Online Appendix

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

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1 Robustness Checks

1.1 Different Model Specifications

The following figures check the robustness of the results presented in the main text. Throughout, solid black lines and shaded areas refer to point estimates and 90% confidence bands of the benchmark specifications.

First, the external instrument VAR (second column in Figures 1-3). The benchmark specification includes log industrial production, the log consumer price index, the one-year government bond rate, and adds each variable of interest as the fourth variable. Figure A1 shows that the puzzling response of real exchange rates this benchmark specification yields are not an artifact of omitting financial market variables (as is the case for puzzling real activity effects, see Herbst and Caldara, 2018). Even when the set of core variables is expanded, the responses remain hard to square with economic theory.

Second, the recursively identified Dynamic Factor Model (third columns in Figure 1-3). The benchmark specification includes $r = 16$ static factors and $q = 4$ dynamic factors (following Forni and Gambetti, 2010). Figure A2 shows that the exact number of static factors r is unimportant for the DFM results. Unsurprisingly, the results are more sensitive - but still quite robust - to the number of dynamic factors q, see Figure A3. This is due to the fact that the identifying assumptions imposed by the recursive Cholesky scheme change as the dimension q changes, see Section 2.1.1.

Third, the dynamic factor model identified via an external instrument (Figure 5 in the main text). This model is robust to both r and q, see Figures A4 and A5, respectively. The fact that the external instrument approach is robust with respect to q follows from the fact that the assumptions underlying this identification scheme are largely independent of q.

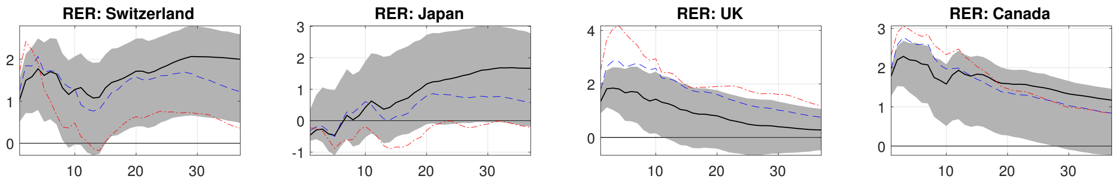
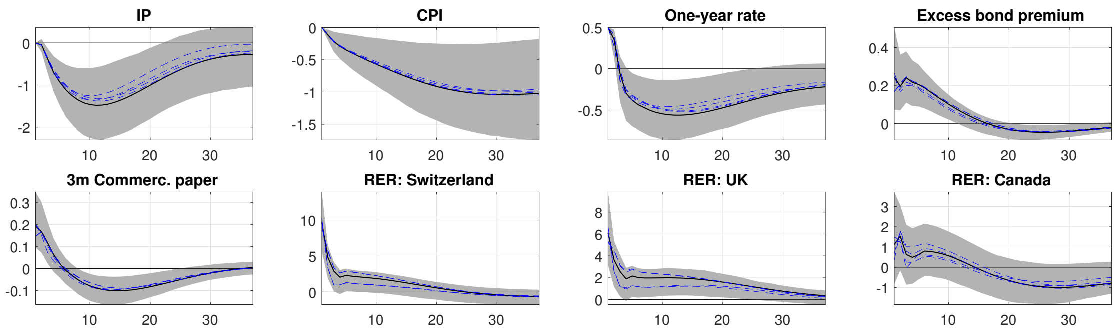


Figure A1: Real Exchange Rate Responses in Larger External Instruments VARs

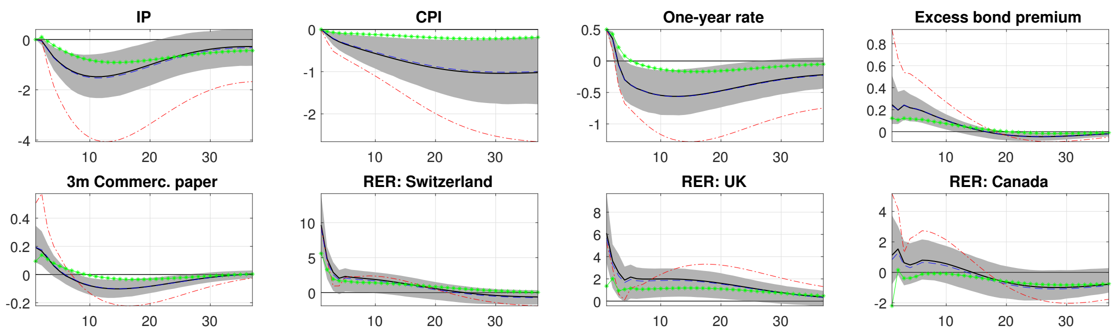
The dashed blue lines refer to five-variable VARs including Gilchrist and Zakrajsek (2012)'s excess bond premium. The red dash-dot line refers to seven-variable VARs further including the 3-month commercial paper spread and the 30-year mortgage spread. In each case, the above plotted exchange rate is added sequentially - one at a time - to the VAR.

Figure A2: Different Number of Static Factors in Cholesky DFM



The dashed blue lines refer to models with $r \in \{14, 15, 17, 18\}$

Figure A3: Different Number of Dynamic Factors in Cholesky DFM



The red dash-dot line refers to $q = 3$, the blue dashed line to $q = 5$, and the green line (*) to $q = 6$.

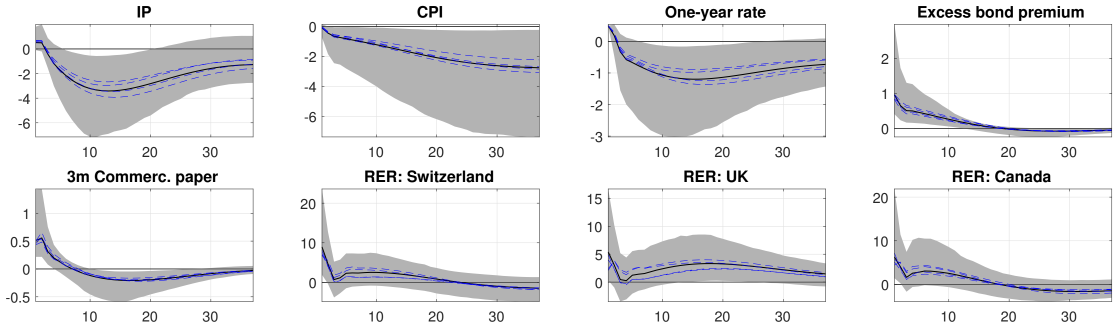


Figure A4: Different Number of Static Factors in External Instrument DFM

The dashed blue lines refer to models with $r \in \{14, 15, 17, 18\}$.

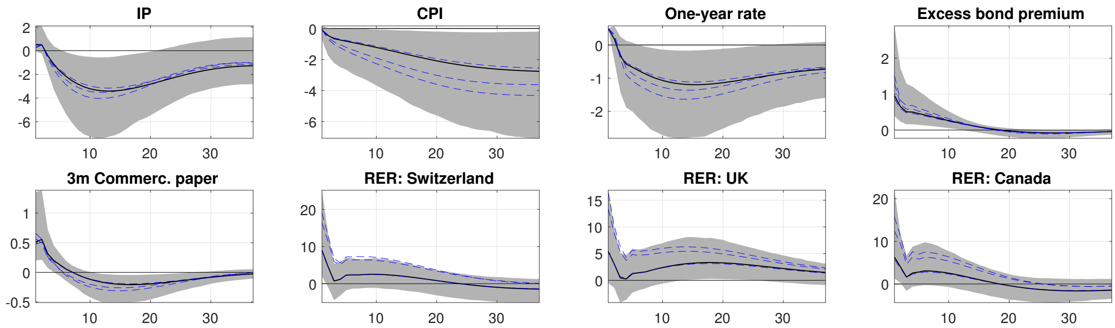


Figure A5: Different Number of Dynamic Factors in External Instrument DFM

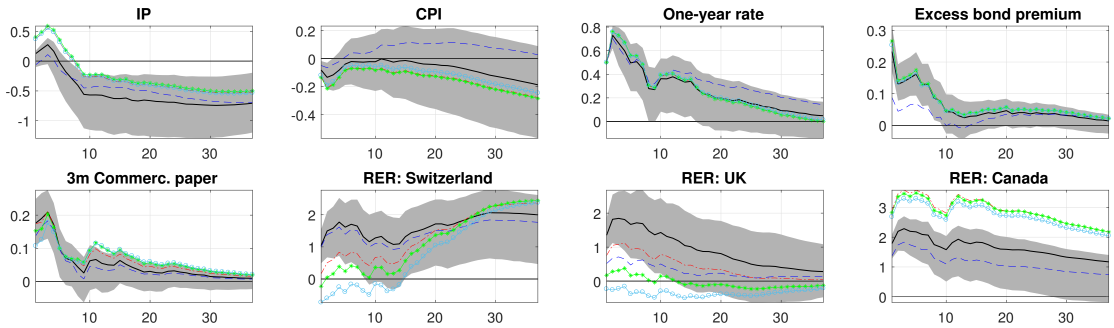
The dashed blue lines refer to models with $q \in \{3, 5, 6\}$.

1.2 Different External Instruments

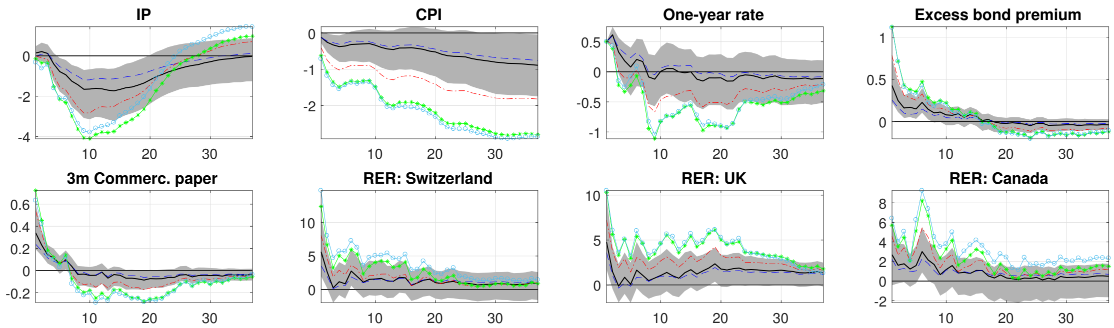
Figure A6 checks the robustness of my results with respect to the set of potential instruments (see Gürkaynak et al., 2005). The benchmark specification uses surprise changes in the three month ahead fed funds future (following Gertler and Karadi, 2015). While the FAVAR and DFM results (last two panels) are largely robust, the VAR results (top panel) exhibit some noteworthy changes. In particular, using any of the three Eurodollar futures as instruments yield expansionary effects on output in the short-run.

Figure A6: Other Futures Surprises as External Instruments

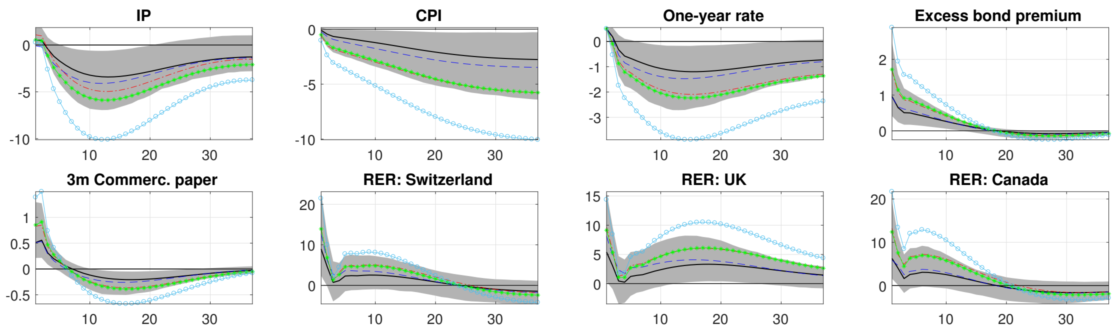
(a) External Instrument VAR



(b) External Instrument FAVAR



(c) External Instrument DFM



Blue dashed lines: current month fed funds future. Red dash-dot lines: three month Eurodollar futures six month ahead. Green lines (*): Eurodollar futures nine month ahead. Light blue lines (o): Eurodollar futures twelve month ahead.

1.3 Subsample Analysis

The following three figures reproduce Figures 1-3 in the main text for various subsamples. The solid black line refers to the entire available sample, i.e. the benchmark choice of 1973:4 to 2016:9. The dashed blue line refers to the pre-crisis sample, i.e. 1973:4 to 2008:6. Note that this is almost identical to the sample used by Forni and Gambetti (2010), which ends in 2007:11. Lastly, the red dash-dot line refers to the sample used by Gertler and Karadi (2015), i.e. 1979:7 to 2012:6. The starting point of their sample coincides with the start of Paul Volcker's tenure as Federal Reserve chair, which they argue marks a regime change in the conduct of US monetary policy.

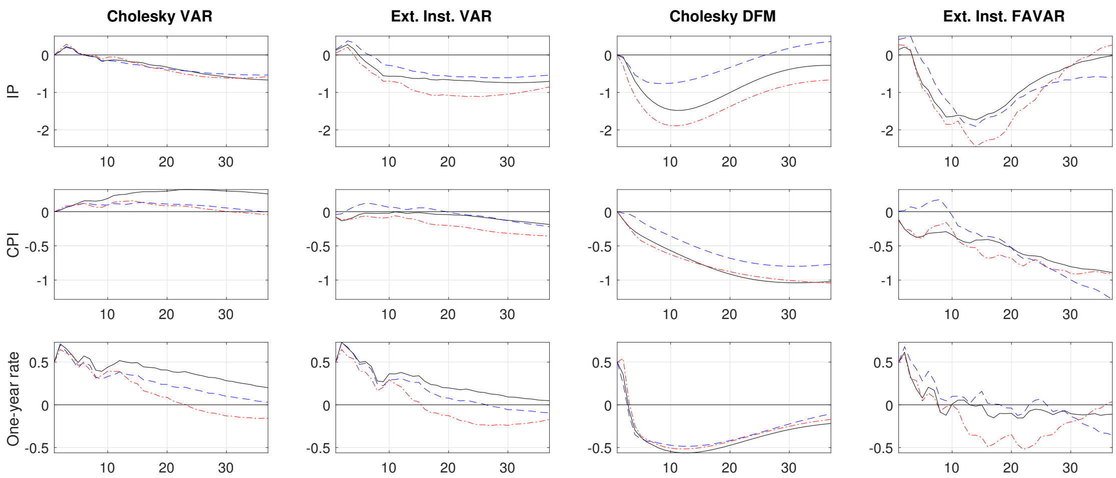


Figure A7: Subsample robustness of Figure 1

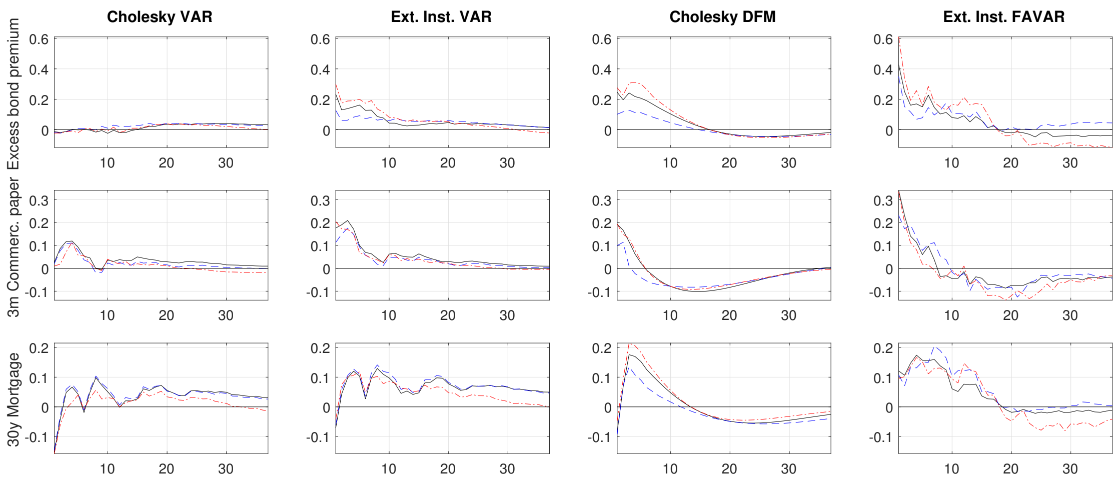


Figure A8: Subsample robustness of Figure 2

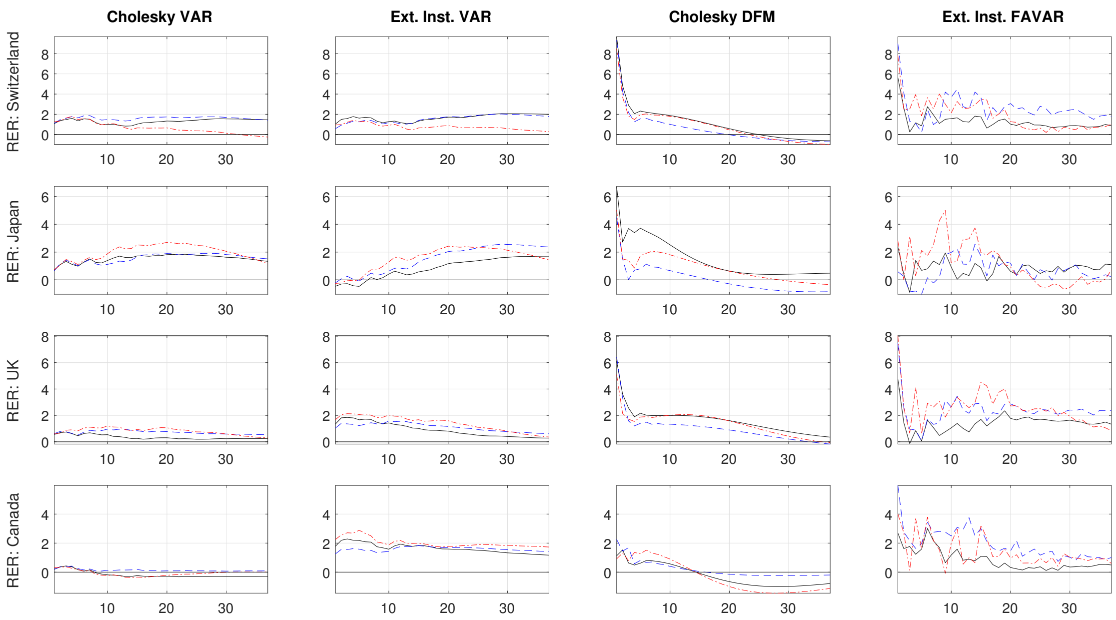


Figure A9: Subsample robustness of Figure 3

2 Further Details

2.1 Identification Schemes

By rearranging Equations (1) and (2) from the main text, one obtains the impulse-response functions, i.e. the effect of structural shocks on observable variables, we are ultimately interested in:

$$\Lambda\Phi(L)^{-1}GH\epsilon_t = \Omega(L)H\epsilon_t. \tag{1}$$

The key challenge is to identify the rotation matrix H, which links the reduced-form shocks u_t to the structural shocks ϵ_t:

$$\underset{q\times 1}{u_t} = \underset{q\times q}{H}\ \underset{q\times 1}{\epsilon_t}\ . \tag{2}$$

2.1.1 Recursive Cholesky

A recursive identification scheme identifies H by imposing zero restrictions on the contemporaneous effect of structural shocks on observable variables. In VARs, this is achieved by setting the identification matrix to the lower triangular Cholesky decomposition of the covariance matrix of the reduced-form shocks, i.e. $H = chol(\Sigma_u)$ with $\Sigma_u = E(u_t u_t')$. Analogously, a recursive identification scheme in the DFM is implemented by picking a $q \times q$ submatrix Ω_0^* and setting $H = \Omega_0^{*-1} chol(\Omega_0^* \Omega_0^{*'})$. Recall that $\Omega_0 H$ captures the impact effect of structural shocks ϵ_t on observable variables X_t.

As in Forni and Gambetti (2010), maximum comparability between VAR and DFM results is ensured by i) using the same number of VAR variables and dynamic factors (i.e. assuming $q = 4$ structural shocks in both cases, see main text), ii) picking the first three rows in Ω_0^* in accordance to the first three variables in Y_t^{VAR}, i.e. industrial production, consumer prices and the one-year government bond rate, and iii) assuming the monetary policy shock to be the third one.

2.1.2 External Instrument

The external instrument identification scheme does not impose any restrictions on the contemporaneous effects of shocks. Rewrite Equation (2)

$$u_t = H\epsilon_t = [H_1 \dots H_q] \begin{pmatrix} \epsilon_{1t} \\ \vdots \\ \epsilon_{qt} \end{pmatrix} \tag{3}$$

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 $\Sigma_{\epsilon\epsilon} = E(\epsilon_t\epsilon_t')$. Since we are only interested in the effects of monetary policy shocks, 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 familiar 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:[1]

$$\begin{bmatrix} E(u_{1t}Z_t) \\ E(u_{\bullet t}Z_t) \end{bmatrix} = E(u_t Z_t) = E(H\epsilon_t Z_t) = [H_1 H_\bullet] \begin{bmatrix} E(\epsilon_{1t}Z_t) \\ E(\epsilon_{\bullet t}Z_t) \end{bmatrix} = H_1\alpha. \tag{4}$$

H_1 is thus identified up to scale and sign by the coefficients of a regression of the instrument Z_t on all reduced-form shocks u_t. To uniquely identify the column H_1 a normalization of the shocks' impact effect on some observable variable suffices.

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

As described in the main text, Z_t is based on futures price movements around FOMC meetings. In order to match the monthly frequency of the other variables, the daily price movements are thus cumulated. The instrument is available from 1991:1 to 2012:6 and updates the original series in Gürkaynak et al. (2005). Since the time spans of Z_t and X_t do not match, I use the full available sample - i.e. 1973:4 to 2016:9 - to estimate the model dynamics, and use the maximum common sample with the instrument - i.e. 1991:1 to 2012:6 - to identify the monetary policy shock (Equation 4).

Importantly, interest rate futures do not only react to decisions about the current policy rate, but also to announcements about the future path of rates ("forward guidance"). Gürkaynak et al. (2005) show that these announcements are the dominant driver behind monetary policy effects and their relevance has evidently increased since the recent crisis. In this sense, the futures series appear well-suited for their use as external instruments.

2.2 Unobservability of the Shock and Instrument Relevance

Recall that the current object of interest - a monetary policy shock - is not completely observable. If it were, the thorny business of identification could be completely avoided after all.[2] Monetary policy shocks are arguably best thought of as unexpected deviations from a policy rule or unexpected changes to the policy rule itself (e.g. via shifts in policy preferences), see Ramey (2016). To ensure that such policy surprises are truly unanticipated, furthermore, high-frequency financial futures data is arguably ideal.

So given Gürkaynak et al. (2005)'s measure of policy surprises, why should we still think of monetary policy shocks as unobservable? A major reason is that Gürkaynak et al. (2005) only incorporate futures surprises around FOMC meetings and official FOMC statements are hardly the only source of information about (future) monetary policy. In fact, market participants exploit a wealth of sources when forming their expectations about monetary policy, including speeches, interviews and testimonies of FOMC members, let alone more informal communication of Fed officials with the media and financial sector (see Cieslak et al., 2016). Indeed, it is arguably impossible to completely capture all the ways in which policy makers potentially influence market expectations about their (future) policy.

Evidently, the futures surprises of Gürkaynak et al. (2005) are therefore best thought of as noisy measures correlated with the monetary policy shock, not as the shock itself. The futures surprises can thus serve as an instrumental variable for the true shock, but since the shock itself is not directly observable, the relevance condition of the instrument is not directly testable either (see e.g. Montiel-Olea et al., 2015).[3] Consequently, the common practice of testing for the "strength of the instrument" appears to be of somewhat questionable merit in the current context.[4]

Having said that, a poor instrument will impede a sharp identification of the monetary policy shock. An indirect approach to assess the nexus between the two is to regress the instrument Z_t on all reduced-form form shocks u_t (cf. Stock and Watson, 2012). In the case of Gertler and Karadi (2015)'s VAR - and FAVAR extensions thereof - this approach yields F-statistics well above the conventional threshold value of ten. For the dynamic factor model, in contrast, the respective F-statistics are considerably lower. As is well known, inference is non-trivial in the presence of weak instruments. Alas, the literature does not yet provide readily available methods to address this issue in the DFM framework, see Stock and Watson (2016) for a recent stocktaking of relevant research, and in particular Montiel-Olea et al. (2015) for an application to VAR models.

[2] Note that this is precisely the strategy some authors have pursued, see e.g. Cochrane and Piazzesi (2002).

[3] This is in contrast to traditional microeconomic settings, where instruments are used for an endogenous - but observable - variable. Here, only the exogeneity condition has to be assumed, whereas the relevance of the instrument can be tested in a "first-stage" regression.

[4] The exposition in Gertler and Karadi (2015) might therefore appear slightly misleading. They try to test the relevance condition by regressing the VAR innovations of their monetary policy equation on candidate instruments. Yet, as pointed out above, the external instrument identification scheme can be applied to an arbitrary column of H. The selection of a VAR equation and its residuals in the first stage regression is thus also to some extent arbitrary.

2.3 Bootstrap Procedure

To account for both estimation and identification uncertainty, I follow Mertens and Ravn (2013) and Gertler and Karadi (2015) and apply the wild bootstrapping procedure developed by Goncalves and Kilian (2004). This procedures generates artificial data samples by changing the sign of the estimated reduced form shocks u_t in Equation (2) and the instrument Z_t for randomly selected time periods.

In the DFM and FAVAR case, one further needs to incorporate the sampling uncertainty of idiosyncratic components. Here I apply the parametric bootstrap suggested by Stock and Watson (2016, p. 56), i.e. each error term e_i is assumed to follow an univariate autoregressive AR(4) process: $e_{it} = \sum_{p=1}^{4} \beta_p^i e_{i,t-p} + \zeta_{it}$. Then, draw $\tilde{\zeta}_i \sim \mathcal{N}(0, \hat{\sigma}_{\zeta_i})$ and use this draw in conjunction with the autoregressive coefficients β_p^i to generate an artificial series of idiosyncratic errors e_i.

The number of bootstrap draws is set to 2000. For the sake of consistency, I apply the same bootstrap method for all empirical models and report 90% confidence bands throughout.

3 Dataset

Table A1: Dataset Description

#	Description	tcode	Note
	Output and income		
1	IP Index	5*	
2	IP: Final Products and Nonindustrial Supplies	5	
3	IP: Final Products (Market Group)	5	
4	IP: Consumer Goods	5	
5	IP: Durable Consumer Goods	5	
6	IP: Nondurable Consumer Goods	5	
7	IP: Business Equipment	5	
8	IP: Materials	5	
9	IP: Durable Materials	5	
10	IP: Nondurable Materials	5	
11	IP: Manufacturing (SIC)	5	
12	IP: Residential Utilities	5	
13	IP: Fuels	5	
14	Capacity Utilization: Manufacturing	1	
15	ISM Manufacturing: Production Index	1	from Datastream
16	Real Personal Income	5	
17	Real personal income ex transfer receipts	5	
	Labor market		
18	Civilian Labor Force	5	
19	Civilian Employment	5	
20	Civilian Unemployment Rate	1	
21	Average Duration of Unemployment (Weeks)	1	
22	Civilians Unemployed - Less Than 5 Weeks	1	
23	Civilians Unemployed for 5-14 Weeks	1	
24	Civilians Unemployed - 15 Weeks & Over	1	
25	Civilians Unemployed for 15-26 Weeks	1	
26	Civilians Unemployed for 27 Weeks and Over	1	
27	Initial Claims	4	
28	All Employees: Total nonfarm	5	
29	All Employees: Goods-Producing Industries	5	
30	All Employees: Mining and Logging: Mining	5	
31	All Employees: Construction	5	
32	All Employees: Manufacturing	5	
33	All Employees: Durable goods	5	
34	All Employees: Nondurable goods	5	
35	All Employees: Service-Providing Industries	5	
36	All Employees: Trade, Transportation & Utilities	5	
37	All Employees: Wholesale Trade	5	
38	All Employees: Retail Trade	5	
39	All Employees: Financial Activities	5	
40	All Employees: Government	5	
41	Avg Weekly Hours : Goods-Producing	1	
42	Avg Weekly Overtime Hours : Manufacturing	1	
43	Avg Weekly Hours : Manufacturing	1	
44	Avg Hourly Earnings : Goods-Producing	5	
45	Avg Hourly Earnings : Construction	5	
46	Avg Hourly Earnings : Manufacturing	5	
47	ISM Manufacturing: Employment Index	1	from Datastream
	Housing		
48	Housing Starts: Total New Privately Owned	4	
49	Housing Starts, Northeast	4	
50	Housing Starts, Midwest	4	
51	Housing Starts, South	4	
52	Housing Starts, West	4	

Table A1: Dataset Description

#	Description	tcode	Note
53	New Private Housing Permits (SAAR)	4	
54	New Private Housing Permits, Northeast (SAAR)	4	
55	New Private Housing Permits, Midwest (SAAR)	4	
56	New Private Housing Permits, South (SAAR)	4	
57	New Private Housing Permits, West (SAAR)	4	
Consumption, orders, and inventories			
58	Real personal consumption expenditures	5	
59	Real Manu. and Trade Industries Sales	5	
60	Retail and Food Services Sales	5	
61	New Orders for Durable Goods	5	
62	New Orders for Nondefense Capital Goods	5	
63	Unfilled Orders for Durable Goods	5	
64	Total Business Inventories	5	
65	Total Business: Inventories to Sales Ratio	1	
66	ISM: PMI Composite Index	1	from Datastream
67	ISM: Supplier Deliveries Index	1	from Datastream
68	ISM: New Orders Index	1	from Datastream
69	ISM: Inventories Index	1	from Datastream
Prices			
70	CPI: All Items	5*	
71	CPI: Apparel	5	
72	CPI: Transportation	5	
73	CPI: Medical Care	5	
74	CPI: Commodities	5	
75	CPI: Durables	5	
76	CPI: Services	5	
77	CPI: All Items Less Food	5	
78	CPI: All Items Less Shelter	5	
79	CPI: All Items Less Medical Care	5	
80	Personal Cons. Expend.: Chain Index	5	
81	Personal Cons. Exp: Durable goods	5	
82	Personal Cons. Exp: Nondurable goods	5	
83	Personal Cons. Exp: Services	5	
84	ISM Manufacturing: Prices Index	1	from Datastream
85	PPI: Finished Goods	5	
86	PPI: Finished Consumer Goods	5	
87	PPI: Intermediate Materials	5	
88	PPI: Crude Materials	5	
89	PPI: Metals and metal products:	5	
90	Crude Oil, spliced WTI and Cushing	5	
Money and credit			
91	M1 Money Stock	5	
92	M2 Money Stock	5	
93	Real M2 Money Stock	5	
94	St. Louis Adjusted Monetary Base	5	
95	Total Reserves of Depository Institutions	5	
96	Commercial and Industrial Loans	5	
97	Real Estate Loans at All Commercial Banks	5	
98	Total Nonrevolving Credit	5	
99	Nonrevolving Consumer Credit to Personal Income	1	
100	MZM Money Stock	5	
101	Consumer Motor Vehicle Loans Outstanding	5	
102	Total Consumer Loans and Leases Outstanding	5	
103	Securities in Bank Credit at All Commercial Banks	5	
Stock market			
104	S&P's Common Stock Price Index: Composite	5	
105	S&P's Common Stock Price Index: Industrials	5	
106	S&P's Composite Common Stock: Dividend Yield	5	

Table A1: Dataset Description

#	Description	tcode	Note
107	S&P's Composite Common Stock: Price-Earnings Ratio	5	
108	VXO	1	
	Interest and exchange rates		
109	Effective Federal Funds Rate	1	
110	3-Month AA Financial Commercial Paper Rate	1	spread over 3M Treasury Bill
111	3-Month Treasury Bill	1	
112	6-Month Treasury Bill	1	
113	1-Year Treasury Rate	1	
114	5-Year Treasury Rate	1	
115	10-Year Treasury Rate	1	
116	Moody's Seasoned Aaa Corporate Bond Yield	1	spread over 10Y Treasury Rate
117	Moody's Seasoned Baa Corporate Bond Yield	1	spread over 10Y Treasury Rate
118	30-Year Fixed Rate Mortgage US	1	from FRED; spread over 10Y Treasury Rate
119	Excess bond premium	1	from Gilchrist and Zakrajsek (2012)
120	Switzerland - U.S. short-term Interest Rate Spread	1	cf. Forni and Gambetti (2010)
121	Japan - U.S. short-term Interest Rate Spread	1	cf. Forni and Gambetti (2010)
122	U.K. - U.S. short-term Interest Rate Spread	1	cf. Forni and Gambetti (2010)
123	Canada - U.S. short-term Interest Rate Spread	1	cf. Forni and Gambetti (2010)
124	Trade Weighted U.S. Dollar Index: Major Currencies	5	
125	Switzerland / U.S. Foreign Exchange Rate	5	
126	Japan / U.S. Foreign Exchange Rate	5	
127	U.K. / U.S. Foreign Exchange Rate	5	
128	Canada / U.S. Foreign Exchange Rate	5	
129	Switzerland / U.S. Real Exchange Rate	4	based on CPI, cf. Forni and Gambetti (2010)
130	Japan / U.S. Real Exchange Rate	4	based on CPI, cf. Forni and Gambetti (2010)
131	U.K. / U.S. Real Exchange Rate	4	based on CPI, cf. Forni and Gambetti (2010)
132	Canada / U.S. Real Exchange Rate	4	based on CPI, cf. Forni and Gambetti (2010)

Note: tcode refers to the applied transformation code (1: level, 4: log-level, 5: log-difference). If not otherwise specified, variables are taken from McCracken and Ng (2016)'s dataset (2017-02 vintage). I retrieve some discontinued series from FRED and Datastream, drop some redundant series, transform private sector interest rates into spreads, and add short-term interest rate spreads and real exchange rates (CPI based) between the US and Switzerland, Japan, the United Kingdom, and Canada. The industrial production and consumer price index (marked *) are kept in log-levels when used as observable variables (see main text).

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