review*, 36(5):975–1000.

Sims, E. R. (2012). News, non-invertibility, and structural VARs. In *Advances in Econometrics*, pages 81–135.

Stock, J. H. and Watson, M. W. (2005). Implications of Dynamic Factor Models for VAR Analysis. NBER Working Paper 11467.

Stock, J. H. and Watson, M. W. (2012). Disentangling the Channels of the 2007-09 Recession. *Brookings Papers on Economic Activity*, 44(1):81 – 156.

Stock, J. H. and Watson, M. W. (2016). Dynamic Factor Models, Factor-Augmented Vector Autoregressions, and Structural Vector Autoregressions in Macroeconomics. Handbook of Macroeconomics 2, pages 415 – 525.