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**The effects of US monetary policy shocks:
applying external instrument identification to
a dynamic factor model**

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Non-technical summary

Research question

What impact does monetary policy have on financial markets and the real economy? Despite being one of the most intensely studied topics in all of macroeconomics, the question remains subject to ongoing debate and research. The perennial challenge lies in the proper identification of monetary policy shocks, since any attempt to identify unexpected policy changes inevitably requires - more or less convincing - assumptions. One recent advance in this respect is arguably the use of external high-frequency instruments, which circumvents many of the criticisms other identification schemes are subject to.

However, the external instrument identification has so far only been applied to conventional vector autoregressions (VARs), which are prone to more fundamental problems. Most importantly, these small-scale models can only incorporate a very limited number of variables. Since economic agents and policymakers base their decision-making on a larger set of variables, VARs might yield invalid results.

Contribution

In this paper I apply the above mentioned external instrument identification scheme to a dynamic factor model (DFM). DFMs directly address the key shortcoming of VARs as they are explicitly designed to capture vast amounts of information in a parsimonious way. I use this novel approach to re-examine the monetary policy effects found by [Forni and Gambetti \(2010a\)](#). Their recursive identification scheme is standard in the literature but it requires rather controversial assumptions about the contemporaneous effects of monetary policy on the real economy and financial markets.

Results

Overall, the monetary policy shock effects I find are very similar to those in [Forni and Gambetti \(2010a\)](#). This is remarkable, considering the fundamental differences between the identifying assumptions. In contrast to the recursive identification scheme, the external instrument approach imposes no restriction whatsoever on the investigated impulse responses. It is solely based on the assumption of instrument relevance and exogeneity.

Importantly, this finding stands in stark contrast to traditional VAR models, which yield decisively different results in the two identification schemes. This highlights the importance of using extended information sets to properly identify monetary policy shocks.

Nichttechnische Zusammenfassung

Fragestellung

Welchen Einfluss hat Geldpolitik auf Finanzmärkte und die Realwirtschaft? Obwohl dies eines der am intensivst untersuchten makroökonomischen Themen ist, bleibt die Frage Gegenstand fortwährender Diskussion und Forschung. Die Herausforderung bei der Beantwortung dieser Frage liegt in der Identifikation von geldpolitischen Schocks, da dies unausweichlich mit - mehr oder weniger überzeugenden - Annahmen einhergeht. Die Verwendung von Hochfrequenzdaten als externe Instrumente ist diesbezüglich ein neuer Fortschritt in der Literatur, da viele der Kritikpunkte anderer Identifikationsmethoden vermieden werden können.

Die Identifizierung durch Hochfrequenzdaten wurde bisher allerdings nur in Verbindung mit vektorautoregressiven (VAR) Modellen angewandt, die ihrerseits anfällig für grundlegendere Probleme sind. Am problematischsten ist, dass in konventionellen VARs nur einige wenige Variablen abgebildet werden können. Da bei der Entscheidungsfindung von Wirtschaftsteilnehmern und Entscheidungsträgern allerdings eine Vielzahl weiterer Variablen eine Rolle spielen, liefern VARs potenziell fehlerhafte Ergebnisse.

Beitrag

Im vorliegenden Aufsatz wende ich die Identifizierung durch Hochfrequenzdaten auf ein dynamisches Faktormodell (DFM) an. Diese Modelle sind explizit darauf ausgelegt, sehr große Informationsmengen zu verarbeiten und vermeiden somit ein grundlegendes Problem von VARs. Ich verwende den Ansatz um die von [Forni and Gambetti \(2010a\)](#) gefundenen Effekte von Geldpolitik nachzuprüfen. Der rekursive Identifikationsansatz, den die beiden Autoren verwenden, ist in der Literatur weitverbreitet. Er basiert allerdings auf möglicherweise problematischen Annahmen über die kontemporären Effekte von Geldpolitik auf Realwirtschaft und Finanzmärkte.

Ergebnisse

Insgesamt sind die von mir gefundenen geldpolitischen Effekte sehr ähnlich zu denen in [Forni and Gambetti \(2010a\)](#). Das ist insoweit bemerkenswert, als dass die zugrundeliegenden Annahmen beider Identifikationsmethoden fundamental unterschiedlich sind. Im Gegensatz zum rekursiven Identifikationsansatz werden bei der Identifizierung durch Hochfrequenzdaten keinerlei Restriktionen auf die Impuls-Antwort-Funktionen der untersuchten Variablen auferlegt. Die Identifikation beruht ausschließlich auf den Annahmen über die Relevanz und Exogenität des verwendeten Instruments.

Dieser Befund steht in starkem Gegensatz zu konventionellen VAR Modellen, die in den beiden Identifikationsansätzen sehr unterschiedliche Ergebnisse liefern. Dies unterstreicht die Bedeutung von großen Informationsmengen zur korrekten Identifikation von geldpolitischen Schocks.

The Effects of US Monetary Policy Shocks: Applying External Instrument Identification to a Dynamic Factor Model

Mark KERSSENFISCHER¹

Abstract

Dynamic factor models and external instrument identification are two recent advances in the empirical macroeconomic literature. This paper combines the two approaches in order to study the effects of monetary policy shocks. I use this novel framework to re-examine the effects found by Forni and Gambetti (2010, JME) in a recursively-identified DFM. Considering the fundamental differences between the identifying assumptions, the results are overall strikingly similar. Importantly, this finding stands in stark contrast to traditional VAR models, which yield decisively different results in the two identification schemes. This highlights the importance of using extended information sets to properly identify monetary policy shocks.

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

JEL classification: C32, E32, E44, E52, F31.

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1 Introduction

Monetary policy shocks are one of the most intensively studied topics in all of applied macroeconomics. In an extensive overview of the literature, [Ramey \(2016\)](#) highlights the perennial challenge of identifying monetary policy shocks and documents the progress made thus far.

This paper contributes to the literature by combining two rather recent empirical approaches: dynamic factor models (DFMs) and external (high-frequency) instruments. The use of external instruments for identification in macroeconometric models goes back to [Stock and Watson \(2012\)](#) and [Mertens and Ravn \(2013\)](#). The basic idea of this approach is to use external information - i.e. additional series outside of the empirical model - as noisy measures of the true shock of interest. So far, this identification scheme has been almost exclusively employed in a traditional small-scale VAR framework. I will instead carry it over to dynamic factor models which are able to incorporate a much larger information set.

[Gertler and Karadi \(2015\)](#) employ the external instrument identification scheme in a conventional VAR model to study monetary policy shocks. They exploit high-frequency futures surprises on Federal Open Market Committee (FOMC) dates as an instrumental variable to identify unexpected Fed policy actions. This way, they isolate the variation in their monetary policy indicator that is due to unanticipated monetary policy shocks. The main virtue of this approach is that it avoids many of the criticisms other identification schemes are subject to. For instance, the usual Cholesky decomposition assumes a contemporaneous causal ordering of the VAR model variables, a no doubt questionable assumption when including financial market data (on monthly, let alone quarterly frequency). Equally serious criticisms apply to many other standard identification schemes, e.g. sign and long-run restrictions (see [Ramey \(2016\)](#) and references therein).

While the assumptions underlying the identification scheme in [Gertler and Karadi \(2015\)](#) are arguably plausible, the conventional VAR framework they employ is subject to more general problems. First, it assumes relevant theoretical concepts of interest (such as “real activity”) are perfectly observable, usually via a single variable like industrial production. Second, VARs suffer from the “curse of dimensionality”, referring to the inevitable proliferation of unknown parameters as further variables (or lags) are added to the VAR. This is problematic, since the selection of variables - often lacking strong a priori criteria - is somewhat arbitrary in nature, and since a researcher might be interested in the effects of numerous variables to a given shock. In the case of [Gertler and Karadi \(2015\)](#), their VAR framework forces them to add various credit spreads and interest rates sequentially to their baseline specification. Strictly speaking, they estimate an entirely new model for each asset price under study. Lastly, and most importantly, a series of influential papers argues convincingly that the limited information set captured by VARs might invalidate their results (see for instance [Hansen and Sargent, 1991](#); [Lippi](#)

and Reichlin, 1994; Fernández-Villaverde et al., 2007). The problem is known as “non-fundamentalness” or “non-invertibility” and is caused by a deficient information set: If the empirical model incorporates less information than economic agents use in their decision-making, the correct structural shocks and impulse response functions cannot be recovered from a history of observed variables. VAR models usually sweep this issue under the rug and simply rule out non-invertibility by assumption.

Motivated by the above mentioned shortcomings of VAR models, dynamic factor models are explicitly designed to handle vast amounts of information. Their basic idea is that a few macroeconomic shocks - e.g. technology, monetary policy, fiscal policy, news or oil shocks - account for the bulk of common dynamics between a vast number of economic time series (Stock and Watson (2016) offer an extensive introduction and overview of the approach). This way, DFMs are able to capture a large information set in a realistic and parsimonious way. Importantly, basically all identification schemes used in a VAR context are applicable to DFMs too. Several recent papers have estimated dynamic factor models to identify monetary policy shocks, either via sign-restrictions (Forni and Gambetti, 2010b; Barigozzi et al., 2014; Luciani, 2015) or the recursive Cholesky identification scheme (Forni and Gambetti, 2010a; Alessi and Kerssenfischer, 2016).

In this paper I will proceed in a similar vein, namely by applying the external instrument identification scheme to a dynamic factor model. I will highlight the usefulness of this approach in an empirical application and show that the monetary policy shock effects found in Forni and Gambetti (2010a) - in a recursively identified DFM - are remarkably robust to this alternative identification scheme. To the best of my knowledge, the only other paper thus far combining dynamic factor models with external instrument identification is Stock and Watson (2012), who investigate the driving macroeconomic forces during the latest recession in the United States.¹

2 The Dynamic Factor Model

The dynamic factor model studied in this paper is due to Forni et al. (2009), who lay out the approach and its assumptions in great detail.² The main feature of this model is to assume that each stationary time series x_{it} of a panel with $i = 1, \dots, N$ variables and time periods $t = 1, \dots, T$ can be decomposed in two mutually orthogonal components: a common component χ_{it} and an idiosyncratic component e_{it} . The latter can be thought

¹Stock and Watson (2012) postulate six structural shocks driving the US economy and they use multiple instruments to identify each one. For the monetary policy shock, the only high-frequency instrument they employ relates to the “target factor” of Gurkaynak et al. (2005).

²For early contributions on closely related models see Forni and Lippi (2001), Giannone et al. (2004), Forni et al. (2005) and Stock and Watson (2005). Dynamic factor models can also be thought of as an extension to the factor-augmented vector autoregression (FAVAR) method by Bernanke et al. (2005).

of as sector specific variation or measurement error and is generally not the object of interest. The common components χ_{it} , on the other hand, account for the bulk of co-movement in the dataset as they are linear combinations of $r \ll N$ static factors F_t . Those are, in turn, driven by $q \leq r$ pervasive dynamic shocks $u_t = (u_{1t}, \dots, u_{qt})'$. Formally (cf. [Stock and Watson, 2012](#)):

$$x_t = \Lambda F_t + e_t \quad (1)$$

$$\Phi(L)F_t = Gu_t \quad (2)$$

with the factor loading matrix Λ , the $r \times r$ matrix polynomial $\Phi(L)$, and G being a maximum rank $r \times q$ matrix, linking the dynamic shocks to the residuals of a VAR estimated on the static factors.³ The approximate factor structure allows for some serial and cross-sectional correlation among idiosyncratic components while the common shocks are assumed to be uncorrelated at all leads and lags with idiosyncratic components. Finally, each series in the dataset can be represented in terms of dynamic shocks and an idiosyncratic component as

$$x_t = \Lambda \Phi(L)^{-1} G u_t + e_t, \quad (3)$$

with $\Lambda \Phi(L)^{-1} G$ being the impulse response function to current and past shocks u_t . This way, a further advantage of DFMs over VARs becomes evident: The factor model offers a unified and internally consistent framework to study the response of a vast number of variables to the shocks of interest.⁴

However, just like in VARs, the dynamic shocks u_t are reduced-form innovations, i.e. they are assumed to be linear combinations of the structural shocks ϵ_t we are ultimately interested in:

$$u_t = H \epsilon_t. \quad (4)$$

Thus, the challenge is to identify the $q \times q$ matrix H , or in our case the column thereof that corresponds to the monetary policy shock.

³In practice, the DFM approach requires the estimation of some key model parameters, in particular the number of common factors and dynamic shocks (r and q , respectively) and the lag length p in equation (2), see [Stock and Watson \(2016\)](#) for an overview of methods and criteria. Since my empirical investigation is based on [Forni and Gambetti \(2010a\)](#), I will simply adopt their benchmark choice of $\hat{r} = 16$, $\hat{q} = 4$ and $\hat{p} = 2$ and perform various robustness checks.

⁴The VAR framework, in contrast, only allows to study the response of a very limited number of variables in a single model. This is why [Gertler and Karadi \(2015\)](#), for instance, add various credit spreads and interest rates one at a time to their baseline specification (which includes industrial production, consumer prices and the one-year government bond yield as the monetary policy indicator). Due to its parsimony, this problem does not emerge in the DFM framework, where the response of arbitrarily many variables can be investigated.

3 External Instrument Identification Scheme

3.1 The monetary policy indicator

Before laying out the identification scheme, it is instructive to point out another advantage of the DFM approach compared to VARs or FAVARs. As mentioned earlier, the selection of variables that are supposed to depict economic concepts like “real activity” is somewhat arbitrary. Importantly, this criticism applies to the monetary policy indicator as well. While most authors use the federal funds rate to study monetary policy effects, this choice is far from ironclad. Historically e.g., many authors used monetary aggregates (like M2) to capture the monetary policy stance. Recently, due to the effective lower bound and unconventional monetary policies, shadow rates or selected central bank balance sheet positions have become more common choices.⁵ Gertler and Karadi (2015), furthermore, employ as an alternative to the federal funds rate the one-year and two-year government bond rate, arguing these series are better able to incorporate the Fed’s forward guidance policy. In sum, there is some debate in the literature as to which variable best captures the monetary policy stance.

In dynamic factor models, the explicit selection of a single policy indicator is not required. Instead, the key requirement to recover the monetary policy shock in a DFM framework is merely that it is spanned by the dynamic shocks u_t .⁶ Put differently, monetary policy is assumed to be one of the pervasive forces driving macroeconomic fluctuations in the dataset. Thus, identification of the monetary policy shock boils down to finding the suitable linear combination of the estimated dynamic shocks.

3.2 Methodology

The identification scheme I employ in this paper is based on external instruments and has been developed - and thus far almost exclusively been used - in a VAR context.⁷ As Stock and Watson (2012) show, however, the method carries over directly to DFMs. In order to work, the identification scheme requires the usual conditions for instrumental variables to hold: First, the instrument has to be contemporaneously correlated with the structural policy shock (relevance condition) and secondly, it has to be contemporaneously uncorrelated with all other shocks (exogeneity condition).

⁵See e.g. Wu and Xia (2016) for the former and Gambacorta et al. (2014) for the latter.

⁶As mentioned above, the FAVAR approach by Bernanke et al. (2005) is somewhat in between VARs and DFMs. While it treats concepts like “economic activity” as unobservable factors, it assumes the federal funds rate to be the perfect measure of monetary policy.

⁷See e.g. Mertens and Ravn (2013), Gertler and Karadi (2015) and Piffer and Podstawski (2016).

Rewrite equation (4)

$$u_t = H\epsilon_t = [H_1 \dots H_q] \begin{pmatrix} \epsilon_{1t} \\ \vdots \\ \epsilon_{qt} \end{pmatrix} \quad (5)$$

with H_1 being the first column of H , ϵ_{1t} the first structural shock, and so forth. Hence, $\Sigma_{uu} = H\Sigma_{\epsilon\epsilon}H'$ and $\Sigma_{\epsilon\epsilon} = E(\epsilon_t\epsilon_t')$. Assuming invertibility, the structural dynamic shocks can be expressed as linear combinations of the (reduced-form) shocks:

$$\epsilon_t = H^{-1}u_t \quad (6)$$

Since we are only interested in the monetary policy shock, we need to identify only one column of H . Without loss of generality, we can assume the monetary policy shock to be the first one (ϵ_{1t}) and hence try to identify H_1 .

Given an instrumental variable Z_t that meets the relevance ($E(\epsilon_{1t}Z_t) = \alpha \neq 0$) and exogeneity condition ($E(\epsilon_{jt}Z_t) = 0, j = 2, \dots, q$), we can write:⁸

$$\begin{bmatrix} E(u_{1t}Z_t) \\ E(u_{\bullet t}Z_t) \end{bmatrix} = E(u_tZ_t) = E(H\epsilon_tZ_t) = [H_1 H_{\bullet}] \begin{bmatrix} E(\epsilon_{1t}Z_t) \\ E(\epsilon_{\bullet t}Z_t) \end{bmatrix} = H_1\alpha. \quad (7)$$

Using a unit effect normalization, i.e. setting the first element in the H_1 column to unity ($H_{11} = 1$), the remaining elements of the column are obtained as

$$H_{1\bullet} = \frac{E(u_{\bullet t}Z_t)}{E(u_{1t}Z_t)}. \quad (8)$$

In practice, the H_1 column is estimated simply as the coefficients of a regression of the instrument Z_t on the reduced-form shocks u_t , and rescaling the first element to unity.

3.3 Instrument Relevance

Since instrumental variables are such a familiar concept to economists, an important caveat is in order: unlike in traditional microeconomic settings, the relevance of the instrument is no longer a directly testable condition in the current macroeconometric setting.

To see this, consider the “returns to education” literature as a prototypical application of instrumental variables. To uncover the causal effect of schooling on income, the seminal study by Angrist and Krueger (1991) uses an individual’s season of birth as an instrumental variable that is correlated with years of schooling but exogenous with respect to all other relevant (and potentially omitted) explanatory variables, such as innate

⁸Here I make use of a partitioning notation, i.e. $u_{\bullet t}$ denotes all shocks except u_{1t} and H_{\bullet} denotes all columns in H except the first.

ability. In this microeconomic setting, only the exogeneity condition has to be assumed, whereas the relevance of the instrument can be tested (in a so called “first-stage” regression).

In the current context, however, the goal is to instrument for monetary policy shocks, which are - unlike schooling - unobservable. Hence, as [Piffer and Podstawski \(2016\)](#) point out, the relevance condition moves from being a testable to a non-testable condition and the common practice of testing for the “strength of the instrument” thus appears to be of questionable merit. Conceptually, the relevance assumption appears to be quite plausible in the current context, given that the instruments are taken from [Gurkaynak et al. \(2005\)](#), cf. next section.

Having said that, a poor instrument will impede a sharp identification of the monetary policy shock. Regarding the current study, the correlation between candidate instruments and reduced-form shocks is indeed low.⁹ Nonetheless, the robust replication of [Forni and Gambetti \(2010a\)](#) in Section 4 indicates a successful identification via external instruments.

3.4 Instrument selection

Following [Gertler and Karadi \(2015\)](#), I consider five candidate instruments for identification. All five are based on unexpected changes in futures rates around FOMC decisions to capture the “future policy path factor” which [Gurkaynak et al. \(2005\)](#) show to be the dominant driver behind monetary policy effects. The high-frequency nature of the data is ideal to ensure that the monetary policy shock is truly unanticipated. In the baseline specification I employ surprises in the three month Eurodollar future one year ahead, as this is arguably the best instrument to account for financial market expectations about the foreseeable stance of monetary policy.¹⁰ In order to match the monthly frequency of the other variables, the high-frequency surprises are cumulated, see [Gertler and Karadi \(2015\)](#) for details.

The macroeconomic dataset in [Forni and Gambetti \(2010a\)](#) covers the time span 1973:3 to 2007:11, whereas the instruments in [Gertler and Karadi \(2015\)](#) are available from 1991:1 to 2012:6. Importantly, this discrepancy is no major obstacle in the current framework, since the identification scheme in Section 3.2 does not have to be based on the same sample period as the reduced-form DFM estimation in Section 2. Thus, I use the full available sample as in [Forni and Gambetti \(2010a\)](#) to estimate the factor model dynamics in equation 3, and then use the maximum common sample with the instrument (i.e. 1991:1 to 2007:11) to identify the monetary policy shock as in equation 8.

⁹More precisely, regressions of the instruments Z_t on the reduced-form shocks u_t yield F -statistics well below the conventional threshold value of ten.

¹⁰Results are also robust with respect to the other four instruments, namely surprises in monthly fed funds futures for the current month and three month ahead and surprises in three month Eurodollar futures six and nine month ahead.

4 Application: The effects of monetary policy shocks

The following figures reproduce the results of the recursively-identified DFM in [Forni and Gambetti \(2010a\)](#) and contrast them with the results of the new external instrument identification scheme.¹¹ Given the fundamental differences between the two identification approaches, the results are overall strikingly similar.

Recall that [Forni and Gambetti \(2010a\)](#) impose a contemporaneous causal ordering to identify monetary policy shocks: industrial production and consumer prices are assumed to be affected by monetary policy surprises only with a lag of at least one month. The external instrument approach, on the other hand, imposes no restriction whatsoever on impulse responses and is based solely on the relevance and exogeneity assumption of the employed instrument.

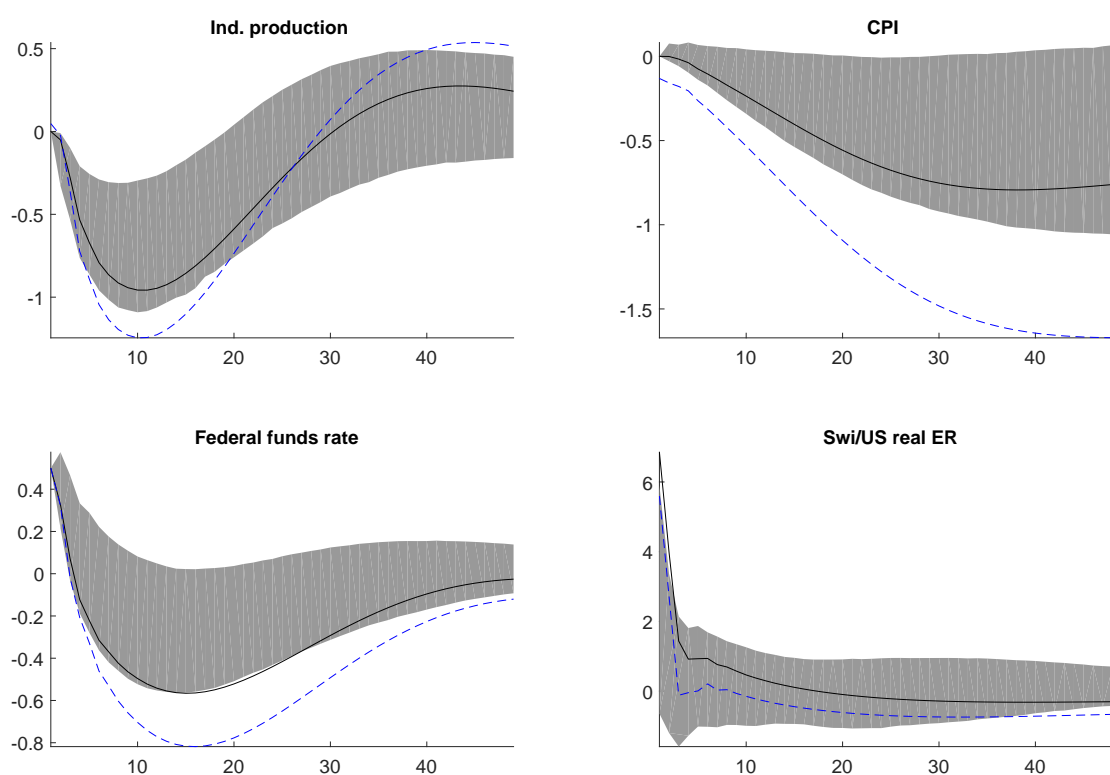


Figure 1: Responses to a contractionary monetary policy shock

The solid black line and shaded areas refer to point estimates and 80% confidence bands of the recursively identified DFM, reproducing Figure 1 in [Forni and Gambetti \(2010a\)](#). The dashed blue line refers to the point estimate employing the external instrument identification scheme, cf. Section 3.

Yet, as Figure 1 shows, both approaches yield very similar results: consistent with

¹¹The underlying dataset consists of 112 monthly US macroeconomic series and confidence bands are based on a non-overlapping block bootstrap technique, see [Forni and Gambetti \(2010a\)](#) for details.

economic theory, an unexpected monetary tightening leads to a contraction in industrial production, a decline in consumer prices, and an immediate and severe appreciation of the domestic currency. With the slight exception of consumer prices, which respond stronger in the external instrument identification case, the point estimates in both identification schemes are remarkably close.

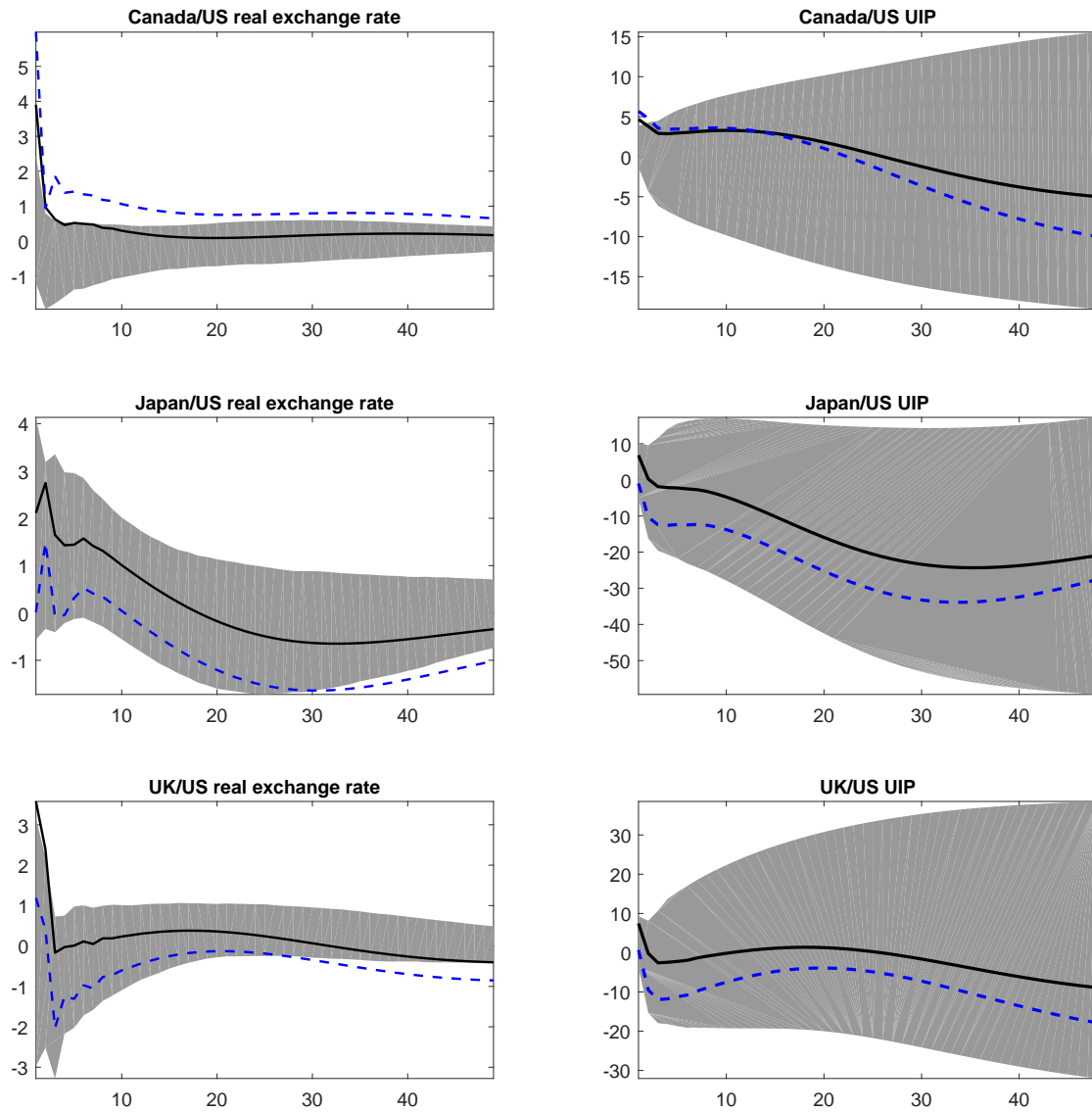


Figure 2: Exchange rate responses to a contractionary monetary policy shock
 The solid black line and shaded areas refer to the recursively identified DFM and reproduce Figure 2 in Forni and Gambetti (2010a). The dashed blue line refers to the external instrument identification scheme. The conditional UIP results are annualized percentage returns.

To put these results into perspective, [Forni and Gambetti \(2010a\)](#) also estimate the effects of an unexpected monetary tightening using a benchmark VAR. As is typical in this framework, the results exhibit the well known “prize puzzle” and “delayed overshooting puzzle” (i.e. a positive price response and a sluggish hump-shaped response of exchange rates). In the dynamic factor model, on the other hand, the responses are consistent with basic macroeconomic theory and no puzzles arise. As I show here, this is not only true with a recursive, but also with an external instrument identification scheme.¹²

[Forni and Gambetti \(2010a\)](#) further report results regarding the uncovered interest parity (UIP), computed as in [Scholl and Uhlig \(2008\)](#), of various currencies vis-a-vis the US dollar, cf. right column of [Figure 2](#). The point estimates in both identification schemes are non-negligible but are overall dwarfed by the large confidence bands.

[Figure A1](#) in the Appendix shows that the resemblance in impulse response functions is also true for many other variables, for instance orders, inventories, housing starts, and various credit and labor market variables. [Forni and Gambetti \(2010a\)](#) offer a short interpretation of the results. Lastly, but not less importantly, the results of the external instrument identification approach are quite robust. [Figures A2 and A3](#) in the Appendix show results for various specifications of the number of static factors and dynamic shocks, respectively. [Figure A4](#) reports results when employing the four remaining candidate instruments in [Gurkaynak et al. \(2005\)](#) (cf. [Section 3.4](#)). Some discrepancies emerge for the shorter-dated futures contracts, especially for the current month fed funds future, but even in this specification the main results are robust.

5 Conclusions

This paper combines two recent empirical advances: dynamic factor models (DFMs) and external instrument identification. The approach has several favorable features. In particular, the use of external instruments sidesteps most of the criticisms other identification schemes are subject to. On top of this, the DFM framework addresses many of the shortcomings of traditional small-scale VARs, for instance: it does not require theoretical concepts like “real activity” to be perfectly observable; it avoids the “curse of dimensionality”; and it significantly enlarges the information set, attenuating the problem of “nonfundamentalness”.

I employ this novel approach to study the effects of monetary policy shocks and compare the results to those found by [Forni and Gambetti \(2010a\)](#) in a recursively identified DFM. Considering the fundamentally different identifying assumptions behind these two methods, I find remarkably similar results. This finding indicates that dynamic factor models - irrespective of the applied identification scheme - are able to properly

¹²However, confidence bands widen substantially in the external instrument identification scheme. This may indicate the presence of a weak instrument, cf. [Section 3.3](#). Results are available upon request.

capture monetary policy shocks. Importantly, the same is not true for traditional small-scale VARs, which yield decisively different results in the two identification schemes (cf. [Gertler and Karadi, 2015](#)).

More generally, the findings highlight the critical importance of using large information sets in empirical investigations. In this regard, dynamic factor models have a clear edge over VARs and are thus a promising approach for future macroeconomic research.

Bibliography

- 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.
- Angrist, J. D. and Krueger, A. B. (1991). Does compulsory school attendance affect schooling and earnings? *The Quarterly Journal of Economics*, 106(4):979–1014.
- Barigozzi, M., Conti, A. M., and Luciani, M. (2014). Do Euro Area Countries Respond Asymmetrically to the Common Monetary Policy? *Oxford Bulletin of Economics and Statistics*, 76(5):693–714.
- Bernanke, B. S., Boivin, J., and Eliasziw, P. (2005). Measuring the effects of monetary policy: A factor-augmented vector autoregressive (favar) approach. *The Quarterly Journal of Economics*, 120(1):387–422.
- 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. (2010a). The dynamic effects of monetary policy: A structural factor model approach. *Journal of Monetary Economics*, 57(2):203–216.
- Forni, M. and Gambetti, L. (2010b). Macroeconomic Shocks and the Business Cycle: Evidence from a Structural Factor Model. Discussion Paper Series 7692, CEPR.
- 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.
- Forni, M., Hallin, M., Lippi, M., and Reichlin, L. (2005). The generalized dynamic factor model: one-sided estimation and forecasting. *Journal of the American Statistical Association*, 100(471):830–840.
- Forni, M. and Lippi, M. (2001). The generalized dynamic factor model: Representation theory. *Econometric Theory*, 17(06):1113–1141.
- Gambacorta, L., Hofmann, B., and Peersman, G. (2014). The effectiveness of unconventional monetary policy at the zero lower bound: A cross-country analysis. *Journal of Money, Credit and Banking*, 46(4):615–642.
- Gertler, M. and Karadi, P. (2015). Monetary Policy Surprises, Credit Costs, and Economic Activity. *American Economic Journal: Macroeconomics*, 7(1):44–76.
- Giannone, D., Reichlin, L., and Sala, L. (2004). Monetary Policy in Real Time. In Gertler, M. and K. Rogoff, editors, *NBER Macroeconomic Annual*. MIT Press.
- Gurkaynak, 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.
- Lippi, M. and Reichlin, L. (1994). Var analysis, nonfundamental representations, blaschke matrices. *Journal of Econometrics*, 63(1):307–325.
- Luciani, M. (2015). Monetary Policy and the Housing Market: A Structural Factor Analysis. *Journal of Applied Econometrics*, 30(2):199–218.
- 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.
- Piffer, M. and Podstawski, M. (2016). Identifying Uncertainty Shocks Using the Price of Gold. Technical report.
- Ramey, V. (2016). Chapter 2 - Macroeconomic Shocks and Their Propagation. volume 2 of *Handbook of Macroeconomics*, pages 71 – 162. Elsevier.
- Scholl, A. and Uhlig, H. (2008). New evidence on the puzzles: Results from agnostic identification on monetary policy and exchange rates. *Journal of International Economics*, 76(1):1–13.
- Stock, J. H. and Watson, M. W. (2005). Implications of Dynamic Factor Models for VAR Analysis. NBER Working Papers 11467, National Bureau of Economic Research, Inc.
- 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). Chapter 8 - Dynamic Factor Models, Factor-Augmented Vector Autoregressions, and Structural Vector Autoregressions in Macroeconomics. volume 2 of *Handbook of Macroeconomics*, pages 415 – 525. Elsevier.
- Wu, J. C. and Xia, F. D. (2016). Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound. *Journal of Money, Credit, and Banking*, 48(2-3).

Appendix

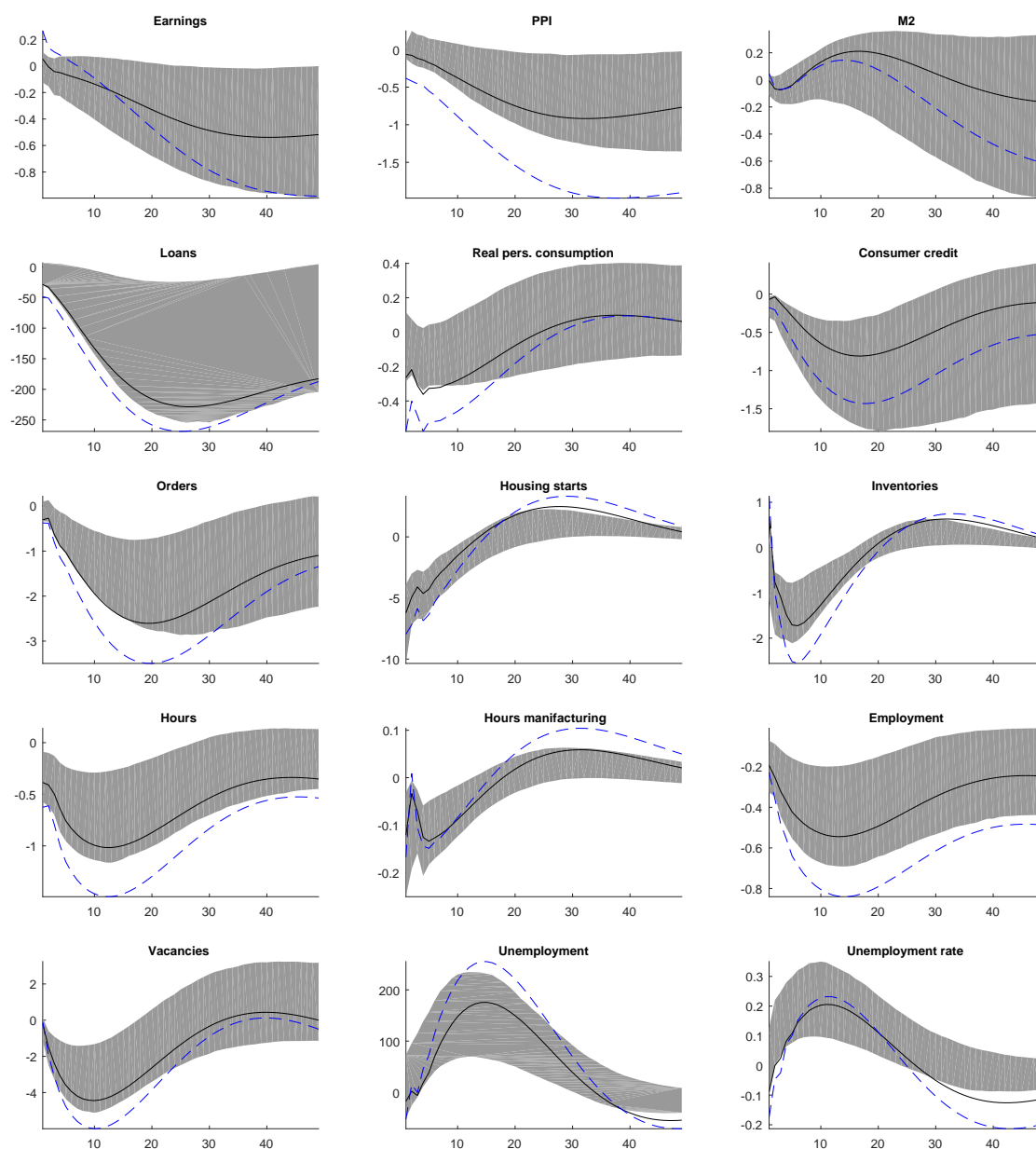


Figure A1: Further responses to a contractionary monetary policy shock
The solid black line and shaded areas refer to the recursively identified DFM and reproduce Figure 3 in Forni and Gambetti (2010a). The dashed blue line refers to the external instrument identification scheme.

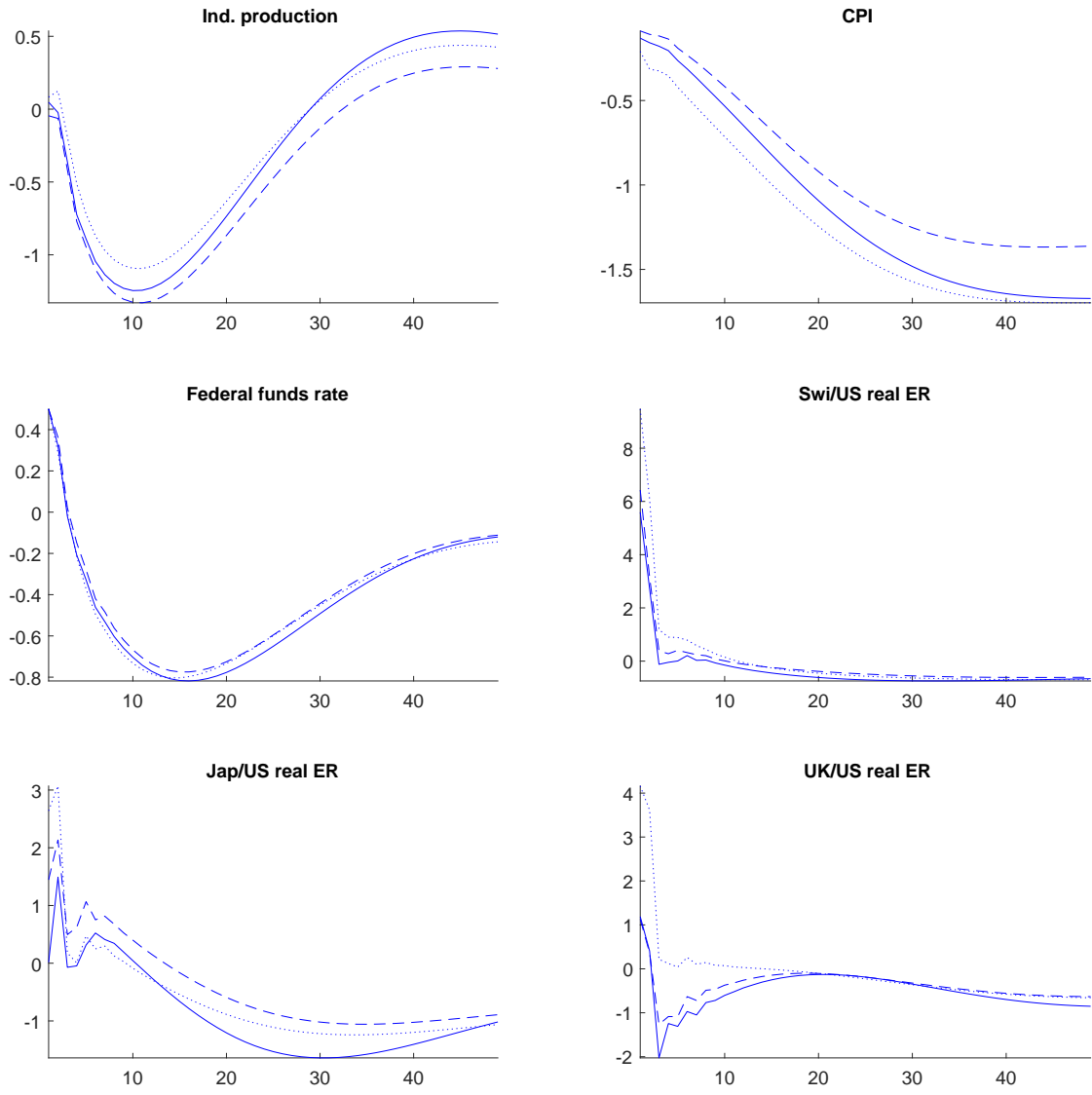


Figure A2: Robustness check: different number of static factors

DFM impulse responses in the external instrument identification scheme, employing different specifications for the number of static factors r . Solid line: $r = 16$ (baseline specification); dashed line: $r = 15$; dotted line: $r = 14$.

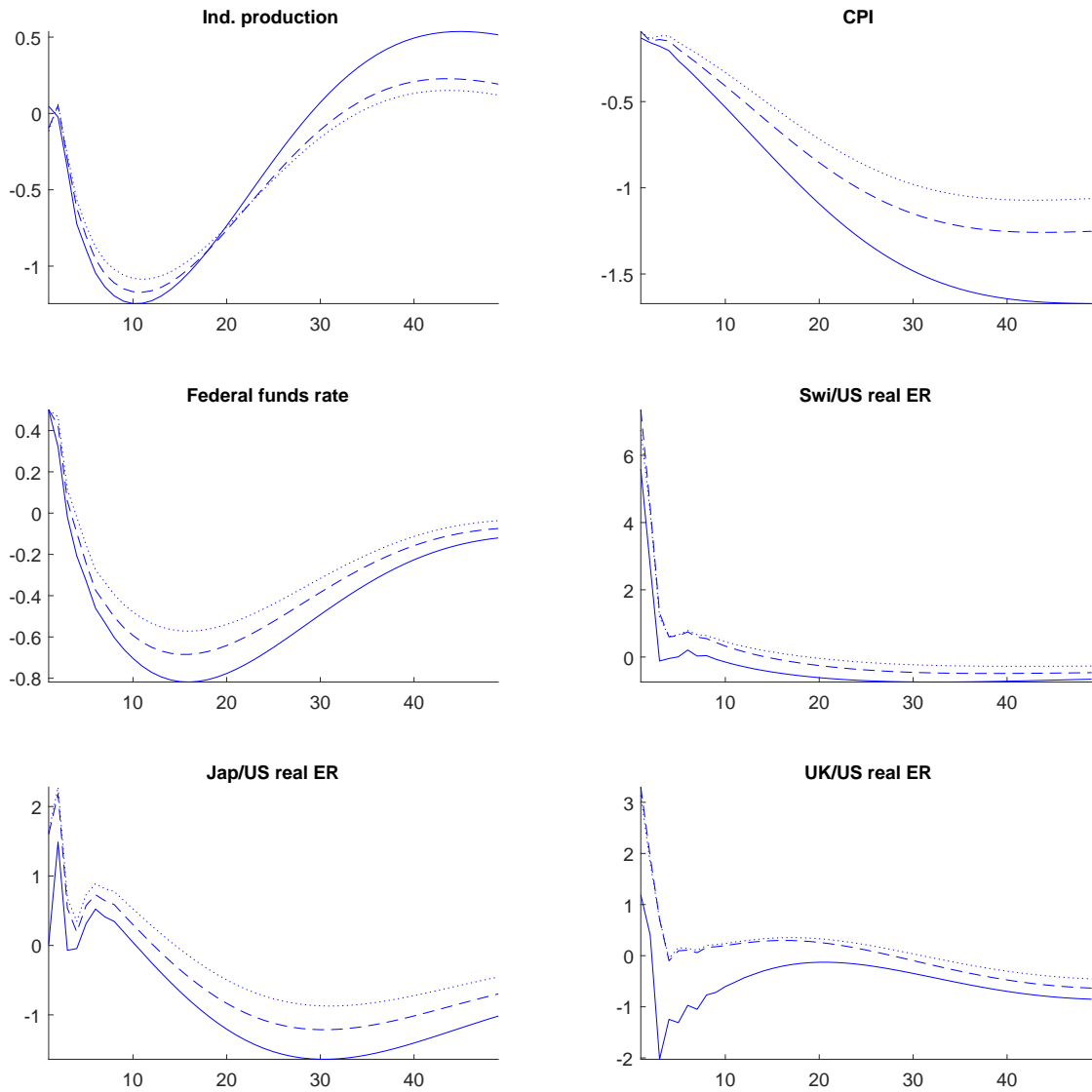


Figure A3: Robustness check: different number of dynamic shocks

DFM impulse responses in the external instrument identification scheme, employing different specifications for the number of dynamic shocks q . Solid line: $q = 4$ (baseline specification); dashed line: $q = 5$; dotted line: $q = 6$.

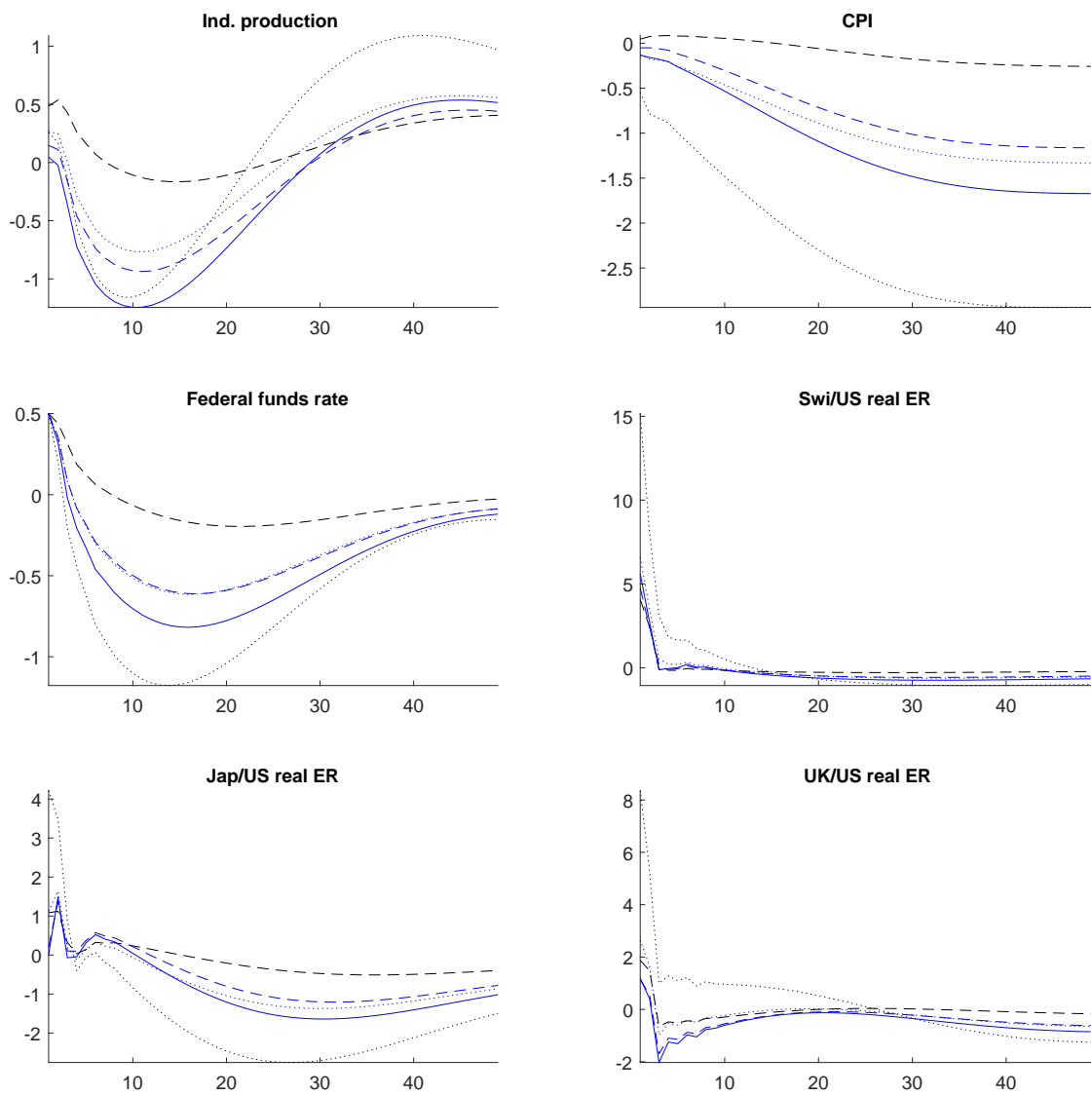


Figure A4: Robustness check: different external instruments

DFM impulse responses in the baseline specification ($r = 16$ and $q = 4$), employing different external instruments for identification of the monetary policy shock. The black lines refer to monthly fed fund futures for the current month (dotted) and three month ahead (dashed). The blue lines refer to three month Eurodollar futures six month (dotted), nine month (dashed) and one year ahead (solid, baseline specification).