The Response of Asset Prices to Monetary Policy Shocks: Stronger Than Thought

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February 2019

Abstract

Standard macroeconomic theory predicts rapid responses of asset prices to monetary policy shocks. Small-scale VARs, however, often find sluggish and insignificant impact effects. Using the same high-frequency instrument to identify monetary policy shocks, we show that a large-scale Dynamic Factor Model finds overall stronger and quicker asset price reactions compared to a benchmark VAR, both on euro area and US data. Our results suggest that incorporating a sufficiently large information set is crucial to estimate monetary policy effects.

Keywords: Asset Prices, Monetary Policy, Dynamic Factor Models, Nonfundamentalness.

JEL classification: C32, E43, E44, E52.

We thank Charles Goodhart, Matteo Luciani, Matteo Barigozzi and Pilar Poncela, as well as anonymous referees, for helpful suggestions. Part of this work has been carried out while both authors were affiliated with the European Central Bank. The views expressed in this paper do not necessarily reflect those of the European Central Bank, European Commission, or Deutsche Bundesbank.

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1 Introduction

How do asset prices react to an unexpected monetary tightening? Standard macroeconomic theory makes a clear prediction: Asset prices should fall, firstly due to higher interest rates and secondly due to lower expected real activity. Given the forward-looking behavior of economic agents, the repricing should also take place abruptly.

Some studies, particularly those exploiting high-frequency data, do indeed find such immediate responses (see e.g. Rigobon and Sack, 2004; Bernanke and Kuttner, 2005; Bohl et al., 2008; Nakamura and Steinsson, 2018). Conventional VARs, on the other hand, often find rather sluggish or even insignificant asset price reactions, especially when employing a recursive identification approach (see e.g. Eichenbaum and Evans (1995) and Grilli and Roubini (1996) for exchange rates, Beckworth et al. (2012) for corporate bond spreads, Li et al. (2010) and Galí and Gambetti (2015) for stock prices, and Iacoviello (2005), Goodhart and Hofmann (2008) and Calza et al. (2013) for house prices).[1]

Two approaches have proven useful to resolve these puzzles: external instruments avoid controversial assumptions about the contemporaneous effect of shocks and factor models significantly enlarge the information set compared to standard VARs (see Gertler and Karadi (2015); Caldara and Herbst (2019) for the former and Forni and Gambetti (2010); Del Negro and Otrok (2007); Luciani (2015); Kerssenfischer (2019b) for the latter). In this paper, we employ both approaches jointly to study the effects of monetary policy shocks for two regions, namely the euro area and the US. In both cases we study the response of a wide set of asset prices (stock and house prices, exchange rates, and corporate bond yields) across two different models, namely a traditional small-scale VAR and a large-scale dynamic factor model. Even though we use the same high-frequency instrument to identify monetary policy shocks, the two models produce starkly different results in both regions. The large-scale factor model finds generally strong and rapid effects of monetary policy on asset prices, consistent with both economic theory and event study evidence. Small-scale VARs, in comparison, yield overall weaker and sometimes counterintuitive responses (see also Jarociński and Karadi, 2018).

These findings are in line with the growing literature on the informational problem known as "nonfundamentalness".[2] Intuitively, an empirical model aimed at identifying monetary policy shocks should capture all information relevant for the central bank's decision-making process. If it does, the shocks are fundamental, i.e. they can be identified by means of that model. If it does not, a systematic reaction of the central bank to information omitted from the model might be erroneously identified as a policy shock. This is particularly relevant for conventional VARs – even when identified via high-frequency data – since the set of indicators central banks monitor is vastly larger than the handful of variables these models can capture.

The paper is structured as follows. In the next section, we outline our empirical approach, Section 3 presents the results, and Section 4 concludes.

2 The Dynamic Factor Model

Forni et al. (2009) show that by enlarging the space of observations one can solve the problem of nonfundamentalness (see also Giannone and Reichlin, 2006). Indeed, nonfundamentalness is not an issue for models which are able to handle very large panels of related time series. In particular, nonfundamentalness is nongeneric in the framework of dynamic factor models, i.e. it occurs with probability zero for $N \to \infty$, with N being the number of series included in the model.

[1] Different data frequencies make a direct comparison between event studies and VARs generally difficult. Note, however, that Bernanke and Kuttner (2005) find similar effects of policy shocks on equity prices both at a daily and monthly frequency.

[2] See e.g. Hansen and Sargent (1991), Lippi and Reichlin (1993, 1994), Fernández-Villaverde et al. (2007) for early contributions, Forni and Gambetti (2010), Sims (2012), Forni and Gambetti (2014), Forni et al. (2014), Ellahie and Ricco (2017) and Canova and Hamidi Sahneh (2017) for more recent papers and Alessi et al. (2011) for a review of the literature.

However, the Dynamic Factor Model (DFM) by Forni et al. (2009), which in turn is a special case of the model in Forni and Lippi (2001) and Forni et al. (2005), requires a stationary setting. Prior to estimation, most authors therefore ensure stationarity by taking first differences of the data, whenever necessary. As is well know, this procedure is not innocuous, as the neglect of cointegration relationships could lead to flawed results.[3]

In what follows, we thus adopt the extension of the DFM framework to a non-stationary setting put forward in Barigozzi et al. (2016a) and Barigozzi et al. (2016b). We limit ourselves to outlining the main features of the model and refer to the above mentioned papers for a detailed description of the underlying assumptions.

2.1 Basics

Denote by Y a panel of N (potentially non-stationary) time series with time dimension T. Besides a deterministic time trend, each variable in Y_t is assumed to be the sum of two unobservable components, namely the common component χ_t and the idiosyncratic component ξ_t. The latter is usually thought of as sector specific variation or measurement error, and is allowed to be mildly cross-correlated, hence the factor model is called *generalized* or *approximate* as opposed to *exact*. The object of interest are the common components, which account for the main bulk of co-movement in the dataset as they are linear combinations of $r \ll N$ static factors F_t. This is the standard representation of a DFM.

Formally,

$$Y_t = \alpha + \beta \cdot t + \chi_t + \xi_t, \qquad \chi_t = \Lambda F_t \tag{1}$$

$$\Phi(L) F_t = e_t, \qquad e_t = H\epsilon_t \tag{2}$$

with the $N \times r$ factor loading matrix Λ and the $r \times r$ matrix polynomial $\Phi(L)$ of lag length p. For both datasets, our benchmark specification is p=6 and r=8.[4] Compared to a standard DFM, the only additional assumption made by Barigozzi et al. (2016a) is that the factors are $I(1)$ and the idiosyncratic components are either $I(0)$ or $I(1)$.[5] As is well known, the shocks e_t are reduced-form, i.e. to allow a structural interpretation an identification matrix H is needed (see Section 2.4).

2.2 Data

For the euro area, the dataset Y contains $N = 88$ macroeconomic series from April 2000 to December 2017. For the US, the dataset includes $N = 95$ series from June 1976 to December 2017. In both cases, the dataset covers measures of real activity, prices, employment, and numerous financial sector variables. The Supporting Information Appendix lists all variables in the two datasets along with the applied transformations.[6] Since we allow for time trends and non-stationarity in our empirical setting, all series are kept either in levels or log-levels.

To study and compare the effect of monetary policy shocks, we use a set of asset prices available for both regions and the entire sample period. In particular, we focus on stock prices, house prices, corporate bond yields and exchange

[3] As Barigozzi et al. (2016b) point out, differencing the data by construction leads all common shocks to have permanent effects. This is at odds with economic theory, which posits that only a few shocks have permanent effects (e.g. technology) while most others have only transitory effects (e.g. monetary policy). Furthermore, the common assumption of stationary idiosyncratic components is usually not valid for macroeconomic datasets.

[4] In principle, the DFM framework allows static factors F_t to have reduced rank, i.e. to be spanned by $q \leq r$ "dynamic" factors, hence the term DFM. Given our external instrument identification scheme, however, results are virtually identical whether or not $q < r$, thus we assume $q = r$ for simplicity. We thank an anonymous referee for pointing this out. The Supporting Information Appendix shows that the information criterion of Bai and Ng (2002) suggests $r = 8$ for both datasets and Figures A1-A3 provide a battery of robustness checks with respect to all parameters.

[5] The formal definition of a rational reduced-rank $I(1)$ family of stochastic processes is given in Definition 4 in Barigozzi et al. (2016a), while Proposition 4 therein states the fundamentalness of e_t in this context.

[6] Boivin and Ng (2006) show that a larger cross-sectional dimension of the dataset can lead to worse factor estimates, especially when the included variables are highly collinear. We therefore use a cleansed version of the US dataset by McCracken and Ng (2016) and construct an analogous dataset for the euro area.

rates. Stock prices refer to the S&P 500 index for the US and the Euro STOXX for the euro area. House prices are taken from Robert Shiller's website for the US and from the ECB for the euro area (interpolated from quarterly frequency using cubic spline). Regarding corporate bonds, we study yields on AAA and BAA rated bonds and an "excess bond premium" measure. Gilchrist and Zakrajsek (2012) compute this premium for the US and Gilchrist and Mojon (2016) for the euro area. In the latter case, the excess premium refers to value-weighted spreads of non-financial euro area corporate bonds with respect to their domestic sovereign counterpart. As regards exchange rates, lastly, we study the response of the Euro and US Dollar vis-a-vis each other and vis-a-vis the British Pound, Canadian Dollar, and Swiss Franc. For the longer US dataset, the EUR/USD exchange rate is backcasted using the German D-Mark.

2.3 Estimation

We apply the estimation procedure presented in Barigozzi et al. (2016b), i.e. we estimate the loading matrix Λ by applying principal component analysis on the first-differenced dataset ΔY_t and recover an estimate of the factors in level form as $\hat{F}_t = \hat{\Lambda}' X_t$, based on the detrended dataset $X_t = Y_t - \hat{\alpha} - \hat{\beta} \cdot t$. Then, we estimate Equation (2) as a conventional VAR on the (non-stationary) static factors. As Sims et al. (1990) show, the parameters of a cointegrated VAR are consistently estimated using an unrestricted VAR in levels. Besides its simplicity, this approach obviates the need to estimate the cointegration relationships. Finally, Barigozzi et al. (2016b) show that when the focus is on short-run impulse responses, as is the case in this study, an unrestricted VAR in levels is superior to a vector error correction model, owing to a faster rate of convergence of the estimator.[7] To generate confidence bands, we employ the wild bootstrap procedure by Goncalves and Kilian (2004), which generates artificial data samples by changing the sign of reduced-form residuals and the external instrument for randomly selected time periods.[8]

2.4 Identification

To identify structural monetary policy shocks from the reduced-form shocks we use an external instrument (see e.g. Stock and Watson, 2012; Gertler and Karadi, 2015). Formally, given a valid instrument Z_t, and assuming (without loss of generality) that the monetary policy shock is the first one, we can rewrite Equation (2) as:

$$E(e_t Z_t) = E(H \epsilon_t Z_t) = [H_1 H_\bullet] \begin{bmatrix} E(\epsilon_{1t} Z_t) \\ E(\epsilon_{\bullet t} Z_t) \end{bmatrix} = H_1 \alpha. \tag{3}$$

To be a valid instrument, Z_t must meet the familiar relevance and exogeneity conditions, i.e. $E(\epsilon_{1t} Z_t) = \alpha \neq 0$ and $E(\epsilon_{\bullet t} Z_t) = 0$. If these conditions are met, H_1 (the identification matrix column we are interested in) is obtained by regressing Z_t on all reduced-form shocks e_t and normalizing the shocks' impact effect. In what follows, we will study contractionary policy shocks that increase the 2-year sovereign bond yield by 50 basis points, since short-term rates have been constrained by an effective lower bound for much of our sample, particularly in the euro area (where we study a rise in the German 2-year rate). Our instrument for euro area monetary policy shocks is constructed from high-frequency data around ECB Governing Council Meetings. More precisely, Z_t captures movements in the German Bobl future – one of the most liquid bond futures in the euro area – from 10 minutes prior to the press release to 20 minutes after

[7] Proposition 2 in Barigozzi et al. (2016a) states the consistency of impulse responses based on an unrestricted VAR. Monte Carlo simulations showing the validity of this specific estimation procedure are available in Table 2 therein.

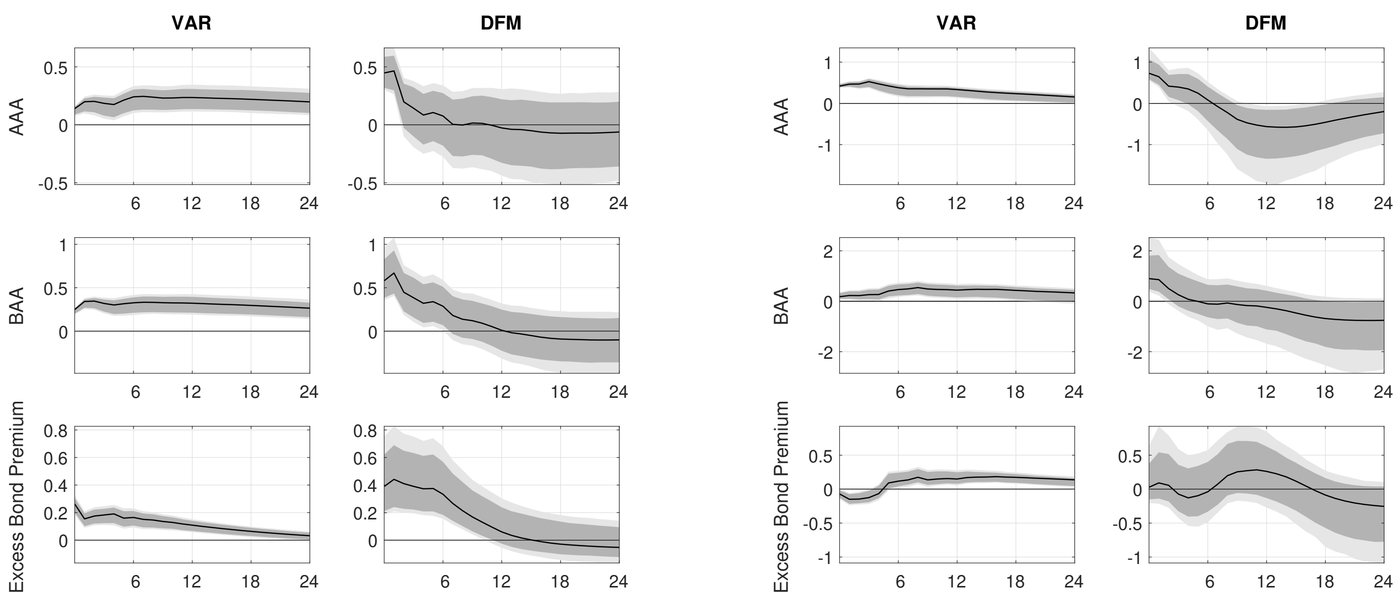
[8] As in Barigozzi et al. (2016b), the bootstrap procedure works as follows: (1) obtain estimates of Λ, F, $\Phi(L)$ and e from the actual dataset Y, (2) resample e via wild bootstrap to obtain artificial factors F^*, (3) use Λ to generate artificial common components χ^* and add ξ to obtain an artificial dataset Y^*, (4) apply the estimation procedure on Y^*. The idiosyncratic components ξ are not bootstrapped. Lastly, we apply the bias-correction method of Kilian (1998) in step (2).

the end of the press conference.[9] The instrument series is taken from Kerssenfischer (2019a) and available from March 2002 onwards, covering 179 Governing Council Meetings. For US monetary policy, we follow Gertler and Karadi (2015) and use the change in the three month ahead fed funds future from 10 minutes prior to 20 minutes after FOMC announcements. In both cases, the relevance and exogeneity condition imply that, within the specified intraday window, movements in the instrument should be driven by unexpected decisions or announcements of the respective central bank and not any other structural shock.

3 Results

Let us now examine the response of asset prices to a contractionary monetary policy shock that raises the 2-year sovereign bond yield by 50 basis points. Besides the large-scale DFM described above, we also estimate standard small-scale VARs for comparison. In particular, we consider 4-variable VARs, with each asset price under study added to a set of core variables, namely industrial production, consumer prices (both in logs), and the 2-year sovereign bond yield. For the sake of consistency, we apply the same identification scheme (see Section 2.4) and use the same lag length (p=6) as in the DFM. Nonetheless, the differences between the VAR and DFM results are substantial.

Figure 1 shows that the factor model finds larger effects on corporate bond yields across the board. The differences are particularly striking on US data, where the reaction of bond yields and of Gilchrist and Zakrajsek (2012)'s excess bond premium is twice as large on impact in the DFM as in the VAR. Similar results hold for euro area bond yields. Estimating the response of the excess bond premium on euro area data, on the other hand, appears to be challenging for both models. While the DFM finds an insignificant response, the small-scale VAR produces a counter-intuitive decline in the bond premium.



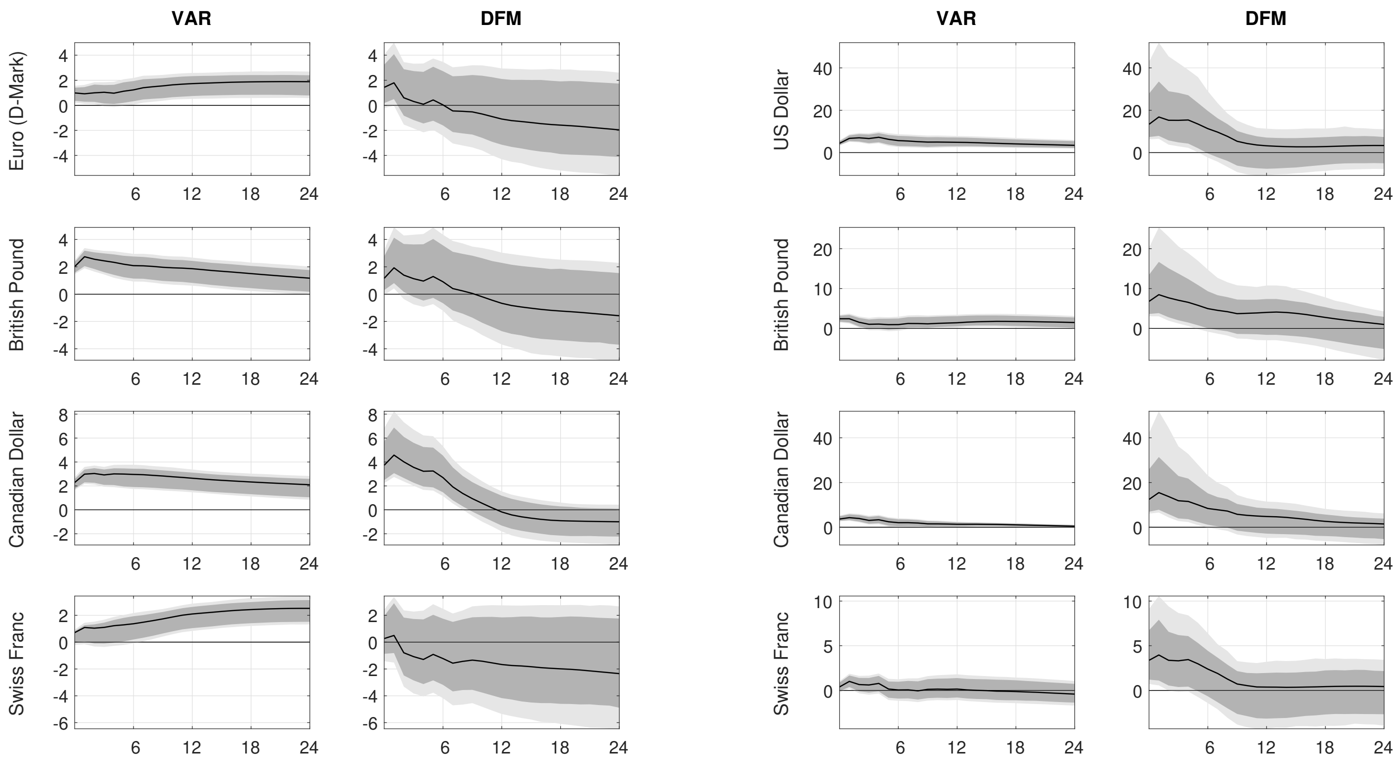
(a) US **(b)** Euro area

Figure 1: Corporate Bond Yields

Black lines refer to point estimates, grey areas to 80% and 90% confidence bands. All responses in percent. Months after the shock on the x-axis.

[9]On regular Governing Council Meeting days, the ECB announces its policy rate decision via a press release at 13:45 CET, followed by a roughly one-hour-long press conference at 14:30. To obtain yield changes around this window, the percentage price change of the Bobl future is divided by the modified duration of the cheapest-to-deliver underlying on that day. The underlying of Bobl futures are German government bonds with a residual maturity between 4.5 and 5.5 years. Figure A4 provides a robustness check of our results with respect to alternative futures with shorter and longer-dated underlyings.

Figure 2 reports results for various exchange rates. On US data, the small-scale VAR and the DFM find similar



(a) US

(b) Euro area

Figure 2: Exchange Rates

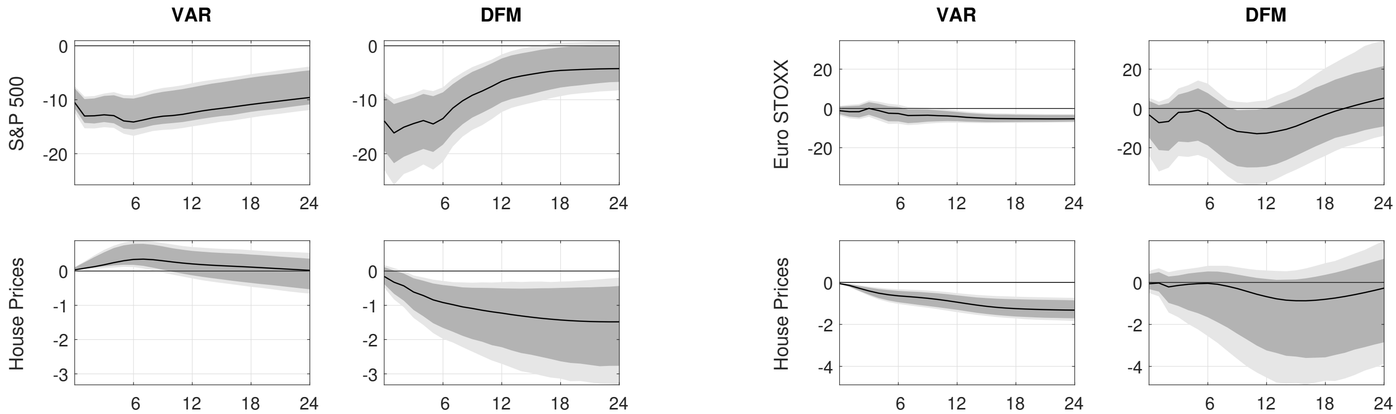
Black lines refer to point estimates, grey areas to 80% and 90% confidence bands. All responses in percent. Exchange rates refer to units of foreign currency per US Dollar (left panel) or per Euro (right panel). Months after the shock on the x-axis.

responses of the domestic currency vis-a-vis the British Pound and Canadian Dollar, though in the latter case the appreciation is almost twice as large in the DFM. The Euro and Swiss Franc exchange rates, in contrast, are less responsive to US monetary policy shocks. In the VAR, both exchange rates exhibit an implausible delayed response. On euro area data, both the VAR and the DFM produce a universal and immediate Euro appreciation after a domestic monetary policy shock, and the magnitude of the effect is larger than in the US, particularly for the factor model.

Figure 3 compares the reaction of two further asset prices, namely stock and house prices. On US data, both models find a sizeable and significant drop in stock prices, but the response is larger and more immediate in the DFM. In the euro area, the VAR yields a puzzlingly small response of stock prices to a contractionary shock, whereas the factor model finds a larger, though still insignificant effect. Turning to house prices, the VAR finds a counterintuitive increase after a contractionary shock in the US, whereas prices decline by around 1.5% over two years in the DFM. On euro area data, on the other hand, the response of house prices is plausible and significant in the VAR but not significantly different from zero in the DFM.[10]

Lastly, Figure 4 plots the impulse response functions of the three "core" variables: industrial production, consumer prices and the 2-year sovereign bond yield. Since we estimate separate VAR models (one for each asset price under study), the figure reports multiple impulse responses in the VAR case. For the US, the difference between VARs and the factor model is striking. In the DFM, both output and prices decline strongly after a monetary policy tightening, in line with basic theory. Most VAR models, on the other hand, find expansionary effects on industrial production and a muted response of consumer prices. These puzzling responses are particularly pronounced if the VAR includes exchange rates

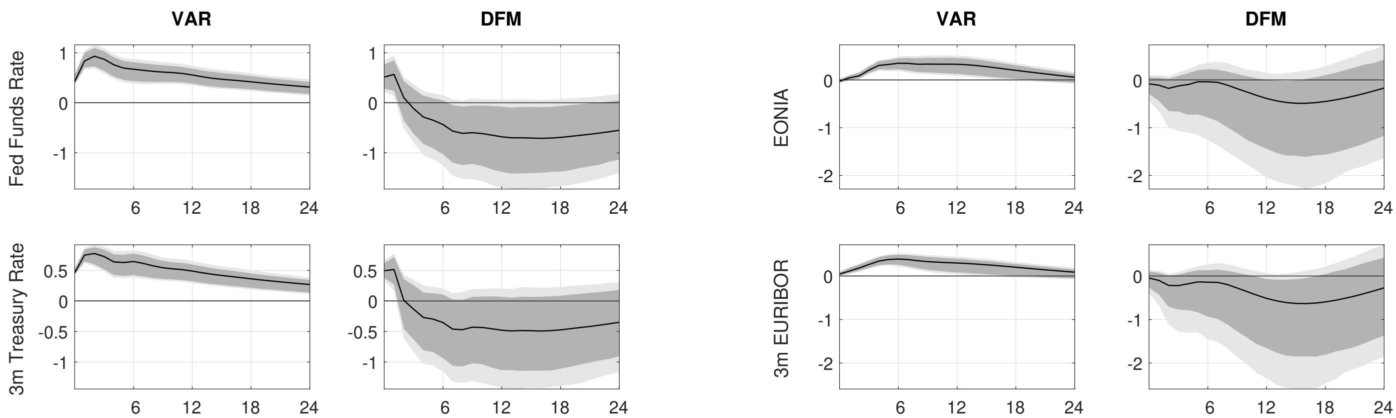
[10]Note that house prices are interpolated as they are only available at a quarterly frequency.



(a) US **(b)** Euro area

Figure 3: Stock and House Prices

Black lines refer to point estimates, grey areas to 80% and 90% confidence bands. All responses in percent. Months after the shock on the x-axis.



(a) US **(b)** Euro area

Figure 4: Core variables

Each impulse response in the left columns refers to a VAR model with log IP, log CPI, the 2-year government bond yield and a different fourth variable. Black lines refer to the models shown in Figure 1, i.e. using corporate bond yields as the fourth variable. Blue dashed lines refer to the models shown in Figure 2, i.e. using exchange rates as the fourth variable. Red dash-dotted lines refer to the models shown in Figure 3, i.e. using stock or house prices as the fourth variable.

as the fourth variable, but also hold for all the other asset prices studied above.[11] On euro area data, VARs yield equally counterintuitive responses which the factor model attenuates, but does not entirely solve.[12]

Overall, the large-scale factor model finds stronger and quicker effects of monetary policy than traditional small-scale VARs. A potential explanation for the remaining differences between US and euro area results, lastly, are "central bank information effects". In particular, recall that the external instrument from Section 2.4 treats any central bank announcement that raises yields as a contractionary policy surprise. The central bank information literature, however, suggests that an announcement can also raise yields by indicating a better-than-expected economic outlook. In either case, the domestic currency should appreciate, but the effect on stock prices and bond premia is diametrically opposite. Insofar as these information effects are more important for the ECB (as Jarociński and Karadi, 2018, argue), they could explain the stronger response of exchange rates and the more muted response of stock prices and bond premia in the

[11] This is in contrast to Caldara and Herbst (2019), who find that the inclusion of corporate credit spreads resolves puzzling VAR results.

[12] Note that 2-year sovereign yields, as well as short-term money market rates (see Supporting Information Appendix), revert back to normal only slowly in VARs, but quickly in factor models. The stronger asset price responses can thus not be explained by the factor model capturing more persistent monetary policy shocks.

euro area compared to the US.

4 Conclusions

According to standard theory, monetary policy shocks should lead to an immediate – and potentially drastic – repricing of assets. While event study evidence is usually consistent with this prediction, conventional VARs often find sluggish responses of asset prices.

Even when unanticipated policy announcements are identified via a high-frequency instrument, some puzzling VAR results persist. We confirm this finding for the euro area and the US and show that it is likely due to the limited information set captured by small-scale VARs, which may lead to the issue of nonfundamentalness of the shocks. In particular, a large-scale factor model – identified via the same external instrument – solves many of the puzzling VAR results. By including a large set of variables, the factor model overcomes the nonfundamentalness issue and finds stronger and more rapid effects of monetary policy on asset prices.

Bibliography

Alessi, L., Barigozzi, M., and Capasso, M. (2011). Non-fundamentalness in structural econometric models: A review. *International Statistical Review*, 79(1).

Bai, J. and Ng, S. (2002). Determining the number of factors in approximate factor models. *Econometrica*, 70(1):191–221.

Barigozzi, M., Lippi, M., and Luciani, M. (2016a). Dynamic Factor Models, Cointegration, and Error Correction Mechanisms. Finance and Economics Discussion Series 018, Board of Governors of the Federal Reserve System.

Barigozzi, M., Lippi, M., and Luciani, M. (2016b). Non-Stationary Dynamic Factor Models for Large Datasets. Finance and Economics Discussion Series 024, Board of Governors of the Federal Reserve System.

Beckworth, D., Moon, K. P., and Toles, H. J. (2012). Can monetary policy influence long-term interest rates? It depends. *Economic Inquiry*, 50(4):1080–1096.

Bernanke, B. S. and Kuttner, K. N. (2005). What Explains the Stock Market's Reaction to Federal Reserve Policy? *Journal of Finance*, 60(3):1221–1257.

Bohl, M. T., Siklos, P. L., and Sondermann, D. (2008). European Stock Markets and the ECB's Monetary Policy Surprises*. *International Finance*, 11(2):117–130.

Boivin, J. and Ng, S. (2006). Are more data always better for factor analysis? *Journal of Econometrics*, 132(1):169–194.

Caldara, D. and Herbst, E. (2019). Monetary Policy, Real Activity, and Credit Spreads: Evidence from Bayesian Proxy SVARs. *American Economic Journal: Macroeconomics*, 11(6):157–192.

Calza, A., Monacelli, T., and Stracca, L. (2013). Housing finance and monetary policy. *Journal of the European Economic Association*, 11:101–122.

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

Del Negro, M. and Otrok, C. (2007). 99 Luftballons: Monetary policy and the house price boom across U.S. states. *Journal of Monetary Economics*, 54(7):1962–1985.

Eichenbaum, M. and Evans, C. L. (1995). Some empirical evidence on the effects of shocks to monetary policy on exchange rates. *The Quarterly Journal of Economics*, 110(4):975–1009.

Ellahie, A. and Ricco, G. (2017). Government purchases reloaded: Informational insufficiency and heterogeneity in fiscal vars. *Journal of Monetary Economics*, 90:13 – 27.

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.

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.

Galí, J. and Gambetti, L. (2015). The Effects of Monetary Policy on Stock Market Bubbles: Some Evidence. *American Economic Journal: Macroeconomics*, 7(1):233–57.

Gertler, M. and Karadi, P. (2015). Monetary Policy Surprises, Credit Costs, and Economic Activity. *American Economic Journal: Macroeconomics*, 7(1):44–76.

Giannone, D. and Reichlin, L. (2006). Does information help recovering structural shocks from past observations? *Journal of the European Economic Association*, 4(2/3):455–465.

Gilchrist, S. and Mojon, B. (2016). Credit risk in the euro area. *The Economic Journal*, 128(608):118–158.

Gilchrist, S. and Zakrajsek, E. (2012). Credit spreads and business cycle fluctuations. *American Economic Review*, 102(4):1692–1720.

Goncalves, S. and Kilian, L. (2004). Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. *Journal of Econometrics*, 123(1):89 – 120.

Goodhart, C. and Hofmann, B. (2008). House prices, money, credit, and the macroeconomy. *Oxford Review of Economic Policy*, 24(1):180–205.

Grilli, V. and Roubini, N. (1996). Liquidity models in open economies: Theory and empirical evidence. *European Economic Review*, 40(3-5):847–859.

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.

Iacoviello, M. (2005). House prices, borrowing constraints, and monetary policy in the business cycle. *The American Economic Review*, 95(3):739–764.

Jarociński, M. and Karadi, P. (2018). Deconstructing monetary policy surprises: the role of information shocks. Working Paper Series 2133, European Central Bank.

Kerssenfischer, M. (2019a). Information Effects of Euro Area Monetary Policy: New Evidence from High-Frequency Futures Data. *Bundesbank Discussion Paper*, forthcoming. https://sites.google.com/site/markkerssenfischer/home.

Kerssenfischer, M. (2019b). The puzzling effects of monetary policy in VARs: Invalid identification or missing information? *Journal of Applied Econometrics*, 34(1):18–25.

Kilian, L. (1998). Small-Sample Confidence Intervals For Impulse Response Functions. *The Review of Economics and Statistics*, 80(2):218–230.

Li, Y. D., Iscan, T. B., and Xu, K. (2010). The impact of monetary policy shocks on stock prices: Evidence from Canada and the United States. *Journal of International Money and Finance*, 29(5):876–896.

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.

Luciani, M. (2015). Monetary Policy and the Housing Market: A Structural Factor Analysis. *Journal of Applied Econometrics*, 30(2):199–218.

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

Nakamura, E. and Steinsson, J. (2018). High-frequency identification of monetary non-neutrality: The information effect. *The Quarterly Journal of Economics*, 133(3):1283–1330.

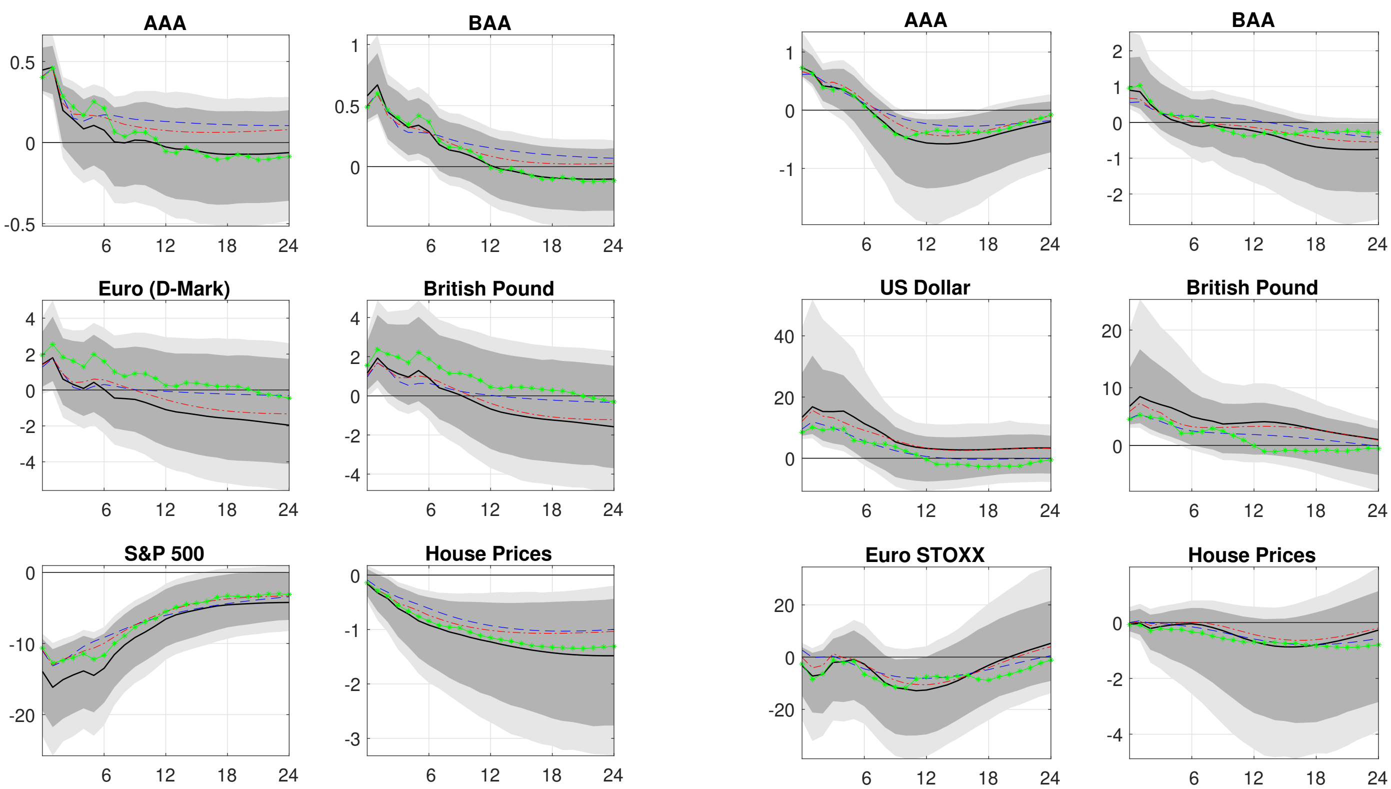
Rigobon, R. and Sack, B. (2004). The impact of monetary policy on asset prices. *Journal of Monetary Economics*, 51(8):1553–1575.

Sims, C. A., Stock, J. H., and Watson, M. W. (1990). Inference in Linear Time Series Models with Some Unit Roots. *Econometrica*, 58(1):113–44.

Sims, E. R. (2012). News, non-invertibility, and structural vars. In *DSGE Models in Macroeconomics: Estimation, Evaluation, and New Developments*, pages 81–135. Emerald Group Publishing Limited.

Stock, J. H. and Watson, M. W. (2012). Disentangling the channels of the 2007-09 recession. *Brookings Papers on Economic Activity*, 43(1 (Spring)):81–156.

5 Robustness Checks

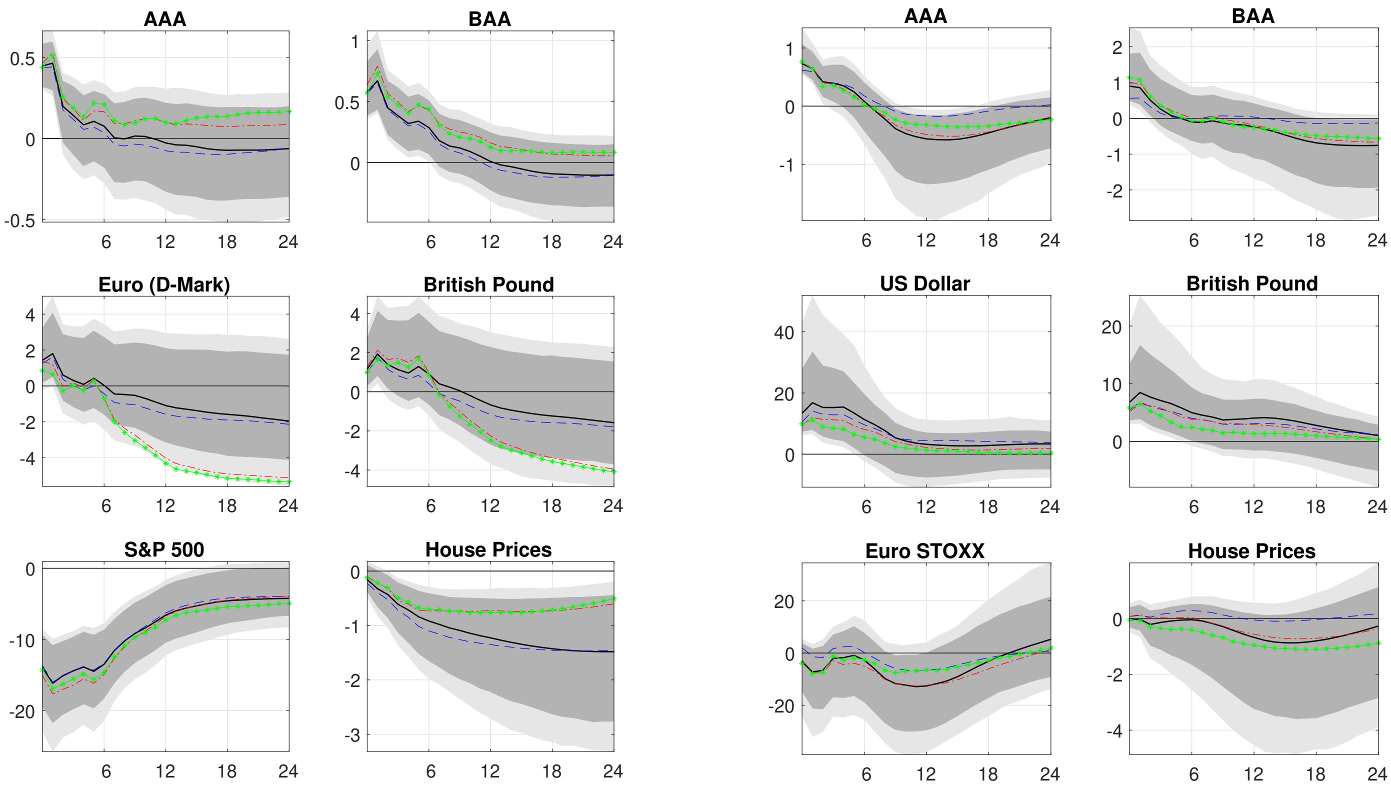


(a) US

(b) Euro area

Figure A1: Lag length

Solid lines and shaded areas refer to refer to point estimates and to 80% and 90% confidence bands of the benchmark model, i.e. with $p = 6$ lags, $r = 8$ static factors and $q = 8$ dynamic factors, see Section 2.1. Blue dashed lines refer to a DFM with $p = 3$, red dash-dotted lines to a DFM with $p = 4$, and green lines (marked with an asterisk) to a DFM with $p = 9$.

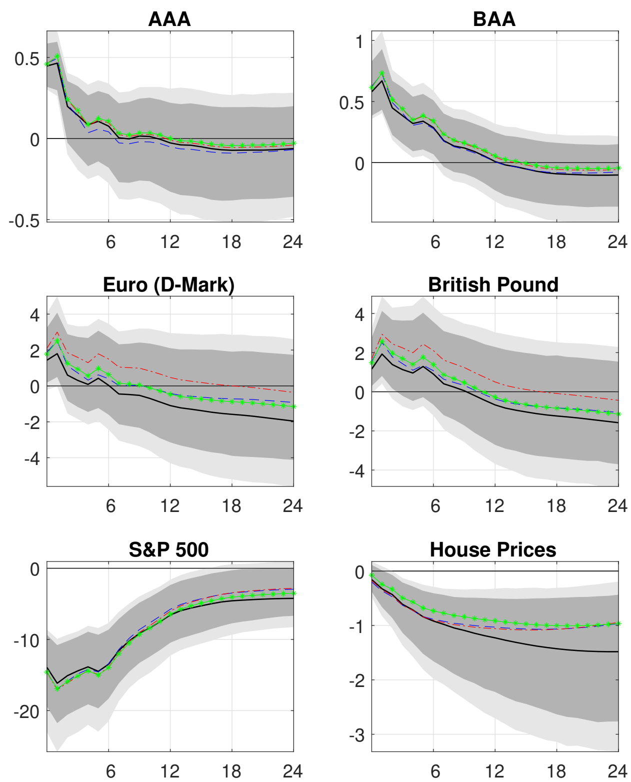


(a) US

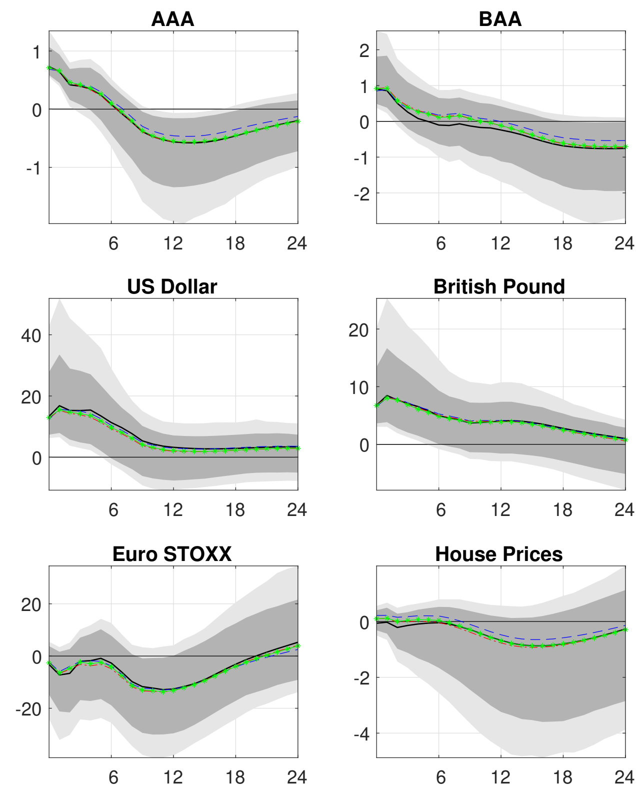
(b) Euro area

Figure A2: Number of static factors

Solid lines and shaded areas refer to refer to point estimates and to 80% and 90% confidence bands of the benchmark model, i.e. with $p = 6$ lags, $r = 8$ static factors and $q = 8$ dynamic factors, see Section 2.1. Blue dashed lines refer to a DFM with $r = q = 7$, red dash-dotted lines to a DFM with $r = 9$, and green lines (marked with an asterisk) to a DFM with $r = 10$.



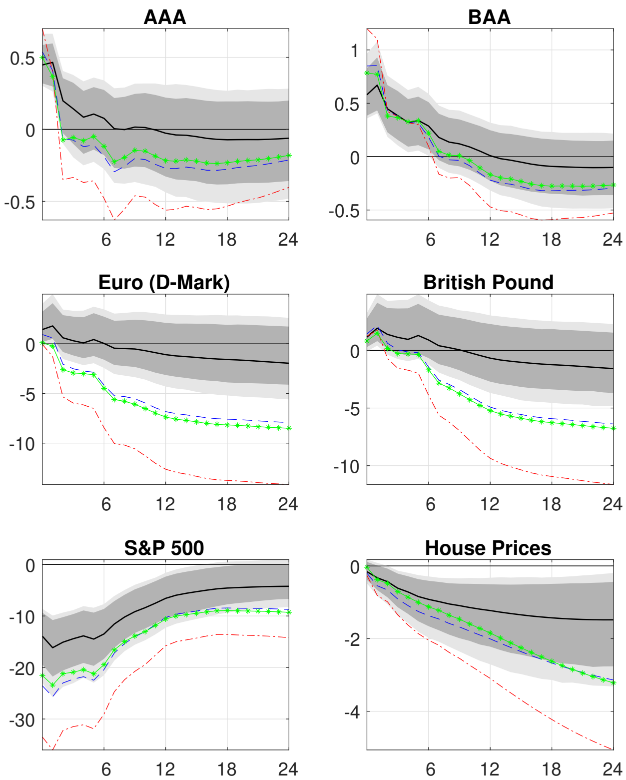
(a) US



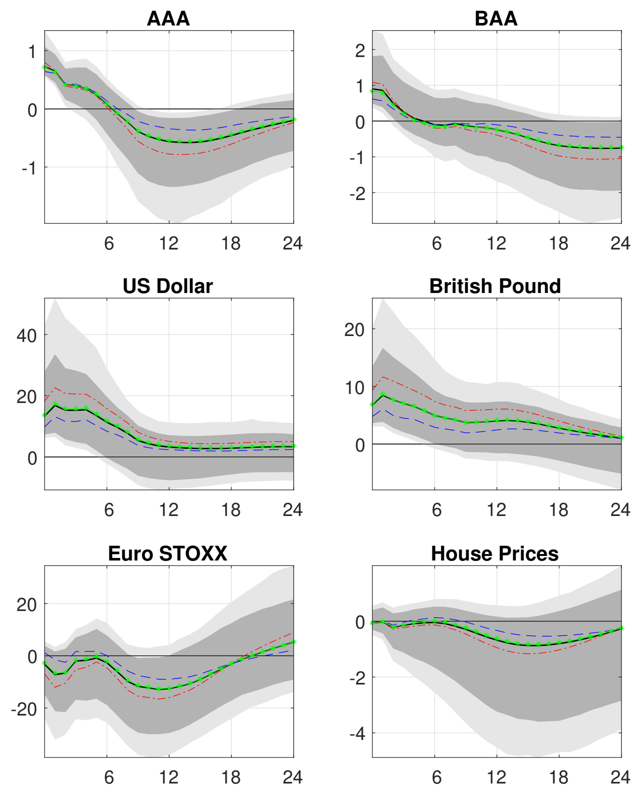
(b) Euro area

Figure A3: Number of dynamic factors

Solid lines and shaded areas refer to refer to point estimates and to 80% and 90% confidence bands of the benchmark model, i.e. with $p = 6$ lags, $r = 8$ static factors and $q = 8$ dynamic factors, see Section 2.1. Blue dashed lines refer to a DFM with $q = 5$, red dash-dotted lines to a DFM with $q = 6$, and green lines (marked with an asterisk) to a DFM with $q = 7$.



(a) US



(b) Euro area

Figure A4: External instrument

Solid lines and shaded areas refer to refer to point estimates and to 80% and 90% confidence bands of the benchmark models, see Section 2.4. For the US (left panel), the benchmark instrument is the three month ahead fed funds future change in a 30-min window around FOMC meetings. Alternative instruments refer to the three month Eurodollar futures three, six, and nine months ahead: blue dashed lines, red dash-dotted lines, and green lines (marked with an asterisk), respectively. For the Euro area (right panel), the benchmark instrument are yield changes in the 5-year Bund future between from 10 minutes prior to the press release to 20 minutes after the end of the press conference on ECB Governing Council Meeting days. Alternative instruments refer to to changes in the 2-year Bund future, changes in the 10-year future, and to the first principal component of all three futures changes: blue dashed lines, red dash-dotted lines, and green lines (marked with an asterisk), respectively.