THE TRANSMISSION OF MONETARY POLICY SHOCKS

Silvia Miranda-Agrippino*
Bank of England and CFM

Giovanni Ricco†
University of Warwick and OFCE - Science Po

First Version: 30 September 2015
This version: 28 February 2017

Abstract

Despite years of research, there is still uncertainty around the effects of monetary policy shocks. We reassess the empirical evidence by combining a new identification that accounts for informational rigidities, with a flexible econometric method robust to misspecifications that bridges between VARs and Local Projections. We show that most of the lack of robustness of the results in the extant literature is due to compounding unrealistic assumptions of full information with the use of severely misspecified models. Using our novel methodology, we find that a monetary tightening is unequivocally contractionary, with no evidence of either price or output puzzles.

Keywords: Monetary Policy, Local Projections, VARs, Expectations, Information Rigidity, Survey Forecasts, External Instruments.

JEL Classification: E52; G14; C32.

*Monetary Analysis, Bank of England, Threadneedle Street, London EC2R 8AH, UK. Email: silvia.miranda-agrippino@bankofengland.co.uk Web: www.silviamirandaagrippino.com

†Department of Economics, The University of Warwick, The Social Sciences Building, Coventry, West Midlands CV4 7AL, UK. Email: G.Ricco@warwick.ac.uk Web: www.giovanni-ricco.com

We are grateful to Refet Gürkaynak for sharing the updated daily US monetary surprises. We thank Gianni Amisano, Philippe Andrade, Matteo Barigozzi, Dario Caldara, Fabio Canova, Matteo Ciccarelli, James Cloyne, Cristina Fuentes-Albero, Raffaella Giacomini, Domenico Giannone, Refet Gürkaynak, James Hamilton, Edward Herbst, Paul Hubert, Marek Jarociński, Oscar Jordà, Alejandro Justiniano, Peter Karadi, Dimitris Korobilis, Michael Pitt, Ricardo Reis, Giuseppe Ragusa, Lucrezia Reichlin, Frank Schorfheide, James Stock, seminars and conference participants at the OFCE/Science-Po EME 2015 Workshop, the 2015 DIW Macroeconometric Workshop, the NBER SBIES 2016, the ECB Workshop on New Techniques and Applications of BVARs 2016, AMES and LAMES 2016, the 2016 Real-Time Data Analysis Methods and Applications Conference, ESOBE 2016, ULB, EUI, Norges Bank, and Banca d'Italia for helpful comments and suggestions. The content of this draft may be subject to change. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank of England, the Monetary Policy Committee, the Financial Policy Committee or the Prudential Regulation Authority.

Introduction

There is still a lot of uncertainty around the effects of monetary policy, despite fifty years of empirical research, and many methodological advances.[1] The dynamic responses of macroeconomic variables that are reported in the literature are often controversial and, under close scrutiny, lack robustness (see Ramey, 2016). Not just the magnitude and the significance, but even the sign of the responses of crucial variables such as output and prices depend on the identification strategy, the sample period, the information set considered, and the details of the model specification.

Studying the effects of monetary policy is a difficult endeavour. Most of the variation in monetary aggregates is accounted for by the way in which policy itself responds to the state of the economy, and not by random disturbances to the central bank's reaction function. Hence, to be able to trace causal effects of monetary policy it is necessary (i) to isolate unexpected exogenous shifts to monetary policy tools that are not due to the systematic response of policy to either current or forecast economic conditions (Sims, 1992, 1998), and (ii) to generate responses of macroeconomic and financial variables over time using an econometric model that is effectively capable of summarising the dynamic interaction among such variables. The empirical practice has typically relied on several identification schemes all justified by models of full-information rational expectations, in conjunction with linear econometric specifications, such as vector autoregressions (VARs) and local projections (LPs, Jordà, 2005). However, as carefully documented in Coibion (2012) and in Ramey (2016), the lack of robustness of the responses to monetary policy shocks ranges through both identification schemes, and empirical specifications.

Moving from these considerations, we reassess the empirical evidence on the effects of monetary policy shocks by adopting an identification strategy that is robust to the presence of informational frictions, in conjunction with a novel econometric method that is robust to model misspecifications of different nature. Our strategy is in two steps. First, we design an instrument for monetary policy shocks that accounts for

[1] Amongst many others, Friedman and Meiselman (1963), Sims (1972, 1980), Bernanke and Blinder (1992), Leeper et al. (1996), Christiano et al. (1999), Romer and Romer (2004), Uhlig (2005), Gertler and Karadi (2015). Comprehensive literature reviews are in Christiano et al. (1999) and in Ramey (2016).

the monetary authority and private agents potentially having non-nested information sets, and hence entertaining different beliefs about the economy.[2] Second, we introduce Bayesian Local Projections (BLP) as a flexible and robust method that spans the space between VARs and LPs and, in doing so, it imposes minimum restrictions on the shape of the estimated impulse response functions (IRFs). We show that most of the lack of stability reported in previous studies can be explained by the compounded effects of the unrealistic assumptions of full information that are often made when identifying the shocks, and the use of severely misspecified models for the estimation of the dynamic responses. We then set to study how monetary policy shocks transmit to the economy, how they affect financial conditions, and how do agents' expectations react to them. We document that responses obtained with our proposed methodology are consistent with standard macroeconomic theory, are stable over time, and seldom display puzzles.[3]

Identification. As observed in Blinder et al. (2008), imperfect and asymmetric information between the public and the central bank are the norm, not the exception, in monetary policy. However, while this observation has informed many theoretical attempts to include informational imperfections in the modelling of monetary policy, it has been largely disregarded in the empirical identification of the shocks.[4] Indeed, popular instruments for monetary policy shocks that are constructed in leading identification schemes can be thought of as assuming that either the central bank (e.g. Romer and Romer, 2004) or market participants (e.g. Gertler and Karadi, 2015) enjoy perfect information. Under these assumptions, controlling for the information set of the perfectly informed agent is sufficient to identify the shock. If all agents in the economy enjoyed full information, different instruments would deliver identical results. On the contrary,

[2]Our methodology builds on the insights provided by models of imperfect – noisy and sticky – information and asymmetric information (e.g. Woodford, 2001; Mankiw and Reis, 2002; Sims, 2003; Mackowiak and Wiederholt, 2009) and, empirically, combines insights from Romer and Romer (2004)'s narrative identification identification and the high-frequency identification (HFI) of Gertler and Karadi (2015).

[3]While not ruling out the possibility of time-variation in the transmission coefficients of monetary policy (see Primiceri, 2005), our results show that the effects of monetary policy are more stable than was previously reported. Our results are robust to a variety of severe tests, amongst others on the sample used, the chosen lag length, the composition of the vector of endogenous variables considered, and the BLP prior specification.

[4]Reviews on models of imperfect information and learning in monetary policy are in Mankiw and Reis (2010), Sims (2010), and Gaspar, Smets and Vestin (2010).

responses may instead diverge with dispersed information.

This paper reviews and expands the evidence on the presence of informational frictions that are relevant for monetary policy. We formally test and reject the null of full information for all the instruments for monetary policy shocks used in leading identification schemes. First, high-frequency instruments are predictable (see also Miranda-Agrippino, 2016) and autocorrelated (see also Ramey, 2016). We interpret this as an indication of the sluggish adjustment of expectations, in line with what documented for different types of economic agents using survey data. This is the emerging feature of models of imperfect information.[5] Second, market-based revisions of expectations that follow policy announcements correlate with central banks' private macroeconomic forecasts (see also Barakchian and Crowe, 2013; Gertler and Karadi, 2015; Ramey, 2016; Miranda-Agrippino, 2016). We think of this as evidence of the 'signalling channel' discussed in Melosi (2013) – i.e. the transfer of central banks' private information implicitly disclosed through policy actions, and due to the information asymmetry between private agents and the central bank (Romer and Romer, 2000). Finally, we show that narrative surprises, obtained with respect to the central bank's information set only (Romer and Romer, 2004), are equally affected by informational frictions. Specifically, they are autocorrelated, predictable by past information, and may contain anticipated policy shifts – e.g. forwards guidance announcements.

Taking stock of this evidence, we define monetary policy shocks as exogenous shifts in the policy instrument that surprise market participants, are unforecastable, and are not due to the central bank's systematic response to its own assessment of the macroeconomic outlook. Hence, we construct an instrument for monetary policy shocks by projecting market-based monetary surprises on their own lags, and on the central bank's information set, as summarised by Greenbook forecasts.[6] We use this informationally-

[5] See, for example, Mankiw et al. (2004), Coibion and Gorodnichenko (2012), Coibion and Gorodnichenko (2015), and Andrade and Le Bihan (2013).

[6] Market-based monetary surprises are the high-frequency price revisions in traded interest rates futures that are triggered by a policy announcement. In using financial markets instruments to measure the unexpected component of monetary policy we connect to a large literature pioneered by Rudebusch (1998) and Kuttner (2001) and whose notable contributions include, among others, Bernanke and Kuttner (2005); Gürkaynak (2005); Gürkaynak, Sack and Swanson (2005); Campbell, Fisher, Justiniano and Melosi (2016); Caldara and Herbst (2016); Gilchrist, López-Salido and Zakrajšek (2015). Barak-

robust instrument to identify the shocks from the stochastic component of an autoregressive model (Stock and Watson, 2012; Mertens and Ravn, 2013).

Transmission. From a classical point of view, choosing between iterated (VAR) and direct (LP) impulse responses involves a trade-off between bias and estimation variance: the iterated method produces more efficient parameters estimates than the direct one, but it is more prone to bias if the model is misspecified. Because it is implausible that generally low-order autoregressive models are correctly specified, the robustness of LP to model misspecification makes them a theoretically preferable procedure. Common misspecifications can in fact easily arise in relation to the chosen lag order, insufficient information set considered, unmodelled moving average components, and non-linearities (Braun and Mittnik, 1993; Schorfheide, 2005). Yet, empirical studies indicate that due to high estimation uncertainty, and over parametrisation, the theoretical gains from direct methods are rarely realised in practice (see Marcellino, Stock and Watson, 2006; Kilian and Kim, 2011).

We think of this as a standard trade-off in Bayesian estimation, and design Bayesian Local Projection (BLP) to effectively bridge between the two specifications.[7] BLP responses are estimated using conjugate priors centred around an iterated VAR estimated on a pre-sample. Intuitively, the prior gives weight to the belief that economic time series processes can be described in first approximation by linear models such as VARs. Extending the argument in Giannone, Lenza and Primiceri (2015), we treat the overall informativeness of the priors as an additional model parameter for which we specify a prior distribution, and choose it as the maximiser of the posterior likelihood. As a result, the posterior mean of BLP IRFs is an optimally weighted combination of VAR and LP-based IRFs. We find that the data tend to deviate from the VAR prior the farther away the horizon, resulting in an optimal level of prior shrinkage that is a monotonic

chian and Crowe (2013) and Miranda-Agrippino (2016) have proposed identifications based on monetary surprises that control for the central bank's internal forecasts. Differently from these papers, our methodology incorporates intuition stemming from models of imperfect information.

[7] Our approach has an alternative classical interpretation provided by the theory of 'regularisation' of statistical regressions (see, for example, Chiuso, 2015). Another approach to LP regularisation has been proposed more recently in Barnichon and Brownlees (2016). A different Bayesian approach to inference on structural IRFs has been proposed by Plagborg-Moller (2015). Barnichon and Matthes (2014) have propounded a method to estimate IRFs using Gaussian basis functions.

non-decreasing function of the forecast horizon, or projection lag.

Empirical Findings. Using our methodology, we study the transmission of monetary policy shocks on a large and heterogenous set of both macroeconomic and financial variables, as well as on private sector expectations, and medium and long-term interest rates. We find that a monetary contraction is unequivocally and significantly recessionary. Output and prices contract and there is no evidence of puzzles. We document evidence compatible with many of the standard channels of monetary transmission (Mishkin, 1996). We analyse in detail the response of interest rates at short, medium, and very long maturities and find important but very short-lived effects of policy on the yield curve (Romer and Romer, 2000; Ellingsen and Soderstrom, 2001). Also, we find evidence of a powerful credit channel that magnifies the size of the economic contraction through the responses of both credit and financial markets (Bernanke and Gertler, 1995; Gertler and Karadi, 2015; Caldara and Herbst, 2016). Moreover, we document a deterioration of the external position sustained by a significant appreciation of the domestic currency. Finally, the expectational channel is activated: agents revise their macroeconomic forecasts in line with the deteriorating fundamentals. Finally, we document that BLP responses optimally deviate from the VAR responses as the horizon grows. As a result of this BLP IRFs revert to trend much faster than VAR IRFs do. This has potentially important implications for the policy debate, and particularly in relation to the length of the policy horizons, the duration of which is typically calibrated on VAR evidence.

1 Identification

The empirical identification of monetary policy shocks relies on specific assumptions on how information is acquired, processed, and dispersed in the economy by the central bank and economic agents. Typically, even when not explicitly stated, the maintained assumption is that of full information rational expectation. In such a world, information is seamlessly processed, agents' expectations reflect the structure of the economy, are perfectly aligned to those of the central bank at all times, and any systematic pattern in the way policy is enacted is correctly inferred by the agents. Hence, expectation (forecast) errors and expectation revisions are orthogonal to past information, and reflect structural shocks. The econometric problem is thus reduced to the often stated principle of aligning the information set of the econometrician to that of the (representative, and fully informed) agents. The two leading identification strategies for monetary policy shocks – Romer and Romer (2004)'s narrative instrument, and Gertler and Karadi (2015)'s high frequency identification – assume different types of agents as the perfectly informed ones. In fact, while the narrative identification focuses solely on the policymaker's information set, the high-frequency identification exploits uniquely market participants' information.

Romer and Romer (2004) measure monetary policy shocks as the changes in the policy rate that are not taken in response to either current or forecast macroeconomic conditions. This is achieved by projecting a series of intended federal funds rates changes on Greenbook forecasts that summarise the inputs of the Fed's reaction function.[8] The monetary policy shock is therefore thought of as a deviation from the policy rule, given the central bank's internal forecasts of relevant macroeconomic aggregates. This approach implicitly assumes that the Fed possesses complete information, and that therefore it is sufficient to control for the Fed's information set to achieve identification. Conversely, Gertler and Karadi (2015) use the average monthly surprise in federal funds futures to identify monetary policy shocks. Under the assumption of a constant risk premium, the changes in the prices of federal funds futures occurring during a narrow window around FOMC announcements provide a measure of the component of monetary policy that is unexpected by market participants. In this case, market participants are implicitly assumed to have a complete information set, and therefore their revision of expectations following a policy announcement is sufficient to identify monetary policy shocks.

If both the central bank and private agents indeed enjoyed full information, using either of the two measures as an instrument for monetary policy shocks should produce

[8]Because intended rate changes are reconstructed using historical accounts, this approach is referred to as 'narrative'. Greenbook forecasts are produced by Federal Reserve staff, are updated ahead of each scheduled FOMC meeting, and concur to form the basis on which the FOMC make their decisions.

identical results. However, as discussed in Coibion (2012) and in Ramey (2016), depending on the chosen modelling framework, the sample, and the set of variables used, narrative-based measures and high-frequency instruments deliver responses to monetary disturbances that are quite diverse, and often times puzzling. Furthermore, recent studies have shown that high-frequency market surprises can be autocorrelated and predictable by both central bank's forecasts and lagged information. In this section, we significantly expand on this evidence, and show that lagged information is also significantly predictive of narrative shock measures, and that they too display a non-zero degree of autocorrelation.

We read these facts through the lenses of models of imperfect and asymmetric information (e.g. Woodford, 2001; Sims, 2003; Mackowiak and Wiederholt, 2009), and interpret the predictability of these instruments as a rejection of the full information paradigm.[9] More generally, we connect these findings to the growing corpus of evidence collected from survey data that shows that economic agents – consumers, central bankers, firms and professional forecasters alike –, are all subject to important informational limitations. These range from information being only slowly processed over time (see, e.g. Coibion and Gorodnichenko, 2012, 2015; Andrade and Le Bihan, 2013), to it being unevenly distributed across agents' types. The asymmetry of information sets across agents is an important dimension along which the divergence of beliefs about the state of the economy develops (see, e.g. Carroll, 2003; Andrade et al., 2014; Romer and Romer, 2000).[10]

Specifically, we observe that three emerging features of models of imperfect information have particularly important implications for the identification of monetary policy

[9] Two general classes of models incorporating deviations from full information have been proposed: the delayed-information models as in Mankiw and Reis (2002), and the noisy-information models such as in Woodford (2001), Sims (2003), and Mackowiak and Wiederholt (2009). Theories incorporating deviations from perfect information have provided frameworks to understand empirical regularities, in monetary economics and beyond, that are challenging for the perfect information framework as, for example, the sluggishness of price adjustments (Mankiw and Reis, 2002; Mackowiak and Wiederholt, 2009) and their discreteness at a micro level (Matejka and Sims, 2011). Other contributions to the theoretical literature on monetary policy are in Reis (2006b,a); Orphanides (2003); Aoki (2003); Nimark (2008b,a). Despite the theoretical modelling efforts, with few exceptions, the empirical literature has seldom departed from the assumption of perfect information.

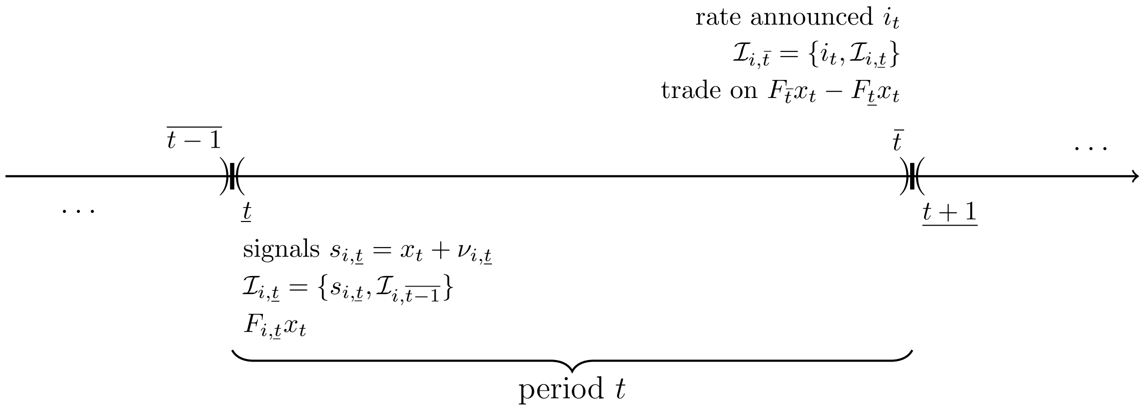
[10] As discussed in Blanchard et al. (2013) and Ricco (2015), the presence of a complex informational structure and of information frictions can crucially modifies the econometric identification problem.

shocks. First, average expectation revisions (and thus high-frequency surprises) – a direct measure of the shocks under full information –, are not orthogonal to either their past or past available information due to the slow absorption of new information over time. Second, narrative measures based on central bank's expectations à la Romer and Romer (2004) may underestimate the extent to which market participants are able to forecast movements in the policy rate, or to incorporate news about anticipated policy actions.[11] Third, observable policy actions can transfer information from the policy maker to market participants. For instance, interest rate decisions can 'signal' information about the central bank's assessment of the economic outlook (see Melosi, 2013; Hubert and Maule, 2016). This implicit disclosure of information can strongly influence the transmission of monetary impulses, and the central bank's ability to stabilise the economy. Empirically, if not accounted for, it can lead to both price and output puzzles. In fact, a policy rate hike can be interpreted by informationally constrained agents either as a deviation of the central bank from its monetary policy rule – i.e. a contractionary monetary shock –, or as an endogenous response to inflationary pressures expected to hit the economy in the near future. Despite both resulting in a visible rate increase, these two scenarios imply profoundly different evolutions for macroeconomic aggregates, and related agents' expectations (see e.g. Campbell et al., 2012, and Section 4). We empirically document the testable implications of these three predictions of models of imperfect information in Section 1.2, and in doing so we also rationalise evidence reported in previous studies (e.g. Barakchian and Crowe, 2013; Gertler and Karadi, 2015; Ramey, 2016; Miranda-Agrippino, 2016) .

In the reminder of this section we show how signal extraction, the autocorrelation of expectation revisions, and central bank's signalling all affect the identification of monetary policy shocks in a simple noisy information model. We then formally test for the presence of informational frictions in the most commonly used measures for monetary policy shocks. Lastly, we construct a measure for monetary policy shocks that explicitly takes into account agents' and central bank's informational constraints.

[11] Also, they potentially overlook information related to developments in financial markets altogether.

FIGURE 1: THE INFORMATION FLOW



Note: Each period t has a beginning $\underline{t}$ and an end $\bar{t}$. At $\underline{t}$ agents (both private and central bank) receive noisy signals $s_{i,\underline{t}}$ about the economy x_t, and update their forecasts $F_{i,\underline{t}}x_t$ based on their information set $\mathcal{I}_{i,\underline{t}}$. At $\bar{t}$ the central bank announces the policy rate i_t based on its forecast $F_{cb,\underline{t}}x_t$. Agents observe i_t, infer $F_{cb,\underline{t}}x_t$, and form $F_{i,\bar{t}}x_t$. Trade is a function of the aggregate expectation revision between $\underline{t}$ and $\bar{t}$.

1.1 A Simple Noisy Information Model

In standard full-information rational expectation models, expectation revisions are orthogonal to past information. Unlike this case, as observed in Coibion and Gorodnichenko (2015), a common prediction of models of imperfect information is that average expectations respond more gradually to shocks to fundamentals than do the variables being forecasted. Hence, revisions of expectations (and subsequent movements in market prices) can be correlated over time, and are likely to be a combination of both current and past structural shocks. Moreover, agents can extract information about the fundamentals from observable policy actions. In this section we introduce a simple model of noisy and asymmetric information that can account for all these features. Derivations of the main formulas are in Appendix A.

Let us consider an economy whose k-dimensional vector of macroeconomic fundamentals evolves following an autoregressive process

$$x_t = \rho x_{t-1} + \xi_t \qquad \xi_t \sim \mathcal{N}(0, \Sigma_\xi) \ . \tag{1}$$

ξ_t is the vector of structural shocks. Any period t is divided into two stages. An opening stage $\underline{t}$, and a closing stage $\bar{t}$. At $\underline{t}$, shocks are realised. Agents and central banks do not observe x_t directly, rather, they use a Kalman filter to form expectations about x_t based on the private signals that they receive. At $\bar{t}$, the central bank sets and announces the interest rate for the current period i_t. Agents can trade securities (e.g. futures contracts) based on i_{t+h}, the realisation of the policy rate at time $t+h$. Having observed the current policy rate, agents update their forecasts, and trade. The price revision in the traded futures contracts that occurs after the rate announcement is a function of both the revision in the aggregate expectation about the fundamentals x_t, and of the policy shift u_t.

At $\underline{t}$, agents receive a signal $s_{i,\underline{t}}$ about x_t. Based on $s_{i,\underline{t}}$, they update their forecasts as follows

$$F_{i,\underline{t}}x_t = K_1 s_{i,\underline{t}} + (1-K_1)F_{i,\overline{t-1}}x_t \ , \tag{2}$$

$$F_{i,\underline{t}}x_{t+h} = \rho^h F_{i,\underline{t}}x_t \qquad \forall h > 0 \ , \tag{3}$$

where

$$s_{i,\underline{t}} = x_t + \nu_{i,\underline{t}} \ , \qquad \nu_{i,\underline{t}} \sim \mathcal{N}(0,\sigma_\nu) \ , \tag{4}$$

is the private signal, $F_{i,\underline{t}}x_t$ denotes the forecast conditional on the information set at $\underline{t}$, and K_1 is the agents' Kalman gain. Agents price futures contracts on i_{t+h} as a function of their aggregate expectation about x_t as follows

$$p_{\underline{t}}(i_{t+h}) = F_{\underline{t}}x_{t+h} + \mu_t, \tag{5}$$

where μ_t is a stochastic component unaffected by the monetary policy shock, such as the risk premium in Gürkaynak et al. (2005), or a stochastic process related to the supply of assets (see Hellwig, 1980; Admati, 1985). At stage $\underline{t}$, the central bank too observes a signal about the current state of the economy

$$s_{cb,\underline{t}} = x_t + \nu_{cb,\underline{t}} \ , \qquad \nu_{cb,\underline{t}} \sim \mathcal{N}(0,\sigma_{cb,\nu}) \ , \tag{6}$$

and updates its forecasts accordingly

$$F_{cb,\underline{t}}x_t \quad = K_{cb}s_{cb,\underline{t}} + (1 - K_{cb})F_{cb,\overline{t-1}}x_t \ , \tag{7}$$

$$F_{cb,\underline{t}}x_{t+h} = \rho^h F_{cb,\underline{t}}x_t \qquad\qquad \forall h > 0 \ . \tag{8}$$

K_{cb} is the bank's Kalman gain.

At $\bar{t}$, conditional on its own forecast, the central bank sets the interest rate using a Taylor rule

$$i_t = \phi_0 + \phi_x' F_{cb,\underline{t}}x_t + u_t \ , \tag{9}$$

where u_t denotes the monetary policy shock. Given the structure of the central banks' expectation formation process, Eq. (9) can be equivalently rewritten as

$$i_t = \left[1 - (1 - K_{cb})\rho\right]\phi_0 + (1 - K_{cb})\rho i_{t-1} + K_{cb}\phi_x' s_{cb,\underline{t}} - (1 - K_{cb})\rho u_{t-1} + u_t \ . \tag{10}$$

Interestingly, the interest rate smoothing in the monetary policy rule in Eq. (14) arises naturally from the signal extraction problem faced by the central bank. Moreover, the policy rate at any time t is a function of current and past signals, and of current and past monetary policy shocks. Private agents observe the interest rate once it is announced at $\bar{t}$. In fact, conditional on i_{t-1}, this is equivalent to observing a public signal (i.e. with common noise) released by the central bank of the form

$$\tilde{s}_{cb,\bar{t}} = x_t + \nu_{cb,\underline{t}} + (K_{cb}\phi_x')^{-1}\left[u_t - (1 - K_{cb})\rho u_{t-1}\right]. \tag{11}$$

Based on the common signal $\tilde{s}_{cb,\bar{t}}$, agents update their forecasts at $\bar{t}$ using Eq. (2). We denote the gain of this second-stage forecast update by K_2.

Because of this forecast update, the price at which futures contracts were traded before the announcement is also revised, and by an amount proportional to the average (in population) revision of expectations, that is

$$p_{\bar{t}}(i_{t+1}) - p_{\underline{t}}(i_{t+1}) \propto (F_{\bar{t}}x_{t+1} - F_{\underline{t}}x_{t+1}) \ , \tag{12}$$

where $F_{\bar{t}}x_{t+1}$ and $F_{\underline{t}}x_{t+1}$ are the average forecast updates following $s_{i,\underline{t}}$ and $\tilde{s}_{cb,\bar{t}}$ respectively. Simple algebraic manipulations allow us to write average expectation revisions as

$$\begin{aligned} F_{\bar{t}}x_t - F_{\underline{t}}x_t =& (1-K_2)(1-K_1)\left[F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t\right] \\ &+ K_2(1-K_1)\xi_t + H\left[\nu_{cb,\underline{t}} - (1-K_1)\rho\nu_{cb,\underline{t-1}}\right] \\ &+ K_2(K_{cb}\phi'_x)^{-1}\left[u_t - \rho(K_1-K_{cb})u_{t-1} + (1-K_1)(1-K_{cb})\rho^2 u_{t-2}\right]. \quad (13) \end{aligned}$$

Hence, in a noisy information environment, expectation revisions are a function of several components. The first term on the right hand side is the autocorrelation of expectation revisions – the trademark of models of imperfect information. The second term is the update of expectations due to the revisions of beliefs about the state of the economy and the structural shocks ξ_t – 'the signalling channel'. The third term is the aggregate noise contained in the policy announcement, and is due to the central bank's noisy observation of the state of the economy. This too can be thought of as another exogenous policy shift (see Orphanides, 2003). The last term contains a combination of monetary policy shocks at different lags. As a result, the presence of informational imperfections can severely affect the high-frequency identification of monetary policy shocks à la Gertler and Karadi (2015). In fact, only a fraction of the variation in the forecasts for the interest rate can be uniquely attributable to momentary policy 'innovations'. Eq. (13) also provides us with testable predictions about price movements around policy announcements: in the presence of imperfect information they are (i) serially correlated; (ii) predictable using other macroeconomic variables; (iii) correlated with the central bank's projections of relevant macroeconomic variables. We formally test for these predictions in Section 1.2.

Let us go back to the central bank's problem and consider the following specification for the Taylor rule in Eq. (9)

$$i_t = \phi_0 + \phi_{\pi_0}F_{cb,\underline{t}}\pi_t + \phi_{\pi_1}F_{cb,\underline{t}}\pi_{t+1} + \phi_{y_0}F_{cb,\underline{t}}y_t + \phi_{y_1}F_{cb,\underline{t}}y_{t+1} + v_t \ . \quad (14)$$

In Eq. (14), the central bank sets the nominal policy rate conditional on its forecasts for current and future inflation and output. The narrative identification proposed in Romer and Romer (2004) amounts to running the regression specified by Eq. (14), and using the residuals as a measure of the shock u_t. Suppose, however, that the deviation from the rule v_t is autocorrelated, and that it includes policy deviations $u^a_{t|t-1}$ announced at $t-1$ and implemented at t, as would e.g. be the case for forward guidance. In this case, we have

$$v_t = \alpha v_{t-1} + u^a_{t|t-1} + u_t \ . \tag{15}$$

If v_t behaves as in Eq. (15), the residual of the projection of the policy rate onto central bank's forecasts is not the structural shock u_t. Moreover, given the predictability of the process, agents can try to forecast v_t using past information, even when informationally constrained. Finally, the projection residuals will also be contaminated by expected policy changes. While the presence of autocorrelation can be tested directly, one can only hope to test for the presence of announced policy shifts indirectly, e.g. by using factors extracted from a panel of macroeconomic and financial variables that may react to announced policy changes.[12]

1.2 Testing for Imperfect Information

The extant literature has unveiled a series of facts that are compatible with the predictions of models of imperfect information. Ramey (2016) notes that Gertler and Karadi (2015)'s high-frequency instruments are predictable by Greenbook forecasts, and that they display a non-negligible degree of autocorrelation. Gertler and Karadi (2015) construct a measure of the Fed's private information as the difference between Greenbook forecasts and Blue Chip forecasts. They find that both level nowcasts for inflation and output growth, as well as nowcast revisions between consecutive meetings are significantly predictive of monetary surprises. Miranda-Agrippino (2016) extends the results in Ramey (2016) to include a larger selection of monetary surprises extracted from different financial contracts, and for both the US and the UK. Central banks' forecasts and

[12] Also, if the central bank sets the policy rate conditioning on other indicators such as financial and fiscal variables (see e.g. Croushore and van Norden, 2017), the projection residuals of Eq. (14) will also be endogenous to these variables. This may show up as predictability with factors.

forecast revisions between consecutive meetings for output, unemployment and inflation, proxied by Inflation Report projections in the case of the UK, are significantly predictive of monetary surprises. Furthermore, Miranda-Agrippino (2016) shows that monetary surprises are significantly predictable also by lagged factors intended to summarise the pre-existing economic and financial conditions in the economy. Again, the predictability holds across financial instruments and countries, and survives a variety of robustness tests.

We expand and systematise these findings and test for the predictions proposed above. Tables 1 to 3 report the tests for (i) correlation with Fed's internal forecasts, (ii) serial correlation, and (iii) predictability, for three commonly used monetary policy instruments. These are the monthly market surprises extracted form the fourth federal funds futures ($FF4_t$), and constructed as the sum of daily series in Gürkaynak et al. (2005); the average monthly market surprise in Gertler and Karadi (2015), $FF4_t^{GK}$; and the Romer and Romer (2004)'s narrative shock series, MPN_t.[13] All regressions displayed are estimated at monthly frequency on all available observations over the sample 1990:01 - 2009:12. We exclude the September 2001 observation from regressions involving financial markets surprises to address the concerns in Campbell et al. (2012). Also, for these series we note that results are not driven by the observations dating earlier than 1994 (see Appendix C).

Table 1 reports F statistics and relative significance levels for the projection of monetary surprises onto own lags and central bank's forecast and revisions to forecasts for output, inflation and unemployment. The narrative instrument is orthogonal to these variables by construction. The null is strongly rejected for both the forecasts themselves and their revision, and for both types of monthly market surprises. We note, however, that the bulk of predictability resides in the forecast revisions between consecutive meetings. This is consistent with the characteristics of the signalling channel, as discussed in Melosi (2013) and Hubert and Maule (2016). In the first row of the table we note that all three series seem to be autocorrelated.

[13] We use an extension of this series up to the end of 2007 constructed in Miranda-Agrippino and Rey (2015).

Table 1: Central Bank Signalling and Slow Absorption of Information

	$FF4_t$			$FF4_t^{GK}$			MPN_t		
$AR(4)$	2.219 [0.068]*			10.480 [0.000]***			16.989 [0.000]***		
Greenbook Forecast		2.287 [0.011]**			3.377 [0.000]***			–	
Greenbook Revision			2.702 [0.007]***			3.719 [0.000]***			–
R^2	0.021	0.080	0.068	0.142	0.129	0.100	0.237	–	–
N	230	238	238	230	238	238	207	–	–

Note: Regressions on Greenbook forecasts and forecast revisions include a constant and 1 lag of the dependent variable. From left to right, the monthly surprise in the fourth federal funds future ($FF4_t$), the instrument in Gertler and Karadi (2015) ($FF4_t^{GK}$), the narrative series of Romer and Romer (2004) (MPN_t). 1990:2009. t-statistics are reported in square brackets, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, robust SE.

We explore the extent of the autocorrelation for these commonly used instruments for monetary policy shocks in Table 2. The numbers confirm the presence of time dependence in all of the three instruments, including the narrative series. Extending the number of lags to 12 does not alter the evidence. Also, we note that while the weighting scheme adopted in Gertler and Karadi (2015) enhances the autocorrelation in the average monthly surprises, the null of no time dependence is rejected also for the unweighted monthly surprises.[14]

In Table 3 we project a set of different measures of monetary policy shocks on a set of lagged macro-financial dynamic factors extracted from the collection of monthly variables assembled in McCracken and Ng (2015). To the narrative and market-based instruments already defined, we add a measure that we specifically construct to be robust to the presence of informational constraints in the economy (MPI_t). A detailed discussion on the construction of our instrument is in Section 1.3. The dataset that we

[14]The irregular pattern of autocorrelation can be due to the uneven scheduling of FOMC meetings in any given year, the only partial overlap of the horizon of the fourth federal funds futures traded in any given month, and the jagged edge of the real time data released every month by the statistical office. Additionally, as pointed out in Coibion and Gorodnichenko (2012), the OLS coefficients can be biased as a consequence of the presence of noisy signals. The bias in our case is likely to be negative, as shown in the Appendix (Eq. A.17).

Table 2: Autoregressive Component in Instruments for Monetary Policy Shocks

	$FF4_t$		$FF4_t^{GK}$		MPN_t	
lag 1	0.058	[0.89]	0.356	[5.47]***	-0.048	[-0.63]
lag 2	-0.013	[-0.20]	-0.199	[-2.86]***	0.207	[2.93]***
lag 3	0.090	[1.38]	0.232	[3.34]***	0.507	[7.15]***
lag 4	0.150	[2.26]**	0.021	[0.29]	0.090	[1.12]
constant	-0.010	[-2.30]**	-0.008	[-2.43]**	-0.006	[-0.54]
R^2	0.021		0.142		0.237	
F	2.219		10.480		16.989	
p	0.068		0.000		0.000	
N	230		230		207	

Note: Regressions are estimated over the sample 1990:2009. From left to right, the monthly surprise in the fourth federal funds future ($FF4_t$), the instrument in Gertler and Karadi (2015) ($FF4_t^{GK}$), the narrative series of Romer and Romer (2004) (MPN_t), and the informationally robust instrument constructed in Section 1.3 (MPI_t). t-statistics are reported in square brackets, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

use for the factors extraction counts over 130 monthly series that cover all the main macroeconomic aggregates, and a number of financial indicators. The factors enter the regressions with a month's lag. Results in Table 3 confirm the predictability of market-based monetary surprises using past information. They also show that narrative accounts of 'unanticipated' interest rate changes are similarly predictable by state variables which are a function of past structural shocks.[15]

1.3 An Informationally-robust Instrument

Taking stock of the evidence discussed, we propose to identify monetary policy shocks as the component of market surprises triggered by policy announcements that are orthogonal to both central bank's economic projections, and to past market surprises. Hence, we capture the effects of shifts to the policy rate that are both unforeseen by market participants, and are not due to central bank's concerns about either current or

[15]Factors are estimated using last vintage data which are likely to incorporate revisions to early estimates variables. While this may not be information readily available to agents, it is worth to observe that in a perfect information world markets aggregate information efficiently, and there is no role for data revisions and national accounting offices.

Table 3: Informational Frictions in Measures for Monetary Policy Shocks

	$FF4_t$		$FF4_t^{GK}$		MPN_t		MPI_t	
$f_{1,t-1}$	-0.012	[-1.97]*	-0.011	[-2.74]***	-0.103	[-4.13]***	0.006	[0.98]
$f_{2,t-1}$	0.001	[0.38]	0.004	[1.79]*	-0.005	[-0.45]	0.005	[1.56]
$f_{3,t-1}$	0.002	[0.41]	-0.001	[-0.23]	-0.035	[-2.21]**	0.001	[0.29]
$f_{4,t-1}$	0.015	[2.09]**	0.008	[1.92]*	0.068	[2.71]***	0.005	[0.70]
$f_{5,t-1}$	0.002	[0.26]	0.001	[0.12]	0.017	[0.61]	0.008	[1.18]
$f_{6,t-1}$	-0.011	[-2.19]**	-0.007	[-2.58]**	0.008	[0.57]	-0.008	[-1.63]
$f_{7,t-1}$	-0.010	[-1.69]*	-0.006	[-1.40]	-0.053	[-2.85]***	-0.004	[-0.54]
$f_{8,t-1}$	-0.001	[-0.35]	0.001	[0.32]	-0.042	[-2.38]**	-0.001	[-0.15]
$f_{9,t-1}$	-0.002	[-0.59]	-0.002	[-0.53]	-0.037	[-1.65]	0.000	[0.07]
$f_{10,t-1}$	0.004	[0.75]	0.000	[-0.03]	-0.030	[-2.54]**	-0.003	[-0.70]
R^2	0.073		0.140		0.202		0.033	
F	2.230		3.572		3.372		2.225	
p	0.014		0.000		0.000		0.014	
N	236		236		213		224	

Note: Regressions include a constant and 1 lag of the dependent variable. 1990:2009. From left to right, the monthly surprise in the fourth federal funds future ($FF4_t$), the instrument in Gertler and Karadi (2015) ($FF4_t^{GK}$), the narrative series of Romer and Romer (2004) (MPN_t), and the informationally robust instrument constructed in Section 1.3 (MPI_t). The ten dynamic factors are extracted from the set of monthly variables in McCracken and Ng (2015). t-statistics are reported in square brackets, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors.

anticipated changes in the economic outlook.

Operationally, we proceed in three steps. First, we build monthly surprises ($FF4_t$ discussed above) as the sum of the daily series in Gürkaynak, Sack and Swanson (2005). These are the price revisions in interest rates futures that are registered following FOMC announcements. The daily series used to construct the monthly monetary policy surprises (mps_t) are the intraday movements in the fourth federal funds futures contracts that are registered within a 30-minute window surrounding the time of the FOMC announcements. These contracts have an average maturity of about three months. Federal funds futures settle based on the average effective federal funds rate prevailing on the expiry month, their price can therefore be thought of as embedding markets' forecasts about future policy rates. Under the assumption of a constant risk premium, a price revision that follows a monetary policy announcement is a measure of the component of policy that is unexpected by market participants, given their pre-announcement information set. This is the assumption made in e.g. Gürkaynak et al. (2005). We think of these series of monthly surprises as a proxy for the revisions in expectations in the aggregate economy that are triggered by central bank's policy decisions. Second, we regress these monthly surprises onto (i) their lags, to mod out the autocorrelation due to the slow absorption of information; and (ii) following Romer and Romer (2004), onto Greenbook forecasts and forecast revisions for real output growth, inflation and the unemployment rate, to control for the central bank's private information.

Specifically, we recover an instrument for monetary policy shocks using the residuals of the following regression:

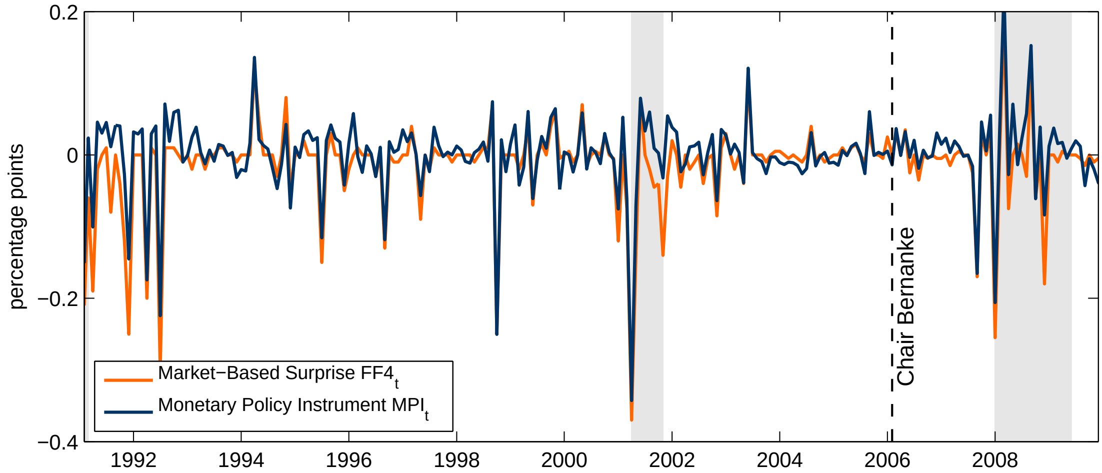
$$\begin{aligned} mps_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i mps_{t-i} + \\ + \sum_{j=-1}^{3} \theta_j F_t^{cb} x_{q+j} + \sum_{j=-1}^{2} \vartheta_j \left[F_t^{cb} x_{q+j} - F_{t-1}^{cb} x_{q+j} \right] + z_t. \end{aligned} \tag{16}$$

mps_t denotes the monetary surprise that follows the FOMC announcements in month t. $F_t^{cb} x_{q+j}$ denotes Greenbook forecasts for quarter $q+j$ made at time t, where q denotes the current quarter. $\left[F_t^{cb} x_{q+j} - F_{t-1}^{cb} x_{q+j} \right]$ is the revised forecast for x_{q+j} between two consecutive meetings. For each surprise, the latest available forecast is used. x_q includes output, inflation, and unemployment.[16]

In Figure 2 we plot the original monetary surprise mps_t ($FF4_t$, orange line) and our instrument for the monetary policy shock z_t (MPI_t, blue line). Despite the many, obvious similarities between the two series, the chart shows that significant discrepancies arise particularly during times of economic distress (see Figure C.1 in Appendix C). Most importantly, however, the difference between these two series is in the numbers in Table 3, where the rightmost columns report the results of the test for the presence of informational frictions in z_t (MPI_t). Consistent with our prior, we do not find evidence of predictability for our instrument given past information.

[16]Following Romer and Romer (2004) we only include the nowcast for the level of the unemployment rate to mitigate the effects of the high correlation between output and unemployment.

Figure 2: Informationally-robust instrument for monetary policy shocks



Note: market-based surprises conditional on private agents' information set $FF4_t$ (orange line), residual to Eq. (16) MPI_t (blue, solid). Shaded areas denote NBER recessions.

2 Transmission

Correct inference of the dynamic effects of monetary policy shocks hinges on the interaction between the identification strategy and the modelling choice. Modern macroeconomics thinks of the residuals of autoregressive models as structural stochastic innovations – combinations of economically meaningful shocks –, and identifies the ones of interest using theory-based assumptions, and often external instruments. Once structural shocks are meaningfully identified, the autoregressive coefficients of the model are employed to study the transmission of the exogenous disturbances over time. Modelling choices are therefore of great importance. First, in separating the stochastic component of the economic processes as distinct from the autoregressive and deterministic ones. Second, in providing a reduced-form description of the propagation of identified shocks over time.

Time series econometrics has provided applied researchers with results that prove the consistency of estimates under the quite restrictive assumption that the model correctly captures the data generating process (DGP). However, it is well understood that when the empirical model – typically a VAR – is misspecified, estimates of the parameters – transmission coefficients and covariance matrix alike – are inconsistent (Braun and Mittnik, 1993). This affects the identification of the disturbances, the variance-covariance decomposition, and the derived impulse response functions (IRFs). These concerns have motivated the adoption of more flexible, 'non-parametric' empirical specifications, such as Jordà (2005)'s local projections (LP).

VARs produce IRFs by iterating up to the relevant horizon the coefficients of a one-step-ahead model. Hence, if the one-step-ahead VAR is misspecified, the resulting errors are compounded at each horizon in the estimated IRFs. Conversely, the local projection method estimates impulse response functions from the coefficients of direct projections of variables onto their lags at the relevant horizon. This makes LP more robust to a number of model misspecifications, and thus a theoretically preferable choice. In practice, however, the theoretical appeal of LPs has to be balanced against the large estimation uncertainty that surrounds the coefficients' estimates. From a classical perspective, one faces a sharp bias-variance trade-off when selecting between VARs and LPs.

In what follows, we review the two methods, and propose a Bayesian approach to Local Projections (BLPs) as an efficient way to bridge between the two, by mean of informative priors. Intuitively, we propose a regularisation for LP-based IRFs which builds on the prior that a VAR can provide, in first approximation, a decent description of the behaviour of most macroeconomic and financial variables. As the horizon grows, however, BLP are allowed to optimally deviate from the restrictive shape of VAR-based IRFs, whenever these are poorly supported by the data. This while the discipline imposed by our prior allows to retain reasonable estimation uncertainty at all horizons.

2.1 Recursive VARs and Direct LPs

The standard practice in empirical macroeconomics is to fit a linear vector autoregression to a limited set of variables. This in order to retrieve their moving average representation, from which it is possible to obtain dynamic responses to the identified shocks. A

VAR can be written in structural form as

$$
\begin{aligned}
A_0 y_{t+1} &= \mathrm{K} + A_1 y_t + \ldots + A_p y_{t-(p-1)} + u_{t+1} \ , \qquad (17)\\
u_t &\sim \mathcal{N}(0, \Sigma_u) \ ,
\end{aligned}
$$

where $t = p+1, \ldots, T$, $y_t = (y_t^1, \ldots, y_t^n)'$ is a $(n \times 1)$ random vector of macroeconomic variables, A_i, $i = 0, \ldots, p$, are $(n \times n)$ coefficient matrices (the 'transmission coefficients'), and $u_t = (u_t^1, \ldots, u_t^n)'$ is an n-dimensional vector of structural shocks. It is generally assumed that $\Sigma_u = \mathbb{I}_n$. VARs are estimated in reduced form, i.e.

$$
\begin{aligned}
y_{t+1} &= C + B_1 y_t + \ldots + B_p y_{t-(p-1)} + \varepsilon_{t+1} \ , \qquad (18)\\
\varepsilon_t &\sim \mathcal{N}(0, \Sigma_\varepsilon) \ ,
\end{aligned}
$$

where $\varepsilon_t = A_0^{-1} u_t$, $\mathbb{E}[\varepsilon_t \varepsilon_t'] = A_0^{-1}(A_0^{-1})' = \Sigma_\varepsilon$, and $B_i = A_0^{-1} A_i$. $C = A_0^{-1} K$.

Given A_0, the IRFs to the identified structural shocks can be recursively computed for any horizon h as

$$
\mathrm{IRF}_h^{\mathrm{VAR}} = \sum_{j=1}^{h} \mathrm{IRF}_{h-j}^{\mathrm{VAR}} B_j \ , \qquad (19)
$$

where $\mathrm{IRF}_0^{\mathrm{VAR}} = A_0^{-1}$ and $B_j = 0$ for $j > p$. $\mathrm{IRF}_h^{\mathrm{VAR}}$ is an $(n \times n)$ matrix whose element (i, j) represents the response of variable i to the structural shock j, h periods into the future.

Despite being a workhorse of empirical macroeconomics, VARs are likely to be misspecified along several dimensions. First, the information set incorporated in a small-size VAR can fail to capture all of the dynamic interactions that are relevant to the propagation of the shock of interest. For example, Caldara and Herbst (2016) argue that the failure to account for the endogenous reaction of monetary policy to credit spreads induces a bias in the shape of the response of all variables to monetary shocks. More generally, there is evidence that policy makers and private agents are likely to assess a large number of indicators when forming expectations and taking decisions (see, for example, the discussion in Faust and Leeper, 2015). Second, the autoregressive lag order of the underlying process may potentially be underestimated. Also, if the disturbances of the underlying DGP are a moving average process, fitting a low-order, or indeed any finite-order VAR may be inadequate.[17] Finally, several possible non-linearities of different nature may be empirically significant – such as time-variation or state-dependency of some of the parameters, and non-negligible higher order terms. In this perspective, to empirically pin down all of the different sources of misspecification in order to parametrise them in a model is almost a self defeating effort.

As an alternative to the recursive VAR impulse response functions, the local projections (LP) à la Jordà (2005) estimate the IRFs directly from the linear regression

$$
\begin{aligned}
& y_{t+h} = C^{(h)} + B_1^{(h)} y_t + ... + B_{\tilde{p}}^{(h)} y_{t-(\tilde{p}+1)} + \varepsilon_{t+h}^{(h)} \ , \\
& \varepsilon_{t+h}^{(h)} \sim \mathcal{N}(0, \Sigma_{\varepsilon}^{(h)}) \qquad \forall \ h = 1, \dots, H \ ,
\end{aligned} \tag{20}
$$

where the lag order $\tilde{p}$ may depend on h. The residuals $\varepsilon_{t+h}^{(h)}$, being a combination of one-step-ahead forecast errors, are serially correlated and heteroskedastic. Given A_0, the structural impulse responses are

$$
\mathrm{IRF}_h^{\mathrm{LP}} = B_1^{(h)} A_0^{-1} \ . \tag{21}
$$

In the forecasting literature, the distinction between VAR-based recursive IRFs and LP-based direct IRFs corresponds to the difference between direct and iterated forecasts (see Marcellino, Stock and Watson, 2006; Pesaran, Pick and Timmermann, 2011; Chevillon, 2007, amongst others). An implicit assumption of both the approaches is that macroeconomic and financial time series possess either approximately linear, or only moderately nonlinear behaviour that can be captured by a linear model, in first approximation. This assumption is supported by a wealth of empirical evidence, amongst all the well established fact that factor models are able to summarise and produce decent forecasts of large panels of macroeconomic variables, due to their underlying approximated factor structure.

[17] If the process is stationary, there exists an infinite moving average representation of it (the Wold representation). Hence, the question is whether a finite VAR representation of the process exists.

If a VAR correctly captures the DGP, its recursively generated IRFs are both optimal in mean square sense, and consistent. Because it is implausible that typically low-order autoregressive models be correctly specified, the robustness of LP responses to model misspecification makes them a more attractive procedure compared to the bias-prone VAR.[18] However, due to the moving average structure of the residuals, and the risk of over parametrisation, local projections are likely to be less efficient, and hence subject to volatile and imprecise estimates (see, for example, the discussion in Ramey, 2013). In fact, empirical studies indicate that the potential gains from direct methods are not always realised in practice. Comparing direct and iterated forecasts for a large collection of US variables of given sample length, Marcellino, Stock and Watson (2006) note that iterated forecasts tend to have, for many economic variables, lower sample MSFEs than direct forecasts. Also, direct forecasts become increasingly less desirable as the forecast horizon lengthens. Similarly, comparing the finite-sample performance of impulse response confidence intervals based on local projections and VAR models in linear stationary settings, Kilian and Kim (2011) find that asymptotic LP intervals are often less accurate than the bias-adjusted VAR bootstrapped intervals, notwithstanding their large average width. Hence, from a classical perspective, choosing between iterated and direct methods involves a sharp trade-off between bias and estimation variance: the iterated method produces more efficient parameters estimates than the direct method, but it is prone to bias if the one-step-ahead model is misspecified.

2.2 Bayesian Local Projections

From a Bayesian perspective, the trade-off between bias and variance involved in the choice between iterated VAR-IRFs and direct LPs-IRFs is a natural one. This is also true for classical 'regularised' regressions, providing an alternative frequentist interpretation of Bayesian techniques (see, for example, Chiuso, 2015). Moving from this observation, we design a new flexible linear method that bridges between iterated VAR responses

[18] In a simulated environment, and with regard to multi-step forecasts, Schorfheide (2005) shows that as the degree of model misspecification increases, and for a given lag length, direct estimators yield a lower prediction risk than iterated ones.

and direct local projections. We refer to this new method as Bayesian Local Projection (BLP). Alternatively, we could speak of 'regularised Local Projections'.

The mapping between VAR coefficients and LP coefficients provides a natural way to inform Bayesian priors about the latter (or to regularise the regression), hence essentially spanning the space between iterated and direct response functions. To provide the gist of our approach, let us consider the $AR(1)$ specification of (19) and (20) – i.e. their companion form. For $h = 1$, both models reduce to a standard VAR(1)

$$y_{t+1} = C + By_t + \varepsilon_{t+1} \ . \tag{22}$$

Iterating the VAR forward up to horizon h, we obtain

$$\begin{aligned} y_{t+h} &= (I-B)^{-1}(I-B^h)C + B^h y_t + \sum_{j=1}^{h} B^{h-j}\varepsilon_{t+j} && (23) \\ &= C^{(\mathrm{VAR},h)} + B^{(\mathrm{VAR},h)} y_t + \varepsilon_{t+h}^{(\mathrm{VAR},h)} \ . && (24) \end{aligned}$$

Coefficients and residuals can now be readily mapped into those of a LP regression in companion form

$$y_{t+h} = C^{(h)} + B^{(h)} y_t + \varepsilon_{t+h}^{(h)} \ , \tag{25}$$

obtaining

$$C^{(h)} \longleftrightarrow C^{(\mathrm{VAR},h)} = (I-B)^{-1}(I-B^h)C \ , \tag{26}$$

$$B^{(h)} \longleftrightarrow B^{(\mathrm{VAR},h)} = B^h \ , \tag{27}$$

$$\varepsilon_{t+h}^{(h)} \longleftrightarrow \varepsilon_{t+h}^{(\mathrm{VAR},h)} = \sum_{j=1}^{h} B^{h-j}\varepsilon_{t+h} \ . \tag{28}$$

The impulse response functions are given by Eq. (27), up to the identification matrix A_0 (and a selection matrix for the companion form):

$$\mathrm{IRF}_h^{\mathrm{VAR}} = B^h A_0^{-1} \ , \tag{29}$$

$$\mathrm{IRF}_h^{\mathrm{LP}} = B^{(h)} A_0^{-1} \ . \tag{30}$$

Three observations are in order. First, conditional on the underlying data generating process being the linear model in Eq. (22), and abstracting from estimation uncertainty, the IRFs computed with the two different methods should coincide. Second, as shown by Eq. (28), conditional on the linear model being correctly specified, LPs are bound to have higher estimation variance due to (strongly) autocorrelated residuals.[19] Third, given that for $h = 1$ VARs and LPs coincide, the identification problem is identical for the two methods. In other words, given an external instrument or a set of theory-based assumptions, the way in which the A_0 matrix is derived from either VARs or LPs coincides.

The map in Eq. (26-28) provides a natural bridge between the two empirical specifications that can be used to inform priors for the LP coefficients used to estimate the IRFs at each horizon. Clearly, if we believed the VAR(p) to be the correct specification, then LP regressions would have to be specified as ARMA($p, h-1$) regressions. Their coefficients could be then estimated by combining informative priors with a fully specified likelihood (see Chan et al., 2016). If, however, the VAR(p) were to effectively capture the DGP, it would be wise to discard direct methods altogether. More generally, if we were to know the exact source of misspecification of any given VAR(p), we could draw inference from a fully parametrised, correctly specified model. However, this is not possible in practice. An alternative, robust approach to the strong parametric assumptions that are typical of Bayesian VAR inference is the adoption of a misspecified likelihood function to conduct inference about the pseudo-true parameters of interest, as proposed in Müller (2013).

2.3 Informative Priors for LPs

For the coefficients of Eq. (20) at each horizon h, and leaving temporarily aside concerns about the structure of the projection residuals, we specify standard conjugate Normal-

[19] Most macroeconomic variables are close to I(1) and even I(2) processes. Hence LP residuals are likely to be strongly autocorrelated.

inverse Wishart informative priors of the form

$$\Sigma_{\varepsilon}^{(h)} \mid \gamma \sim \mathcal{IW}\left(\Psi_0^{(h)}, d_0^{(h)}\right) ,$$
$$\beta^{(h)} \mid \Sigma_{\varepsilon}^{(h)}, \gamma \sim \mathcal{N}\left(\beta_0^{(h)}, \Sigma_{\varepsilon}^{(h)} \otimes \Omega_0^{(h)}(\gamma)\right) , \tag{31}$$

where $\beta^{(h)} \equiv vec(b^{(h)}) = vec\left(\left[C^{(h)}, B_1^{(h)}, \ldots, B_{\tilde{p}}^{(h)}\right]'\right)$ is the vector containing all the local projection coefficients at horizon h. We use $\beta_0^{(h)}$ to denote the prior mean, and γ for the generic vector collecting all the priors' hyperparameters.

As in Kadiyala and Karlsson (1997), we set the degrees of freedom of the inverse-Wishart distribution to $d_0^{(h)} = n+2$, the minimum value that guarantees the existence of the prior mean for $\Sigma_{\varepsilon}^{(h)}$, equal to $\Psi_0^{(h)}/(d_0^{(h)}-n-1)$. As is standard in the macroeconomic literature, we use sample information to fix some some of the hyperparameters of the prior beliefs. In particular, at each horizon we set the prior scale $\Psi_0^{(h)}$ to be equal to

$$\Psi_0^{(h)} = diag\left(\left[(\sigma_1^{(h)})^2, \ldots, (\sigma_n^{(h)})^2\right]\right) ,$$

where $(\sigma_i^{(h)})^2$ are the HAC-corrected variances of the autocorrelated univariate local projection residuals. Similarly, we set $\Omega_0^{(h)}$ as

$$\underset{(n\tilde{p}+1\times n\tilde{p}+1)}{\Omega_0^{(h)}(\gamma)} = \begin{pmatrix} \epsilon^{-1} & 0 \\ 0 & \mathbb{I}_{\tilde{p}} \otimes (\lambda^{(h)})^2 diag\left(\left[(\sigma_1^{(h)})^2, \ldots, (\sigma_n^{(h)})^2\right]\right)^{-1} \end{pmatrix},$$

where we take ϵ to be a very small number, thus imposing a very diffuse prior on the intercepts. One single hyperparameter, $\lambda^{(h)}$, controls the overall tightness of the priors at each horizon h, i.e. $\gamma \equiv \lambda^{(h)}$.

Analogous to the case of standard macroeconomic priors (Litterman, 1986), this specification implies the following first and second moments for the IRF coefficients

$$\mathbb{E}\left[B_{ij}^{(h)} \mid \Sigma_{\varepsilon}^{(h)}\right] = B_{0,ij}^{(h)}, \tag{32}$$

$$\mathbb{V}ar\left[B_{ij}^{(h)} \mid \Sigma_{\varepsilon}^{(h)}\right] = (\lambda^{(h)})^2 \frac{(\sigma_i^{(h)})^2}{(\sigma_j^{(h)})^2}, \tag{33}$$

where $B_{ij}^{(h)}$ denotes the response of variable i to shock j at horizon h, and $B_0^{(h)}$ is such that $\beta_0^{(h)} = vec(B_0^{(h)})$.

There are many possible ways to inform the prior mean $\beta_0^{(h)}$. Our preferred one is to set it to be equal to the posterior mean of the coefficients of a VAR(p) iterated at horizon h. The VAR used to inform the BLP prior is estimated with standard macroeconomic priors over a pre-sample T_0, that is then discarded.[20] In the notation of model (22) this translates into

$$\beta_0^{(h)} = vec(B_{T_0}^h), \tag{34}$$

where $B_{T_0}^h$ is the h-th power of the autoregressive coefficients estimated over the pre-sample. Intuitively, the prior gives weight to the belief that a VAR can describe the behaviour of economic time series, at least first approximation.

Having not explicitly modelled the autocorrelation of the residuals has two important implications. First, the priors are conjugate, hence the posterior distribution is of the same Normal inverse-Wishart family as the prior probability distribution. Second, the Kronecker structure of the standard macroeconomic priors is preserved. These two important properties make the estimation analytically and computationally tractable. Conditional on the observed data, the posterior distribution takes the following form

$$\begin{aligned} \Sigma_{\varepsilon}^{(h)} \mid \gamma^{(h)}, \mathrm{y} &\sim \mathcal{IW}\left(\Psi^{(h)}, d\right) \\ \beta^{(h)} \mid \Sigma_{\varepsilon}^{(h)}, \gamma^{(h)}, \mathrm{y} &\sim \mathcal{N}\left(\tilde{\beta}^{(h)}, \Sigma_{\varepsilon}^{(h)} \otimes \Omega^{(h)}\right) \ , \end{aligned} \tag{35}$$

[20] An obvious alternative is the generalisation of the standard macroeconomic priors proposed in Litterman (1986), centred around the assumption that each variable follows a random walk process, possibly with drift. Results using this alternative prior are discussed in Section 3. Also, one could specify a hyperprior distribution for the first autocorrelation coefficients, as a generalisation of Litterman (1986), and conduct inference following the approach in Giannone et al. (2015).

where $d = d_0^{(h)} + T$, and T is the sample size.

Because of the structure of the residuals, however, this parametrisation is misspecified. The shape of the true likelihood is asymptotically Gaussian and centred at the Maximum Likelihood Estimator (MLE), but has a different (larger) variance than the asymptotically normal sampling distribution of the MLE in Eq. (35). This implies that if one were to draw inference about $\beta^{(h)}$ – i.e. the horizon-h responses –, from the misspecified likelihood in Eq. (35), one would be underestimating the variance albeit correctly capturing the mean of the distribution of the regression coefficients. Müller (2013) shows that posterior beliefs constructed from a misspecified likelihood such as the one discussed here are 'unreasonable', in the sense that they lead to inadmissible decisions about the pseudo-true values, and proposes a superior mode of inference – i.e. of asymptotically uniformly lower risk –, based on artificial 'sandwich' posteriors.[21] Hence, in line with the classical practice, we conduct inference about $\beta^{(h)}$ by replacing the original posterior with an artificial Gaussian posterior centred at the MLE but with a HAC-corrected covariance matrix. This allows us to remain agnostic about the source of model misspecification as in Jordà (2005). Specifically, following Müller (2013), we replace Eq. (35) with an artificial likelihood defined as

$$\begin{aligned} &\Sigma_{\varepsilon,\text{HAC}}^{(h)} \mid \gamma^{(h)}, \mathrm{y} \sim \mathcal{IW}\left(\Psi_{\text{HAC}}^{(h)}, d\right), \\ &\beta^{(h)} \mid \Sigma_{\varepsilon,\text{HAC}}^{(h)}, \gamma^{(h)}, \mathrm{y} \sim \mathcal{N}\left(\tilde{\beta}^{(h)}, \Sigma_{\varepsilon,\text{HAC}}^{(h)} \otimes \Omega^{(h)}\right). \end{aligned} \tag{36}$$

Lastly, it is worth noting that by specifying $\beta_0^{(h)}$ as in Eq. (34), BLP IRFs effectively span the space between VARs and local projections. To see this, note that given the prior in (31), the posterior mean of BLP responses takes the form

$$B_{\text{BLP}}^{(h)} \propto \left(X'X + \left(\Omega_0^{(h)}(\gamma)\right)^{-1}\right)^{-1} \left(X'Y^{(h)} + \left(\Omega_0^{(h)}(\gamma)\right)^{-1} B_{\text{VAR}}^{h}\right), \tag{37}$$

where $B_{\text{BLP}}^{(h)}$ is such that $\tilde{\beta}^{(h)} = vec(B_{\text{BLP}}^{(h)})$. $(X'X)^{-1}(X'Y^{(h)}) = B_{\text{LP}}^{(h)}$, where $Y^{(h)} \equiv$

[21] For the purpose of this work, the 'decisions' concern the description of uncertainty around $\beta^{(h)}$ obtained via two-sided equal-tailed posterior probability intervals.

$(y_{p+1+h}, \ldots, y_T)'$, $X \equiv (x_{p+1+h}, \ldots, x_T)'$, and $x_t \equiv (1, y'_{t-h}, \ldots, y'_{t-(p+h)})'$. At each horizon h, the optimal combination between VAR and LP responses is regulated by $\Omega_0^{(h)}(\gamma)$ and is a function of the overall level of informativeness of the prior $\lambda^{(h)}$. When $\lambda^{(h)} \to 0$, BLP IRFs collapse into VAR IRFs (estimated over T_0). Conversely, if $\lambda^{(h)} \to \infty$ BLP IRFs coincide with those implied by standard LP.

2.4 Optimal Priors

In our model, the informativeness of the priors is controlled by the hyperparameter $\lambda^{(h)}$ that regulates the covariance matrix of all the entries in $\beta^{(h)}$ at horizon h. We treat $\lambda^{(h)}$ as an additional model parameter, for which we specify a prior distribution, or hyperprior $p(\lambda^{(h)})$, and estimate it at each h in the spirit of hierarchical modelling. As observed in Giannone et al. (2015), the choice of the informativeness of the prior distribution is conceptually identical to conducting inference on any other unknown parameter of the model. As such, the hyperparameters can be estimated by evaluating their posterior distribution, conditional on the data

$$p(\lambda^{(h)}|\mathrm{y}^{(h)}) = p(\mathrm{y}^{(h)}|\lambda^{(h)}) \cdot p(\lambda^{(h)}) \ , \tag{38}$$

where $p(\mathrm{y}^{(h)}|\lambda^{(h)})$ is the marginal density of the data as a function of the hyperparameters, and $\mathrm{y}^{(h)} = vec(Y^{(h)})$. Under a flat hyperprior, the procedure corresponds to maximising the marginal data density (or marginal likelihood, ML), which can be thought of as a measure of the forecasting performance of a model.[22]

Extending the argument in Giannone et al. (2015) we write the ML as

$$p(\mathrm{y}^{(h)}|\lambda^{(h)}) \propto \underbrace{\left| \left(V_{\varepsilon^{(h)}}^{posterior} \right)^{-1} V_{\varepsilon^{(h)}}^{prior} \right|^{\frac{T-(\tilde{p}+h)+d}{2}}}_{\text{Fit}} \underbrace{\prod_{t=\tilde{p}+1}^{T-h} \left| V_{t+h|t} \right|^{-\frac{1}{2}}}_{\text{Penalty}} \qquad \forall h \ , \tag{39}$$

where $V_{\varepsilon^{(h)}}^{posterior}$ and $V_{\varepsilon^{(h)}}^{prior}$ are the posterior and prior mean of $\Sigma_{\varepsilon}^{(h)}$, and $V_{t+h|t}$ =

[22]As discussed in Giannone et al. (2015), estimating the hyperparameters by maximising the ML – i.e. their posterior under a flat hyperprior – is an Empirical Bayes method, which has a clear frequentist interpretation.

$\mathbb{E}_{\Sigma_\varepsilon^{(h)}}\left[\mathbb{V}ar(y_{t+h}|\mathrm{y}^t, \Sigma_\varepsilon^{(h)})\right]$ is the variance (conditional on $\Sigma_\varepsilon^{(h)}$) of the h-step-ahead forecast of y, averaged across all possible a priori realisations of $\Sigma_\varepsilon^{(h)}$.[23] The first term in Eq. (39) relates to the model's in-sample fit, and it increases when the posterior residual variance falls relative to the prior variance. The second term is related to the model's (pseudo) out-of-sample forecasting performance, and it increases in the risk of overfitting (i.e. with either large uncertainty around parameters' estimates, or large a-priori residual variance). Thus, everything else equal, the ML criterion favours hyperparameters values that generate both smaller forecast errors, and low forecast error variance, therefore essentially balancing the trade-off between model fit and variance.

Empirically, the optimal level of informativeness of BLP priors may depend, amongst other characteristics of the data, on the size of the time series, the level of noise, and the degree of misspecification of the VAR. However, it is natural to expect that deviations from the VAR will be smaller for smaller h, where the compounded effect of the potential misspecifications is relatively milder. Consistent with this intuition, to set $\lambda^{(h)}$ we choose from a family of Gamma distributions and let the hyperprior be more diffuse the higher the forecast horizon (or projection lag). In particular, we fix the scale and shape parameters such that the mode of the Gamma distribution is equal to 0.4, and the standard deviation is a logistic function of the horizon that reaches its maximum after $h = 36$. Figures B.1a and B.1b in the Appendix provide details.

3 VAR, LP, and BLP

We start our empirical exploration by comparing the IRFs estimated using the three methods discussed in the previous section – VAR, LP, and BLP (Figure 3). The matrix of contemporaneous transmission coefficients A_0 is the same in the three cases (recall that for $h = 1$ BLP and the VAR coincide. See Section 2.2.) and is estimated using our informationally robust series MPI_t as an external instrument.[24] The contractionary

[23] The derivation of this formula follows as in the online Appendix of Giannone et al. (2015).

[24] Specifically, if u_t and ξ_t denote, respectively, the monetary policy shock and the vector of all other shocks, the identifying assumptions are

$$\mathbb{E}[\ u_t z_t'\ ] = \phi, \qquad \mathbb{E}[\ \xi_t z_t'\ ] = 0,$$

monetary policy shock raises the policy rate by 1% on impact. In the top row, we compare BLP and VAR responses. The bottom row compares BLP and LP. The vector of endogenous variables, y_t, includes an index of industrial production, the unemployment rate, the consumer price index, a commodity price index, and the policy rate.[25] The composition of y_t is a fairly standard one in empirical macro, and matches those used in both Coibion (2012) and Ramey (2016) for ease of comparability with these studies. It should be stressed that the information set considered is likely to be misspecified due to the small number of variables considered. We choose the 1-year nominal rate as our policy variable as in Gertler and Karadi (2015). Unless otherwise stated, we set $p = \tilde{p} = 12$ and use the observations between 1969:01 and 1979:01 as a pre-sample to centre the prior for the BLP coefficients. All variables are at monthly frequency from 1979:01 to 2014:12. The resilience of BLP responses to the chosen lag length is plotted in Figure C.2 in Appendix C.

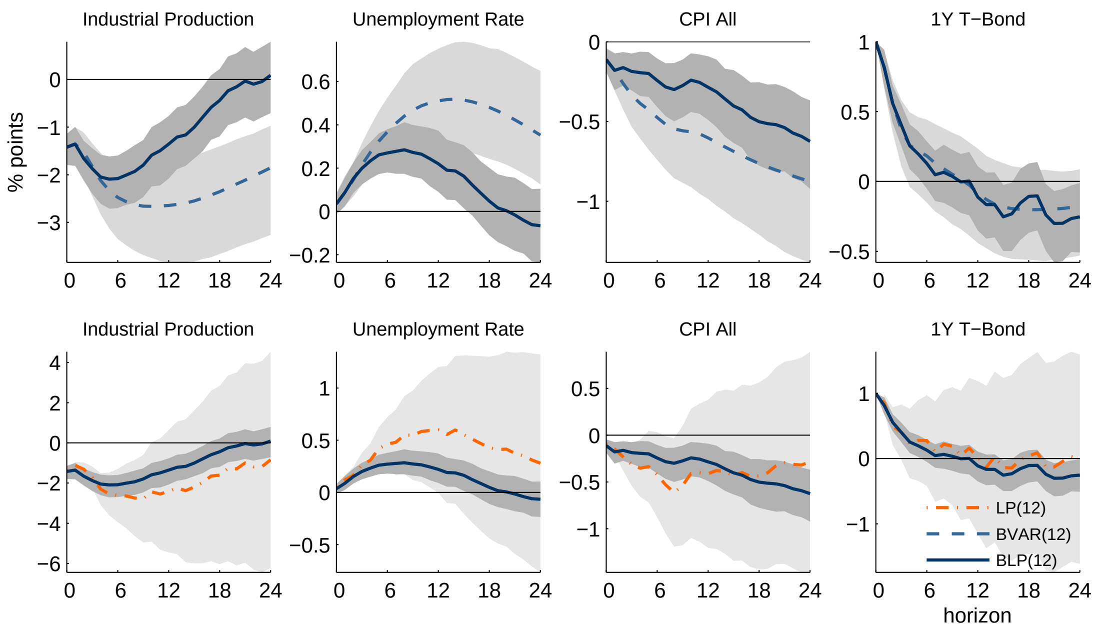
A few features emerging from this comparison are worth noticing. Overall, over this sample, results are qualitatively consistent across methods: the policy rate returns to equilibrium level within the first two quarters after the shock, and real activity and prices contract under the three modelling alternatives. The length of the sample used, combined with the small size of y_t, also limits the erratic nature of LPs. Because many sample observations are available at each horizon, the estimates of projection coefficients are relatively well behaved in this instance. However, notwithstanding the relatively long sample available for the analysis, LP responses quickly become non-significant after the first few horizons. The width of 90% LP confidence bands dwarfs those of BLP responses, which are instead comparable to those of the VAR (BLP responses are the same in the top and bottom row of the figure). In this case the shape of LP and VAR responses displayed in Figure 3 is qualitative similar. This is not necessarily the case, as results in Sections 4 and 5 show.

VAR responses are, by construction, the smoothest. Based on the same one-step-

where ϕ is non singular and z_t is the chosen external instrument – i.e. one of either $FF4_t^{GK}$, MPN_t, or MPI_t (see Stock and Watson, 2012; Mertens and Ravn, 2013, for details). An alternative would be to add the instruments to y_t in a 'hybrid' VAR (see e.g. Ramey, 2016). Results would coincide, provided that no autocorrelation is present in the instrument, and that the same time span is adopted.

[25] See Table C.2 in Appendix C for details on series included.

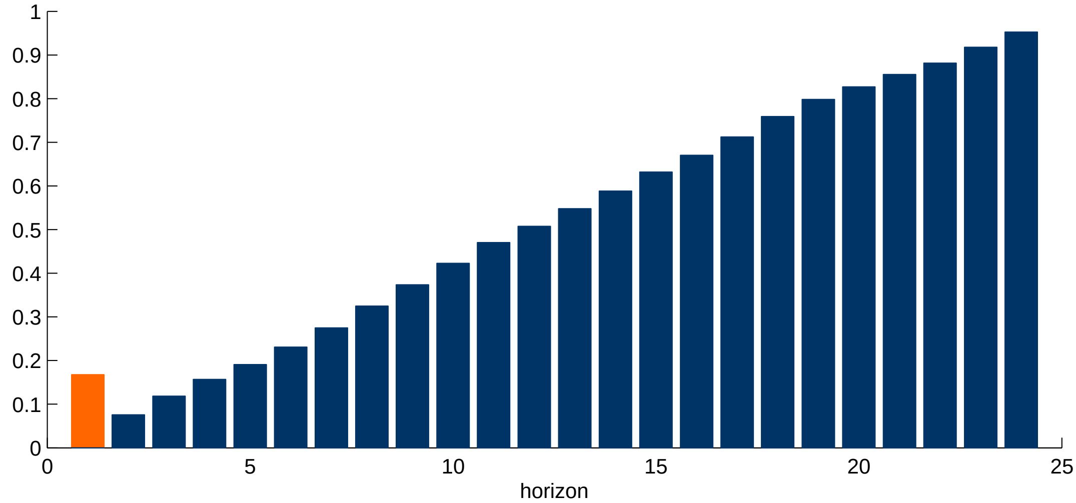
Figure 3: VAR, LP and BLP responses



TOP ROW: VAR (teal, dashed) and BLP (blue, solid) impulse responses. BOTTOM ROW: LP (orange, dash-dotted) and BLP (blue, solid) impulse responses. Shaded areas are 90% posterior coverage bands.

ahead model iterated forward, VAR responses naturally also have tighter bands than LP do (Eq. 28). This feature, however, also results in VARs implying stronger and more persistent effects than BLPs (and LPs) do. Conditional on a very similar path for the policy rate response, BLP-IRFs tend to revert to equilibrium faster than VAR-IRFs do, and tend to imply richer adjustment dynamics. This may indicate that some of the characteristics of the responses of the VAR may depend on the dynamic restrictions imposed by the recursive structure, rather then being genuine features of the data. The blue bars in Figure 4 display the optimal prior shrinkage hyperparameters that maximise $p(\lambda^{(h)}|\mathrm{y}^{(h)})$ for $h = 2, \ldots, 24$ in the BLP responses in Figure 3. The VAR prior is optimally loosened as the horizon increases, suggesting that VAR responses tend to be progressively rejected by the data. In particular, we observe that BLP peak responses are registered significantly earlier than VAR peaks, and are often realised within the first year after the shock. This again holding an equivalent shape for the policy rate response across the two methods. The discussion in the next section explores the deviation from the VAR prior further, and shows that, again holding everything else fixed, the iterative

Figure 4: optimal prior tightness

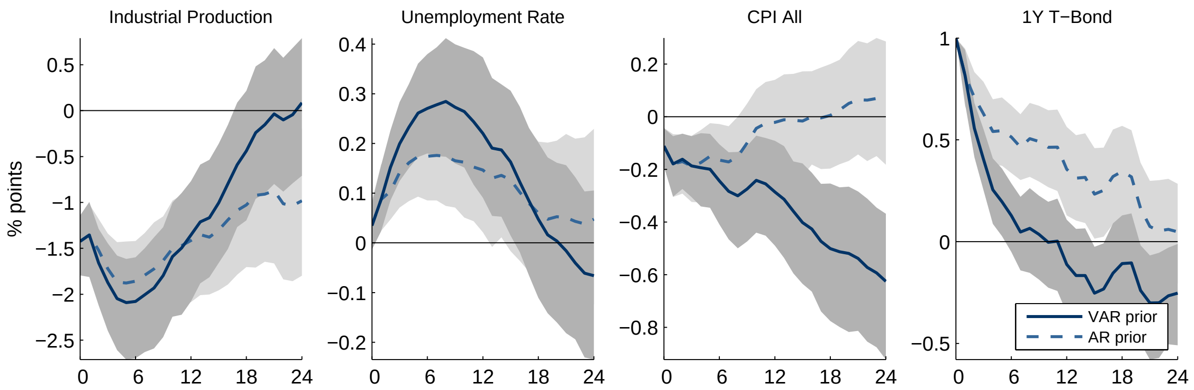


Note: The orange bar is the optimal shrinkage of the Litterman (1986) prior for the VAR coefficients at $h = 1$. Blue bars are for the optimal tightness of the VAR prior for BLP coefficients for $h > 1$.

nature of VAR responses can at times contribute to the emergence of puzzles which are absent in BLP responses.

Finally, we explore the role of our choice for the prior mean in Figure 5. Here, the dashed lines are BLP responses obtained by replacing at each horizon h the VAR(12) prior with a simpler univariate autoregressive (AR) prior in the spirit of Litterman (1986). BLP responses with our preferred VAR prior are the solid blue lines, and are the same as in Figure 3. We note that BLP responses are robust to the choice of the prior for the LP coefficients. However, the AR prior potentially discards important information in the off-diagonal entries of the matrices of autoregressive coefficients that are relevant for the dynamic responses of correlated variables to the shock.

FIGURE 5: BLP RESPONSES: VAR VS RW PRIOR



Note: BLP(12) with *RW* prior (teal, dashed), and BLP(12) with VAR(12) prior (blue, solid). 1979:2014. Pre-Sample 1969:1979.

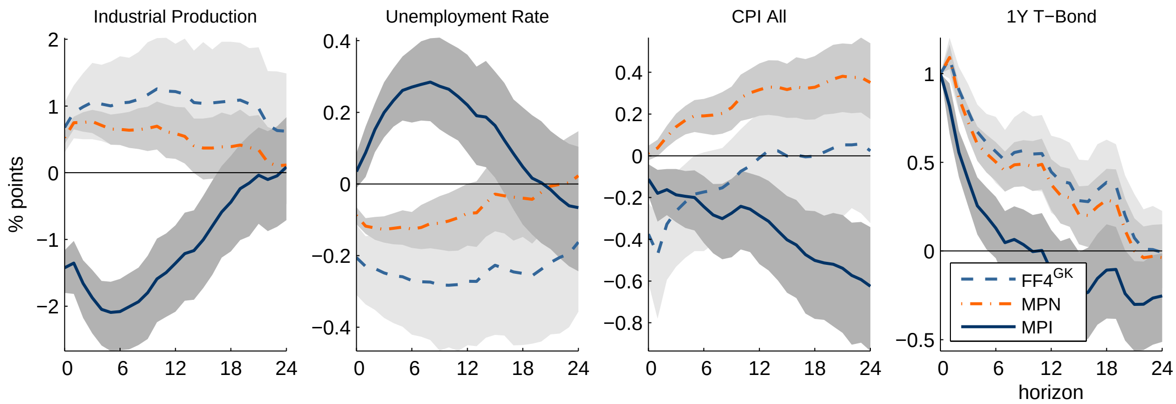
4 On the Emergence of Puzzles

In this section we document how much of the lack of stability reported in previous studies can be explained by the compounded effects of the assumptions of full information that are commonly made when identifying monetary policy shocks, and the use of severely misspecified models for the estimation of the dynamic responses. To disentangle the contributions, we compare responses to shocks obtained either by using the same empirical specification and changing the external instrument, or using the same (informationally-robust) instrument and changing the empirical specification. All other features are kept fixed and in line with the ones adopted in the previous section.

4.1 The Role of Different Identifying Assumptions

The IRFs in Figure 6 depict responses obtained using different identifications and the same empirical specification (BLP). The contractionary monetary policy shock is normalised in all cases to induce a 1% increase in the policy rate on impact, and the sample used for the estimation is 1979:1 to 2014:12. The difference among the IRFs reported in the charts lies in the informational assumptions made in order to identify the shock. The dashed teal lines report the responses to a monetary policy shock identified using the average market surprises surrounding the policy announcements as in Gertler and

Figure 6: BLP responses to monetary policy shock under different identifications



Note: Shock identified with Gertler and Karadi (2015)'s average monthly market surprise (teal, dashed), extended narrative measure of Romer and Romer (2004) (orange, dash-dotted), informationally robust MPI_t series (dark blue lines). The shock is normalised to induce a 100 basis point increase in the 1-year rate. Sample 1979:1 - 2014:12. $BLP(6)$ with VAR(12) prior over 1969:01 - 1979:01. Shaded areas are 90% posterior coverage bands.

Table 4: Reliability of alternative instruments

	MPI_t			$FF4_t^{GK}$			MPN_t		
F statistic	9.571	[5.581	11.256]	13.147	[5.354	18.954]	61.167	[49.090	68.549]
reliability	0.074	[0.056	0.081]	0.070	[0.038	0.094]	0.267	[0.223	0.294]

Note: TOP ROW: F statistics of the stage-1 regression of the reduced-form innovations on the instrument. BOTTOM ROW: reliability of the instrument. 90% confidence intervals in square brackets.

Karadi (2015) – $FF4_t^{GK}$. The orange (dash-dotted) lines, on the other hand, are responses to shocks identified using the narrative instrument of Romer and Romer (2004) – MPN_t. Lastly, the blue solid lines indicate the effects of a monetary disturbance identified using the informationally robust instrument proposed in Section 1.3, MPI_t. In each case, we use these series as external instruments for the identification.[26]

A few features are noteworthy. First, both the narrative and Gertler and Karadi (2015)'s high-frequency instruments imply a much more persistent response for the policy rate compared to our new measure. The response of the policy rate is still

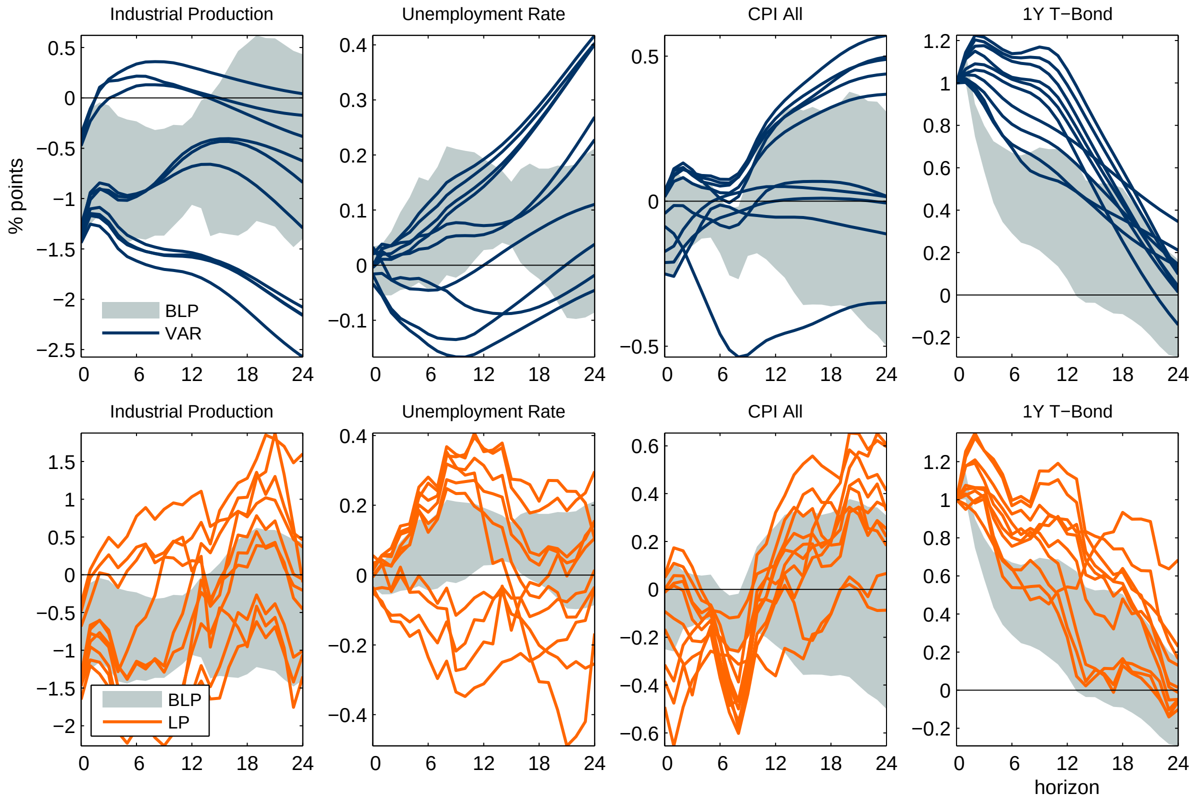
[26] In each case, we use the common sample between the VAR innovations and the external instrument to estimate the relevant entries of A_0.

significant 20 months after the shock, and is nearly identical in the two cases. Second, and quite crucially, both instruments induce significant and long lived real activity puzzles. Third, while the average market surprise elicits an immediate contraction in prices, the narrative series triggers a sustained price puzzle. Similar evidence is documented in Ramey (2016) and Miranda-Agrippino (2016). Consistent with standard macroeconomic theory, on the other hand, our instrument identifies a contractionary monetary policy shock that induces a contraction in output, a rise in unemployment, and a reduction in prices. As noted, in a full-information rational expectation setting, the use of either instrument should deliver identical results. Conversely, and holding fixed the specification of the VAR/BLP, the heterogeneity of the responses in Figure 6 can be thought of as an indirect indication of the different informational content of the three instruments. In particular, responses seem to confirm that both the narrative and high-frequency instruments are autocorrelated and not orthogonal to the state of the economy (see Section 1.2). As discussed, the signalling channel of monetary policy – i.e. the information transferred by the central bank to private agents via policy actions – can contaminate high-frequency instruments thereby inducing empirical puzzles. Finally, it is worth mentioning that the heterogeneity of the responses, and relative puzzling outcomes, are a strong indication of the contamination of the high-frequency and the narrative instrument by other macroeconomic shocks. While this casts a shade on the exogeneity of the instruments, it can explain the statistical results on their relevance (Table 4).

4.2 The Role of Different Modelling Choices

Figure 7 compares the responses obtained using VAR, LP and BLP over a set of 24-year subsamples from 1981 to 2014, using our novel instrument. The information set used in this exercise is reduced by choice to the core of the macroeconomic variables virtually employed in all the empirical applications in the literature. As such, it discards many variables potentially important in the transmission of monetary policy shocks in the

Figure 7: VAR, BLP and LP responses across subsamples



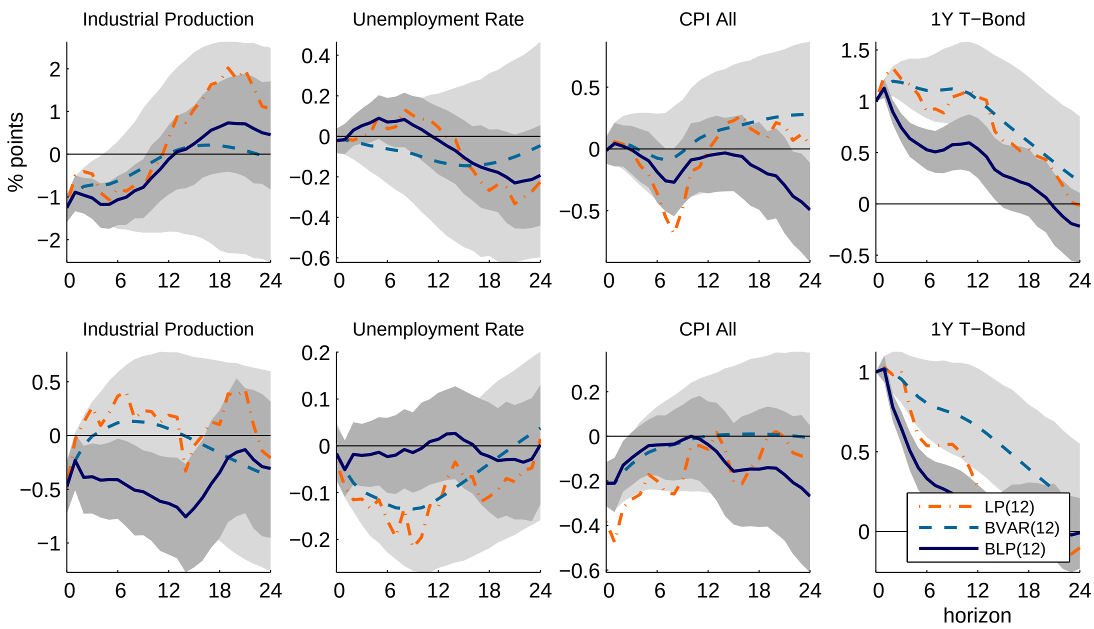
Note: TOP ROW: VAR(12) (blue, solid), and BLP(12) (grey, area) responses. BOTTOM ROW: LP(12) (orange, solid), and BLP(12) (grey, area) responses. Subsamples 1981:2005, 1982:2006, ..., 1990:2014.

economy, hence amplifying the information set misspecification of the system.[27] This specification is helpful to assess how different methods cope with potentially severely misspecified models and short samples. Indeed, it can be thought of as a severe test on the robustness of BLP with respect to model bias. In all cases A_0 is estimated using the MPI series as an external instrument. The blue lines in the top row of the figure are the VAR responses for each of the subsamples. Similarly, the orange lines in the bottom row are LP responses in each of the subsamples. Conversely, the grey areas in both rows cover all the space occupied by the BLP responses in those same sub-periods. We abstract from estimation uncertainty.

Again, a few elements are worth attention. First, the responses of the policy variable

[27]With respect to the previous specification, here we drop the commodity price index that has large instabilities over the subsamples considered, and could appear as a confounding factor in the analysis.

Figure 8: var, blp and lp responses across subsamples



Note: *BLP*(12) with VAR(12) prior (blue, solid), VAR(12) (teal, dotted) and *LP*(12) (orange, dash-dotted) responses to a contractionary monetary policy shock. top row: estimation sample 1990:01 - 2012:12, pre-sample 1969:01 - 1979:12. bottom row: estimation sample 1983:01 - 2007:12, pre-sample 1969:01 - 1982:12.

are markedly more persistent when estimated with a VAR. In a number of occasions, moreover, the policy rate stays above the 1% impact increase for over a year. Second, the reaction of real variables to a monetary contraction is decisively recessionary for BLP. The same does not hold for VAR responses which, in some cases, lead to puzzling expansionary effects, with production increasing and unemployment decreasing after the shock. Additionally, even when of the 'correct' sign, some of the VAR responses for these two variables seem to imply equally puzzling exploding behaviours. Lastly, we note that BLP responses for prices display a less clear-cut interpretation over longer horizons. Conversely, VAR responses in equivalent subsamples imply strong price puzzles. Turning the attention to the bottom row of the figure, we see how the erratic nature of LP responses is exacerbated by the small samples used. In particular, we note that LP too can lead to puzzling responses for both production and unemployment in some instances. In a further robustness check, we test the behaviour of BLP focusing on two subsamples which have been recognised as being particularly problematic because of either output or price puzzles (see e.g. Ramey, 2016). In the top row of Figure 8, IRFs are estimated over the period 1990:01 - 2012:12, while those in the bottom row refer to the years 1983:01 - 2007:12. In both cases BLP responses register a contraction of output and prices, and a muted response of unemployment. Importantly, the same does not hold for both VAR and LP IRFs. Our experiments confirm that BLP can sensibly reduce the impact of compounded biases over the horizons, effectively dealing with model misspecifications.

5 The Transmission of Monetary Disturbances

Monetary policy decisions are thought to affect economic activity and inflation through several channels, collectively known as the transmission mechanism of monetary policy. In this section we report our empirical results on the effects of monetary policy shocks on a large number of variables, and provide evidence compatible with the activation of several of the potential channels that have been discussed in the literature (see e.g. Mishkin, 1996; Bernanke and Gertler, 1995, for a review).[28] As before, monetary policy shocks are identified by using the instrument defined in Section 1.3. Results, in the form of dynamic responses and obtained using the BLP approach, are presented in Figures 9 to 11. Unless otherwise specified, responses are from a $BLP(6)$ estimated from 1979:01 to 2014:12. As in the previous section, prior beliefs for the local projections are obtained from a VAR(12) estimated over the pre-sample 1969:01 - 1979:01. A_0 is estimated over the sample common to the external instrument (MPI_t) and the VAR innovations. The shock is normalised to raise the 1-year rate (policy variable) by 1%. Shaded areas are 90% posterior coverage bands.[29]

In line with results shown in previous sections, a contractionary monetary policy

[28]Increasing the conditioning set of variables is likely to reduce the model misspecifications by including variables relevant to the transmission of disturbances. Also, it allows for a landscape view of the effects of monetary shocks.

[29]We set $\tilde{p} = 6$ to reduce the number of parameters to be estimated in this large specification, hence controlling for the risk of over parametrisation in LP. As previously discussed, results are robust to the lag length. VAR and LP responses are displayed in Appendix C. Variables used are listed in Table C.2.

shock is unequivocally and significantly recessionary also in a larger model (Figure 9). Tight monetary policy depresses real activity and reduces prices. Production, capacity utilisation, and inventories all contract, with peak effects often realised within the first year following the shock. The labour market is also significantly and negatively affected, but with delay. Both the unemployment rate and total hours worked display muted responses on impact, with peak effects realised after two quarters. This is suggestive of the presence of frictions in the labour market, such as contractual obligations, which delay the adjustments. Wages too take about a quarter before they start shrinking. Conversely, the contraction in prices, whether measured using the CPI index or the personal consumption deflator, is typically more sudden, with non persistent effects. In line with models of imperfect information and model in which a number of both real and nominal frictions are at play (e.g. Smets and Wouters, 2007), the prices do not fully adjust on impact but keep sliding over a few months to reach a negative peak of about half a percentage point within the first six months after the shock.

Real income suffers a prolonged contraction that survives for over a year after the shock. Consumption and investment spending both contract, dragging aggregate demand down. Real durable consumption increases slightly on impact, to shrink by about 2% after the first quarter. The initial response of real durable consumption is likely due to the stickiness of consumers' plans on durable goods, combined with the drop in prices. Nondurable consumption seems to be less affected by the shock.

The shock induces a significant impact rotation of the yield curve whereby for a 1% rise in the 1-year rate, we see up to a 50 basis point contraction in the term spread (Figure 9). Both responses are sudden and temporary: the increase in the policy variable dissipates completely within the first two quarters. We explore further the details of the responses of interest rates at different maturities in Figure 10. Here each subplot is horizon-specific, and maturities (in years) are reported on the horizontal axes. All interest rates rise on impact with responses that are both smaller in magnitude and quicker to revert to trend the higher the maturity. The long end of the yield curve (20-year rate) does not move, in line with what expected for the effects of a temporary monetary contraction (see also discussion in Romer and Romer, 2000; Ellingsen and

Soderstrom, 2001). All the curve's responses are not significant at the two-year horizon, with a slightly negative median response. This could be taken as a weak indication of the the endogenous reaction of the central bank to the swift weakening of the economic outlook.

To better understand the strong real effects discussed above, particularly in light of the relatively muted movements of the long end of the curve, we investigate the responses of financial and credit variables. The effects reported in Figure 9 are consistent with a deterioration of household wealth working through both a reduction of labor income, and of financial wealth. The decline in financial wealth is likely the product of negative valuation effects triggered by the contraction in asset prices. The reaction of asset prices is spread across different asset classes. House prices fall and the stock market suffers important losses. Housing investment collapse, with immediate falls well beyond the 10% mark. These effects have a detrimental impact on both equity and assets valuation, making collaterals become more costly.

The strong effects on both real activity and output are likely magnified by the reaction of credit and financial markets, consistently with the 'financial accelerator' hypothesis and the existence of a credit channel for monetary policy (Bernanke et al., 1999). Lending dips significantly, particularly so for businesses. This is consistent with a number of possible mechanisms, all of which find some degree of support. On the one hand, it is the supply of credit that shrinks. Bank lending can contract for several reasons. First, contractionary monetary policy reduces cash flows and increases indirect expenses, with direct effects on the amount of new loans granted. Second, through its effect on asset prices, contractionary policy has a direct valuation effect on lenders' balance sheets. Higher rates mean lower net margins, and thus lower profits going forward. Also, the drop in asset prices can imply a reduction in bank capital which may in turn induce deleveraging in the form of less credit supplied (see Boivin et al., 2010). On the other hand, however, the demand for credit may slow down due to borrowers being less willing to undertake new investment projects. One important reason why this may be the case is that borrowing costs rise. Following the shock, corporate bond spreads and premia both significantly rise on impact, and remain high for about half a year. This is consistent with a surge in the external finance premium, that is, the wedge between external (e.g. equity/debt issuance) and internal (e.g. retained earnings) funding costs (see Bernanke and Gertler, 1995; Gertler and Karadi, 2015). Opposite to what discussed above, this mechanism operates through the borrowers' balance sheet: the lower the borrower's net worth, the higher the finance premium. Variations in the net worth affect investment and spending decisions, with magnifying effects on borrowing costs, real spending and real activity. The mechanism affects both businesses and households alike. The fall in house prices, the contraction in housing investments, and the sharp and sudden increase in mortgage spreads all concur to curtail lending to households as well.[30]

After the shock, the dollar appreciates suddenly, and in real terms, against a basket of foreign currencies. This appears to also activate an exchange rate channel. In fact, exports become more costly due to the appreciation, and contract as a result. Notwithstanding the stronger purchasing power sustained by the appreciation of the domestic currency, the ensuing recession, accompanied by a contraction of internal demand, also makes imports contract, and significantly so. Overall, the external position tends to deteriorate slightly over the first year.

While the sign and magnitude of the effects discussed so far is largely consistent with standard macroeconomic theory, the BLP approach allows us to uncover effects with an average duration that is significantly shorter than what was previously reported. BLPs, optimised at each horizon to better model variables' responses, lack the persistence that the recursive nature of the VAR approach forces on the estimated IRFs. Figure 9 shows that, with the exception of very few cases, all variables are back to trend levels within a year after the shock. This can have potentially important implications for the policy debate, and in particular for what concerns the adequateness of the policy horizon, the duration of which is typically calibrated based on VAR evidence.

As observed in Woodford (2011), modern monetary policy is not simply a matter of controlling overnight interest rates, but rather one of shaping market expectations of the

[30]The response of mortgage spreads is calculated over a shorter sample (1990:01 - 2014:12) due to data being available only since the late seventies. The observations from 1979:01 to 1989:12 inform the BLP prior in this case.

forward path of interest rates, inflation and income. To study how agents' expectations respond to policy changes, we augment a set of variables relevant for the analysis of the standard interest rate channel with Consensus Economics forecast data.[31] Each month, experts from public and private economic institutions – mostly investment banks and economic research institutes –, are surveyed about their projections for the main macroeconomic and financial variables. Neither central banks nor governments participate in the survey. Survey respondents contribute fixed-event forecasts relative to realisations in the current and the following calendar year. To avoid issues relative to the forecast horizon shrinking as the survey date approaches the end of each year, we approximate median one-year-ahead forecasts as a weighted average of median fixed-event annual forecasts.[32]

The responses to the identified monetary policy shock are collected in Figure 11. Industrial production and CPI are converted to year-on-year growth rates for ease of comparison, to match the forecasts units. Agents' median expectations adjust in line with the deteriorating fundamentals. It is important to stress here that this result follows only once the effects of signalling are appropriately accounted for. Conversely, as documented in Campbell et al. (2012, 2016) and Nakamura and Steinsson (2013), identifying disturbances using instruments that do not control for such a transfer of information, makes expectations adjust in the 'wrong' direction, as agents interpret the interest rate move as an endogenous policy reaction to stronger than expected economic developments. Consistent with theory, we find instead that as a result of a contractionary monetary policy shock agents expect both inflation and output to slow down over time. In particular, forecasts for prices, production, consumption and investment are all

[31] Consensus Economics forecasts are only available since 1993. To address issues related to the short sample, and hence the small number of observations that are available to consistently estimate LP coefficients, we only calculate BLP IRFs over a 12-month horizon. Responses are estimated using data from 1999:01 - 2014:12. The years from 1993 to 1999 inform the BLP prior.

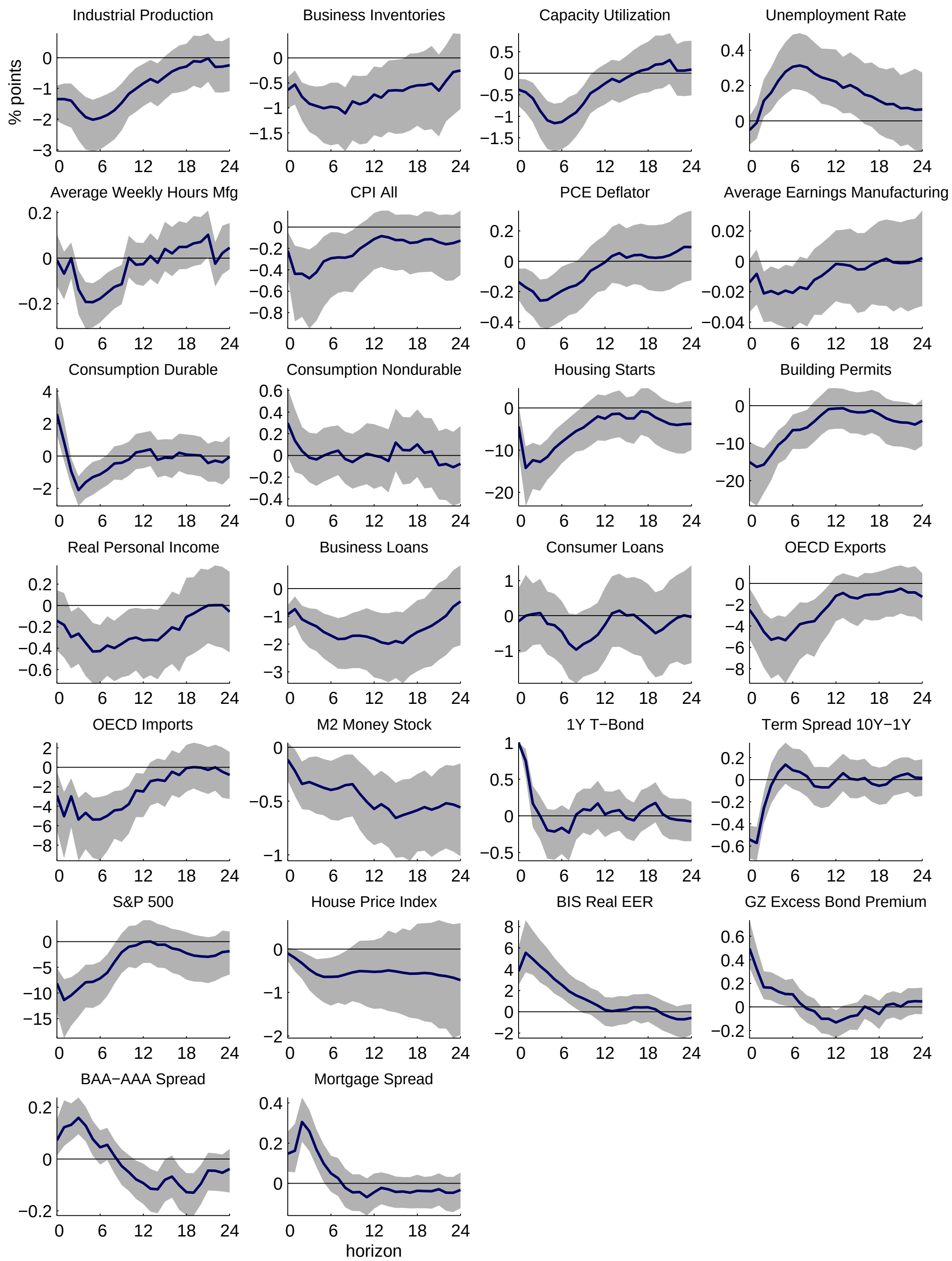
[32] Specifically, the rolling twelve-month-ahead forecasts are computed as

$$F_t x_{t+12} = \frac{h}{12} F_t x_{t+h} + \frac{12-h}{12} F_t x_{t+12+h},$$

where $F_t x_{t+h}$ is the h-month-ahead median forecast of variable x made at time t. The forecasts produced by the respondents are $\{F_t x_{t+h}, F_t x_{t+12+h}\}$ with horizons $h \in \{1, 2, \ldots, 12\}$ and $h + 12$ months (see Dovern et al., 2012).

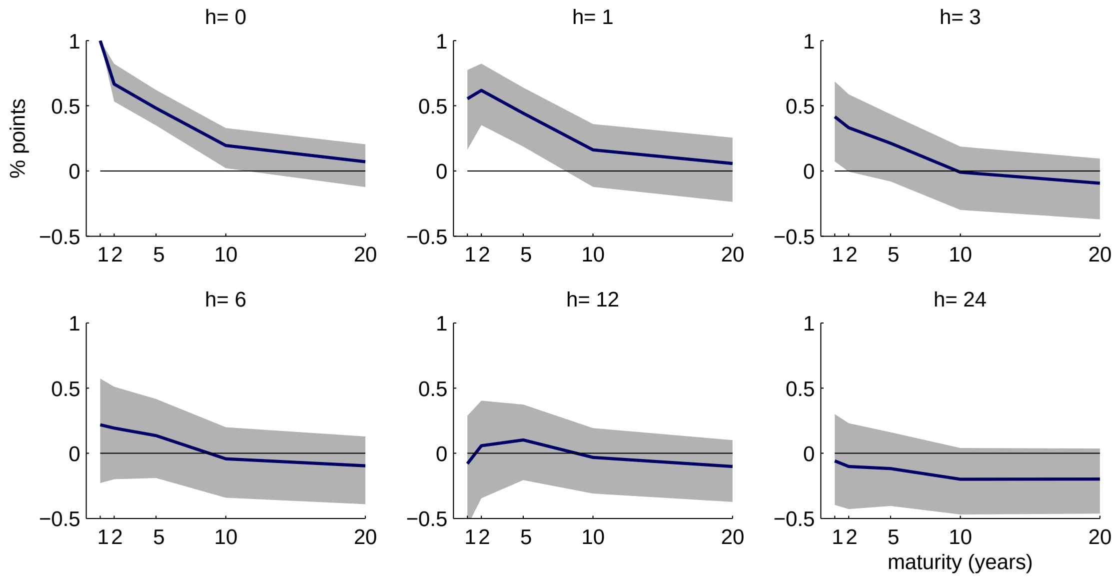
revised downward, while the opposite holds for unemployment forecasts. Interestingly, consistent with the literature on the presence of informational frictions, we find that while the direction of the revision of expectation is in line with a recessionary outlook, forecasters revise their assessment in a sluggish fashion. Notably, while production falls by 4% in annual terms, the movement in the forecasts is more gradual over the horizons. Annual CPI inflation drops by 1%, while agents revise their forecasts gradually downward. This type of behaviour is compatible with information being only partially and slowly processed over time. Conversely, with full information forecasts should immediately adjust to shocks, and by the same amount as the variable being forecasted (see discussion in Coibion and Gorodnichenko, 2012).

Figure 9: The Effects of MP Shocks



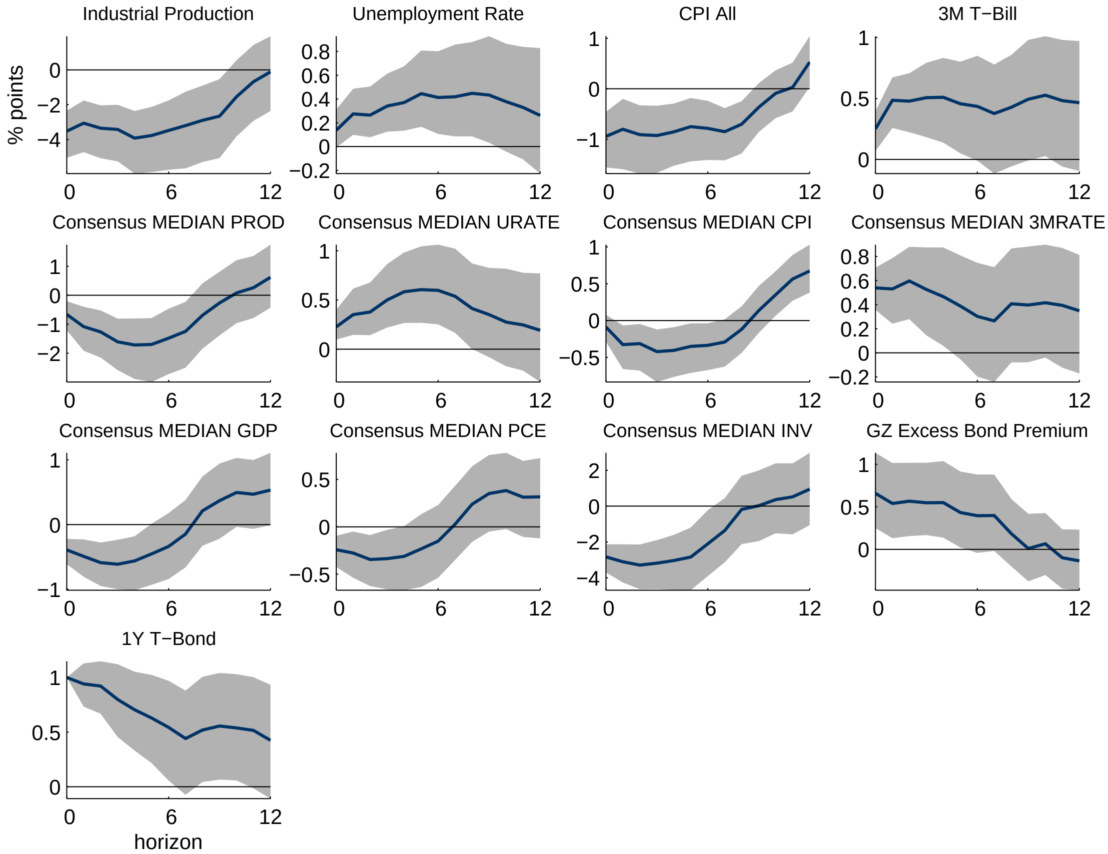
Note: BLP responses to a contractionary monetary policy shock. Shock identified with the $MPShock$ series and normalisedto induce a 100 basis point increase in the 1-year rate. Sample 1979:01 - 2014:12. $BLP(6)$ with $VAR(12)$ prior over 1969:01 - 1979:01. Shaded areas are 90% posterior coverage bands. VAR and LP responses in Figure C.3.

Figure 10: Yield Curve Response to MP Shocks



Note: BLP responses to a contractionary monetary policy shock. Shock identified with the $MPShock$ series and normalised to induce a 100 basis point increase in the 1-year rate. Sample 1979:01 - 2014:12. $BLP(6)$ with $VAR(12)$ prior over 1969:01 - 1979:01. Shaded areas are 90% posterior coverage bands. VAR and LP responses in Figure C.4.

Figure 11: Response of Expectations to MP Shocks



Note: BLP responses to a contractionary monetary policy shock. Shock identified with the $MPShock$ series and normalised to induce a 100 basis point increase in the 1-year rate. Sample 1999:01 - 2014:12. $BLP(6)$ with $VAR(12)$ prior over 1993:01 - 1999:01. Shaded areas are 90% posterior coverage bands. VAR and LP responses in Figure C.5.

6 Conclusions

What are the effects of monetary policy? Despite being one of the central questions in macroeconomics, and the numerous theoretical and methodological advances, the discussion on the effects of monetary policy appears to be still surrounded by a substantial degree of uncertainty. In fact, not just the magnitude and the significance, but even the sign of the responses of crucial variables – prices and output being a prime example – depends on the chosen identification strategy, the sample period, the information set considered, and the details of the model specification.

This paper helps rationalising unstable and puzzling previous results by using a novel flexible econometric model that optimally bridges between standard VARs and the Local Projection approach, and an identification strategy coherent with the intuitions stemming from models of asymmetric and imperfect information.

Results proposed show that following a monetary tightening economic activity and prices contract, lending to consumers and businesses cools down, and expectations move in line with fundamentals. Moreover, the currency appreciates, and equity prices fall. Finally, the slope of the yield curve flattens, borrowing costs rise and so do corporate spreads. These effects are both sizeable and persistent, suggesting that monetary policy is a powerful tool for both economic stabilisation and financial stability. These findings are robust to a number of severe tests.

References

Admati, Anat R, "A Noisy Rational Expectations Equilibrium for Multi-asset Securities Markets," *Econometrica*, May 1985, *53* (3), 629–57.

Andrade, P., R. Crump, S. Eusepi, and E. Moench, "Fundamental disagreement," Working papers 524, Banque de France 2014.

Andrade, Philippe and Hervé Le Bihan, "Inattentive professional forecasters," *Journal of Monetary Economics*, 2013, *60* (8), 967–982.

Aoki, Kosuke, "On the optimal monetary policy response to noisy indicators," *Journal of Monetary Economics*, April 2003, *50* (3), 501–523.

Barakchian, S. Mahdi and Christopher Crowe, "Monetary policy matters: Evidence from new shocks data," *Journal of Monetary Economics*, 2013, *60* (8), 950–966.

Barnichon, Régis and Christian Brownlees, "Impulse Response Estimation By Smooth Local Projections," CEPR Discussion Papers 11726, C.E.P.R. Discussion Papers December 2016.

_ **and Christian Matthes**, "Gaussian Mixture Approximations of Impulse Responses and the Nonlinear Effects of Monetary Shocks," Working Paper 16-8, Federal Reserve Bank of Richmond March 2014.

Bernanke, Ben S and Alan S Blinder, "The Federal Funds Rate and the Channels of Monetary Transmission," *American Economic Review*, September 1992, *82* (4), 901–21.

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

_ **and Mark Gertler**, "Inside the Black Box: The Credit Channel of Monetary Policy Transmission," *Journal of Economic Perspectives*, Fall 1995, *9* (4), 27–48.

_ **,** _ **, and Simon Gilchrist**, "The financial accelerator in a quantitative business cycle framework," in J. B. Taylor and M. Woodford, eds., *Handbook of Macroeconomics*, Vol. 1 of *Handbook of Macroeconomics*, Elsevier, 1999, chapter 21, pp. 1341–1393.

Blanchard, Olivier J., Jean-Paul L'Huillier, and Guido Lorenzoni, "News, Noise, and Fluctuations: An Empirical Exploration," *American Economic Review*, December 2013, *103* (7), 3045–70.

Blinder, Alan S., Michael Ehrmann, Marcel Fratzscher, Jakob De Haan, and David-Jan Jansen, "Central Bank Communication and Monetary Policy: A Survey of Theory and Evidence," *Journal of Economic Literature*, December 2008, *46* (4), 910–45.

Boivin, Jean, Michael T. Kiley, and Frederic S. Mishkin, "How Has the Monetary Transmission Mechanism Evolved Over Time?," in Benjamin M. Friedman and Michael Woodford, eds., *Handbook of Monetary Economics*, Vol. 3 of *Handbook of Monetary Economics*, Elsevier, 2010, chapter 8, pp. 369–422.

Braun, Phillip A. and Stefan Mittnik, "Misspecifications in vector autoregressions and their effects on impulse responses and variance decompositions," *Journal of Econometrics*, October 1993, *59* (3), 319–341.

Caldara, Dario and Edward Herbst, "Monetary Policy, Real Activity, and Credit Spreads : Evidence from Bayesian Proxy SVARs," Finance and Economics Discussion Series 2016-049, Board of Governors of the Federal Reserve System (U.S.) May 2016.

Campbell, Jeffrey R., Charles L. Evans, Jonas D.M. Fisher, and Alejandro Justiniano, "Macroeconomic Effects of Federal Reserve Forward Guidance," *Brookings Papers on Economic Activity*, 2012, *44* (1 (Spring)), 1–80.

_ , Jonas D. M. Fisher, Alejandro Justiniano, and Leonardo Melosi, "Forward Guidance and Macroeconomic Outcomes Since the Financial Crisis," in "NBER Macroeconomics Annual 2016, Volume 31" NBER Chapters, National Bureau of Economic Research, Inc, February 2016.

Carroll, Christopher D., "Macroeconomic Expectations Of Households And Professional Forecasters," *The Quarterly Journal of Economics*, February 2003, *118* (1), 269–298.

Chan, Joshua C.C., Eric Eisenstat, and Gary Koop, "Large Bayesian VARMAs," *Journal of Econometrics*, 2016, *192* (2), 374–390.

Chevillon, Guillaume, "Direct Multi-Step Estimation and Forecasting," *Journal of Economic Surveys*, 2007, *21* (4), 746–785.

Chiuso, Alessandro, "Regularization and Bayesian Learning in Dynamical Systems: Past, Present and Future," *CoRR*, 2015, *abs/1511.01543.*

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans, "Monetary policy shocks: What have we learned and to what end?," in J. B. Taylor and M. Woodford, eds., *Handbook of Macroeconomics*, Vol. 1 of *Handbook of Macroeconomics*, Elsevier, 1999, chapter 2, pp. 65–148.

Coibion, Olivier, "Are the Effects of Monetary Policy Shocks Big or Small?," *American Economic Journal: Macroeconomics*, April 2012, *4* (2), 1–32.

_ and Yuriy Gorodnichenko, "What Can Survey Forecasts Tell Us about Information Rigidities?," *Journal of Political Economy*, 2012, *120* (1), 116 – 159.

_ and _ , "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts," *American Economic Review*, 2015, *105* (8), 2644–78.

Croushore, Dean and Simon van Norden, "Fiscal Forecasts at the FOMC: Evidence from the Greenbooks," *Review of Economics and Statistics*, 2017, *forthcoming.*

Dovern, Jonas, Ulrich Fritsche, and Jiri Slacalek, "Disagreement Among Forecasters in G7 Countries," *The Review of Economics and Statistics*, November 2012, *94* (4), 1081–1096.

Ellingsen, Tore and Ulf Soderstrom, "Monetary Policy and Market Interest Rates," *American Economic Review*, December 2001, *91* (5), 1594–1607.

Faust, Jon and Eric M. Leeper, "The Myth of Normal: The Bumpy Story of Inflation and Monetary Policy," mimeo, Federal Reserve Bank of Kansas City's Jackson Hole Symposium August 2015.

Friedman, Milton and David Meiselman, "The Relative Stability of Monetary Velocity and the Investment Multiplier in the United States, 1897-1958.," in "Commission on Money and Credit: Stabilization Policies," prentice-hall ed. Handbook of Macroeconomics, Englewood Cliffs, 1963, pp. 165–268.

Gaspar, Vitor, Frank Smets, and David Vestin, "Inflation Expectations, Adaptive Learning and Optimal Monetary Policy," in Benjamin M. Friedman and Michael Woodford, eds., *Handbook of Monetary Economics*, Vol. 3 of *Handbook of Monetary Economics*, Elsevier, 2010, chapter 19, pp. 1055–1095.

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

Giannone, Domenico, Michele Lenza, and Giorgio E. Primiceri, "Prior Selection for Vector Autoregressions," *The Review of Economics and Statistics*, May 2015, *2* (97), 436–451.

Gilchrist, Simon, David López-Salido, and Egon Zakrajšek, "Monetary Policy and Real Borrowing Costs at the Zero Lower Bound," *American Economic Journal: Macroeconomics*, January 2015, *7* (1), 77–109.

Gürkaynak, Refet S, "Using federal funds futures contracts for monetary policy analysis," Finance and Economics Discussion Series 2005-29, Board of Governors of the Federal Reserve System (U.S.) 2005.

_ , Brian Sack, and Eric Swanson, "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*, May 2005, *1* (1).

Hellwig, Martin F., "On the aggregation of information in competitive markets," *Journal of Economic Theory*, June 1980, *22* (3), 477–498.

Hubert, Paul and Becky Maule, "Policy and macro signals as inputs to inflation expectation formation," Bank of England working papers 581, Bank of England January 2016.

Jordà, Òscar, "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, March 2005, *95* (1), 161–182.

Kadiyala, K Rao and Sune Karlsson, "Numerical Methods for Estimation and Inference in Bayesian VAR-Models," *Journal of Applied Econometrics*, March-Apr 1997, *12* (2), 99–132.

Kilian, Lutz and Yun Jung Kim, "How Reliable Are Local Projection Estimators of Impulse Responses?," *The Review of Economics and Statistics*, November 2011, *93* (4), 1460–1466.

Kuttner, Kenneth N., "Monetary policy surprises and interest rates: Evidence from the Fed funds futures market," *Journal of Monetary Economics*, June 2001, *47* (3), 523–544.

Leeper, Eric M., Christopher A. Sims, and Tao Zha, "What Does Monetary Policy Do?," *Brookings Papers on Economic Activity*, 1996, *27* (2), 1–78.

Litterman, Robert B, "Forecasting with Bayesian Vector Autoregressions-Five Years of Experience," *Journal of Business & Economic Statistics*, January 1986, *4* (1), 25–38.

Mackowiak, Bartosz and Mirko Wiederholt, "Optimal Sticky Prices under Rational Inattention," *American Economic Review*, June 2009, *99* (3), 769–803.

Mankiw, N. Gregory and Ricardo Reis, "Sticky Information Versus Sticky Prices: A Proposal To Replace The New Keynesian Phillips Curve," *The Quarterly Journal of Economics*, November 2002, *117* (4), 1295–1328.

_ and _ , "Imperfect Information and Aggregate Supply," in Benjamin M. Friedman and Michael Woodford, eds., *Handbook of Monetary Economics*, Vol. 3 of *Handbook of Monetary Economics*, Elsevier, 2010, chapter 5, pp. 183–229.

_ , _ , and Justin Wolfers, "Disagreement about Inflation Expectations," in "NBER Macroeconomics Annual 2003, Volume 18" NBER Chapters, National Bureau of Economic Research, Inc, November 2004, pp. 209–270.

Marcellino, Massimiliano, James H. Stock, and Mark W. Watson, "A comparison of direct and iterated multistep AR methods for forecasting macroeconomic time series," *Journal of Econometrics*, 2006, *135* (1-2), 499–526.

Matejka, Filip and Christopher A. Sims, "Discrete Actions in Information-Constrained Tracking Problems," CERGE-EI Working Papers wp441, The Center for Economic Research and Graduate Education - Economics Institute, Prague June 2011.

McCracken, Michael W. and Serena Ng, "FRED-MD: A Monthly Database for Macroeconomic Research," Working Papers 2015-12, Federal Reserve Bank of St. Louis June 2015.

Melosi, Leonardo, "Signaling Effects of Monetary Policy," PIER Working Paper Archive 13-029, Penn Institute for Economic Research, Department of Economics, University of Pennsylvania March 2013.

Mertens, Karel and Morten O. Ravn, "The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States," *American Economic Review*, 2013, *103* (4), 1212–47.

Miranda-Agrippino, Silvia, "Unsurprising Shocks: Information, Premia, and the Monetary Transmission," Staff Working Paper 626, Bank of England 2016.

_ and Hélène Rey, "World Asset Markets and the Global Financial Cycle," Working Paper, London Business School 2015.

Mishkin, Frederic S., "The Channels of Monetary Transmission: Lessons for Monetary Policy," NBER Working Papers 5464, National Bureau of Economic Research, Inc February 1996.

Müller, Ulrich K., "Risk of Bayesian Inference in Misspecified Models, and the Sandwich Covariance Matrix," *Econometrica*, 2013, *81* (5), 1805–1849.

Nakamura, Emi and Jón Steinsson, "High Frequency Identification of Monetary Non-Neutrality," NBER Working Papers 19260, National Bureau of Economic Research, Inc July 2013.

Nimark, Kristoffer, "Dynamic pricing and imperfect common knowledge," *Journal of Monetary Economics*, March 2008, *55* (2), 365–382.

_ , "Monetary policy with signal extraction from the bond market," *Journal of Monetary Economics*, November 2008, *55* (8), 1389–1400.

Orphanides, Athanasios, "Monetary policy evaluation with noisy information," *Journal of Monetary Economics*, April 2003, *50* (3), 605–631.

Pesaran, M. Hashem, Andreas Pick, and Allan Timmermann, "Variable selection, estimation and inference for multi-period forecasting problems," *Journal of Econometrics*, September 2011, *164* (1), 173–187.

Plagborg-Moller, Mikkel, "Bayesian Inference on Structural Impulse Response Functions," Harvard mimeo, C.E.P.R. Discussion Papers October 2015.

Primiceri, Giorgio E., "Time Varying Structural Vector Autoregressions and Monetary Policy," *Review of Economic Studies*, 2005, *72* (3), 821–852.

Ramey, Valerie, "Comment," *NBER Macroeconomics Annual*, 2013, *27* (1), 147 – 153.

Ramey, Valerie A., "Macroeconomic Shocks and Their Propagation," Working Paper 21978, National Bureau of Economic Research February 2016.

Reis, Ricardo, "Inattentive consumers," *Journal of Monetary Economics*, November 2006, *53* (8), 1761–1800.

_ , "Inattentive Producers," *Review of Economic Studies*, 2006, *73* (3), 793–821.

Ricco, Giovanni, "A new identification of fiscal shocks based on the information flow," Working Paper Series 1813, European Central Bank June 2015.

Romer, Christina D. and David H. Romer, "Federal Reserve Information and the Behavior of Interest Rates," *American Economic Review*, 2000, *90* (3), 429–457.

_ **and** _ , "A New Measure of Monetary Shocks: Derivation and Implications," *American Economic Review*, September 2004, *94* (4), 1055–1084.

Rudebusch, Glenn D, "Do Measures of Monetary Policy in a VAR Make Sense?," *International Economic Review*, November 1998, *39* (4), 907–31.

Schorfheide, Frank, "VAR forecasting under misspecification," *Journal of Econometrics*, September 2005, *128* (1), 99–136.

Sims, Christopher A., "Money, Income, and Causality," *The American Economic Review*, 1972, *62* (4), pp. 540–552.

Sims, Christopher A, "Macroeconomics and Reality," *Econometrica*, January 1980, *48* (1), 1–48.

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

Sims, Christopher A, "Comment on Glenn Rudebusch's "Do Measures of Monetary Policy in a VAR Make Sense?"," *International Economic Review*, November 1998, *39* (4), 933–41.

Sims, Christopher A., "Implications of rational inattention," *Journal of Monetary Economics*, April 2003, *50* (3), 665–690.

_ , "Rational Inattention and Monetary Economics," in Benjamin M. Friedman and Michael Woodford, eds., *Handbook of Monetary Economics*, Vol. 3 of *Handbook of Monetary Economics*, Elsevier, 2010, chapter 4, pp. 155–181.

Smets, Frank and Rafael Wouters, "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach," *American Economic Review*, June 2007, *97* (3), 586–606.

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

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

Woodford, M., *Interest and Prices: Foundations of a Theory of Monetary Policy*, Princeton University Press, 2011.

Woodford, Michael, "Imperfect Common Knowledge and the Effects of Monetary Policy," NBER Working Papers 8673, National Bureau of Economic Research, Inc December 2001.

A Derivations

A.1 Aggregate Expectation Revisions

Recall from Section 1 that at $\underline{t}$ both agents and the central bank receive signals about the economy, and as a result of that, update their expectations. Specifically, at opening time $\underline{t}$ each agent i observes a private noisy signal of the state of the economy x_t

$$s_{i,\underline{t}} = x_t + \nu_{i,\underline{t}} \ , \qquad \nu_{i,\underline{t}} \sim \mathcal{N}(0, \sigma_{n,\nu}) \ . \tag{A.1}$$

Given the signals, agents update their expectations using

$$\begin{aligned} F_{i,\underline{t}} x_t &= K_1 s_{i,\underline{t}} + (1 - K_1) F_{i,\overline{t-1}} x_t \ , && \text{(A.2)} \\ F_{i,\underline{t}} x_{t+h} &= \rho^h F_{i,\underline{t}} x_t \qquad \forall h > 0 \ , && \text{(A.3)} \end{aligned}$$

where K_1 is the Kalman gain which represents the relative weight placed on new information relative to previous forecasts. When the signal is perfectly revealing $K_1 = 1$, while in the presence of noise $K_1 < 1$. Thus $(1 - K_1)$ is the degree of information rigidity faced by the agents. The central bank observes

$$s_{cb,\underline{t}} = x_t + \nu_{cb,\underline{t}} \ , \qquad \nu_{cb,\underline{t}} \sim \mathcal{N}(0, \sigma_{cb,\nu}) \ . \tag{A.4}$$

We can assume without loss of generality that the signal observed by the central bank is more precise than the one observed by agents: $\sigma_{cb,\nu} < \sigma_{n,\nu}$. Given the signal, the central bank updates its expectations via the Kalman filter

$$\begin{aligned} F_{cb,\underline{t}} x_t &= K_{cb} s_{cb,\underline{t}} + (1 - K_{cb}) F_{cb,\overline{t-1}} x_t \ , && \text{(A.5)} \\ F_{cb,\underline{t}} x_{t+h} &= \rho^h F_{cb,\underline{t}} x_t \qquad \forall h > 0 \ , && \text{(A.6)} \end{aligned}$$

where K_{cb} is the bank's Kalman gain.

At $\bar{t}$ agents observe the policy rate (i.e. a common signal from the central bank) and update their forecasts using

$$F_{i,\bar{t}}x_t \quad = K_2\tilde{s}_{cb,\bar{t}} + (1-K_2)F_{i,\underline{t}}x_t \ , \tag{A.7}$$

$$F_{i,\bar{t}}x_{t+h} = \rho^h F_{i,\bar{t}}x_t \qquad\qquad \forall h > 0 \ , \tag{A.8}$$

where $\tilde{s}_{cb,\bar{t}}$ indicates the generic public signal that agents extract from the interest rate decision, and K_2 is the Kalman gain given the noise in the public signal $\tilde{\nu}_{cb,\underline{t}}$.

Combining Eq. (A.7) with Eq. (2), and using Eq. (1) and Eq. (A.8) we find

$$\begin{aligned} F_{i,\bar{t}}x_t - F_{i,\underline{t}}x_t &= K_2\left[\tilde{s}_{cb,\bar{t}} - F_{i,\underline{t}}x_t\right] \\ &= K_2(x_t + \tilde{\nu}_{cb,\bar{t}}) - K_2\left[K_1(x_t + \nu_{i,\bar{t}}) + (1-K_1)F_{i,\overline{t-1}}x_t\right] \\ &= K_2(1-K_1)x_t + K_2\tilde{\nu}_{cb,\bar{t}} - K_2K_1\nu_{i,\bar{t}} - K_2(1-K_1)F_{i,\overline{t-1}}x_t \\ &= K_2(1-K_1)\rho\left[x_{t-1} - F_{i,\overline{t-1}}x_{t-1}\right] + K_2\left[(1-K_1)\xi_t + \tilde{\nu}_{cb,\bar{t}} - K_1\nu_{i,\bar{t}}\right] . \end{aligned} \tag{A.9}$$

To find an expression for the forecast error $\left(x_{t-1} - F_{i,\overline{t-1}}x_{t-1}\right)$ in Eq. (A.9), first note that Eq. (A.7) implies

$$x_t - F_{i,\bar{t}}x_t = K_2^{-1}(1-K_2)\left(F_{i,\bar{t}}x_t - F_{i,\underline{t}}x_t\right) - \tilde{\nu}_{cb,\bar{t}}. \tag{A.10}$$

Then Eq. (A.10) one period earlier can be written as

$$\begin{aligned} x_{t-1} - F_{i,\overline{t-1}}x_{t-1} &= K_2^{-1}(1-K_2)\left[F_{i,\overline{t-1}}x_{t-1} - F_{i,\underline{t-1}}x_{t-1}\right] - \tilde{\nu}_{cb,\overline{t-1}} \\ &= K_2^{-1}(1-K_2)\rho^{-1}\left[F_{i,\overline{t-1}}x_t - F_{i,\underline{t-1}}x_t\right] - \tilde{\nu}_{cb,\overline{t-1}} \ . \end{aligned} \tag{A.11}$$

Substituting Eq. (A.11) into Eq. (A.9) yields

$$\begin{aligned} F_{i,\bar{t}}x_t - F_{i,\underline{t}}x_t =& (1-K_2)(1-K_1)\left[F_{i,\overline{t-1}}x_t - F_{i,\underline{t-1}}x_t\right] \\ &+ K_2\left[(1-K_1)\xi_t + \left(\tilde{\nu}_{cb,\bar{t}} - (1-K_1)\rho\tilde{\nu}_{cb,\overline{t-1}}\right) - K_1\nu_{i,\bar{t}}\right] \ . \end{aligned} \tag{A.12}$$

The characteristics of the common noise $\tilde{\nu}_{cb,\bar{t}}$ are derived from the Taylor rule in Eq. (9), and the signal extraction problem of the central bank in Eq. (7). Specifically:

$$
\begin{aligned}
i_t &= \phi_0 + \phi_x' F_{cb,\underline{t}} x_t + u_t \\
&= \phi_0 + \phi_x' \left[K_{cb} s_{cb,\underline{t}} + (1 - K_{cb}) F_{cb,\overline{t-1}} x_t \right] + u_t \\
&= \phi_0 + \phi_x' \left[K_{cb} s_{cb,\underline{t}} + (1 - K_{cb}) \rho F_{cb,\overline{t-1}} x_{t-1} \right] + u_t \\
&= \phi_0 + K_{cb} \phi_x' s_{cb,\underline{t}} + (1 - K_{cb}) \rho (i_{t-1} - \phi_0 - u_{t-1}) + u_t \\
&= \left[1 - (1 - K_{cb}) \rho\right] \phi_0 + (1 - K_{cb}) \rho i_{t-1} + K_{cb} \phi_x' s_{cb,\underline{t}} - (1 - K_{cb}) \rho u_{t-1} + u_t \ , \qquad \text{(A.13)}
\end{aligned}
$$

with $F_{cb,\overline{t-1}} x_{t-1} = F_{cb,\underline{t-1}} x_{t-1}$. Thus, conditional on i_{t-1}, at announcement agents observe the common signal

$$
\tilde{s}_{cb,\bar{t}} = x_t + \nu_{cb,\underline{t}} + \left(K_{cb} \phi_x'\right)^{-1} \left[u_t - (1 - K_{cb}) \rho u_{t-1}\right] \ , \qquad \text{(A.14)}
$$

where

$$
\tilde{\nu}_{cb,\underline{t}} = \nu_{cb,\underline{t}} + \left(K_{cb} \phi_x'\right)^{-1} \left[u_t - (1 - K_{cb}) \rho u_{t-1}\right] \ . \qquad \text{(A.15)}
$$

Plugging Eq. (A.15) into Eq. (A.12) yields

$$
\begin{aligned}
F_{i,\bar{t}} x_t - F_{i,\underline{t}} x_t =& (1 - K_2)(1 - K_1) \left[F_{i,\overline{t-1}} x_t - F_{i,\underline{t-1}} x_t \right] \\
&+ K_2 (1 - K_1) \xi_t + K_2 \left[\left(\nu_{cb,\bar{t}} - (1 - K_1) \rho \nu_{cb,\overline{t-1}} \right) - K_1 \nu_{i,\bar{t}} \right] \\
&+ K_2 \left(K_{cb} \phi_x'\right)^{-1} \left[u_t - (K_1 - K_{cb}) \rho u_{t-1} - \rho (1 - K_1)(1 - K_{cb}) \rho^2 u_{t-2} \right] \ .
\end{aligned}
\qquad \text{(A.16)}
$$

Eq. (13) follows by taking the average of Eq. (A.16) over the agents i.

A.2 Bias in OLS Regression

Recall Eq. (13):

$$
\begin{aligned}
F_{\bar{t}}x_t - F_{\underline{t}}x_t =& (1-K_2)(1-K_1)\left[F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t\right] \\
& + K_2(1-K_1)\xi_t + K_2\left[\nu_{cb,\underline{t}} - (1-K_1)\rho\nu_{cb,\underline{t-1}}\right] \\
& + K_2(K_{cb}\phi_x')^{-1}\left[u_t - \rho(K_1 - K_{cb})u_{t-1} + (1-K_1)(1-K_{cb})\rho^2 u_{t-2}\right] .
\end{aligned}
$$

For simplicity, let us consider the vector x_t to be univariate. Suppose one runs a regression of the form (e.g. Table 2)

$$
F_{\bar{t}}x_t - F_{\underline{t}}x_t = \beta\left[F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t\right] + error_t \ .
$$

Then, using $\mathbb{E}[F_{\overline{t-1}}x_t\xi_t] = 0$ and $\mathbb{E}[F_{\overline{t-1}}x_t u_t] = 0$ we get

$$
\begin{aligned}
\hat{\beta}^{OLS} =& \frac{\mathbb{E}\left[(F_{\bar{t}}x_t - F_{\underline{t}}x_t)(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)\right]}{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)^2\right]} \\
=& (1-K_2)(1-K_1) - K_2(1-K_1)\rho\frac{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)\nu_{cb,\underline{t-1}}\right]}{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)^2\right]} \\
& - K_2(K_{cb}\phi_x')^{-1}(K_1 - K_{cb})\rho\frac{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)u_{t-1}\right]}{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)^2\right]} + \mathcal{O}(\rho^3) \\
=& (1-K_2)(1-K_1) - K_2(1-K_1)\rho\frac{\mathbb{E}\left[\rho F_{\overline{t-1}}x_{t-1}\nu_{cb,\underline{t-1}}\right]}{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)^2\right]} \\
& - K_2(K_{cb}\phi_x')^{-1}(K_1 - K_{cb})\rho\frac{\mathbb{E}\left[\rho F_{\overline{t-1}}x_{t-1}u_{t-1}\right]}{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)^2\right]} + \mathcal{O}(\rho^3) \\
=& (1-K_2)(1-K_1) - K_2(1-K_1)\rho^2\frac{\Sigma_{\nu_{cb}}}{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)^2\right]} \\
& - K_2(K_{cb}\phi_x')^{-1}(K_1 - K_{cb})\rho^2\frac{\Sigma_u}{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)^2\right]} + \mathcal{O}(\rho^3) \ . \qquad \text{(A.17)}
\end{aligned}
$$

The size of the last term in Eq. (A.17) depends on the relative magnitude of K_1 and K_{cb}. The Kalman gain of the agents and the central bank are likely to be similar, due to similar degree of precision of the signals. Hence, the third term is negligible, resulting in an overall negative bias.

B Optimal Prior Tightness

Following Giannone, Lenza and Primiceri (2015), we treat the overall tightness of the prior $\lambda^{(h)}$ as an additional model parameter, and estimate it at each horizon h by treating the model as a hierarchical one. This accounts to specifying a prior probability distribution for each $\lambda^{(h)}$, and estimating them as the maximisers of their posterior distribution, conditional on the data.

Specifically, we maximise

$$p(\lambda^{(h)}|\mathrm{y}^{(h)}) = p(\mathrm{y}^{(h)}|\lambda^{(h)}) \cdot p(\lambda^{(h)}) \ , \tag{B.1}$$

where $p(\mathrm{y}^{(h)}|\lambda^{(h)})$ is the marginal density of the data as a function of the hyperparameters

$$p(\mathrm{y}^{(h)}|\lambda^{(h)}) = \int p(\mathrm{y}^{(h)}|\lambda^{(h)}, \theta)p(\theta|\lambda^{(h)})d\theta \ \forall h \ , \tag{B.2}$$

and $p(\theta|\lambda^{(h)})$ is the prior distribution of the remaining model's parameters conditional on $\lambda^{(h)}$. $\mathrm{y}^{(h)} = vec(\mathrm{Y}^{(h)})$ where $Y^{(h)} \equiv (y_{p+1+h}, \ldots, y_T)'$.

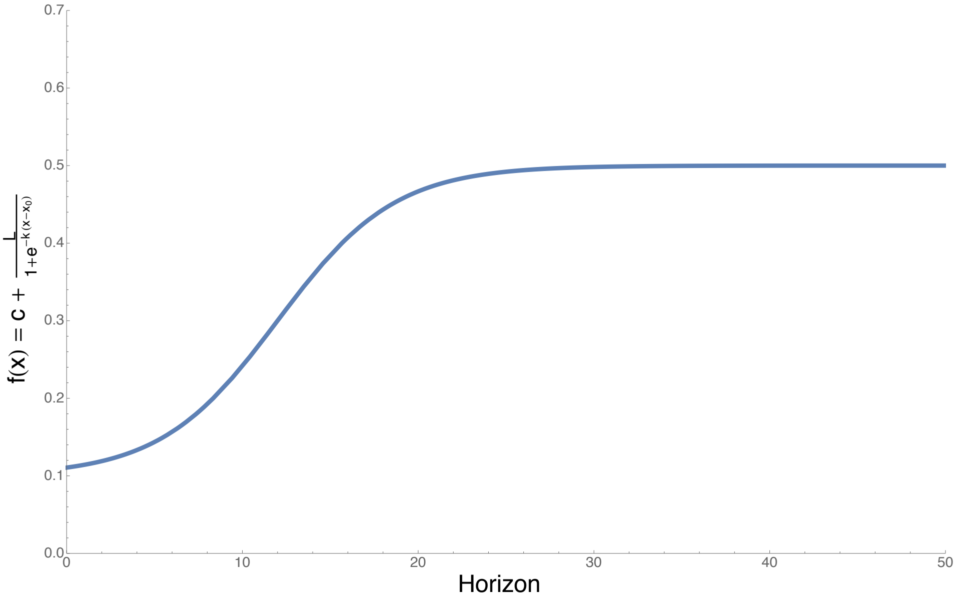
For the hyperpriors $p(\lambda^{(h)}),\ p = 1, \ldots, H$, we choose from a family of Gamma distributions. This choice allows to retain conjugacy and thus both analytical and computational tractability. Consistent with the idea that, if present, VAR misspecifications compound as the horizon grows, we specify the Gamma hyperprior to be more diffuse the larger h.

This is accomplished by choosing the scale and shape parameters of the Gamma in such a way that the mode of the distribution is fixed at 0.4, and the standard deviation is a Logistic function of h that reaches its maximum at horizons larger than $h = 36$. The Logistic function is specified as follows

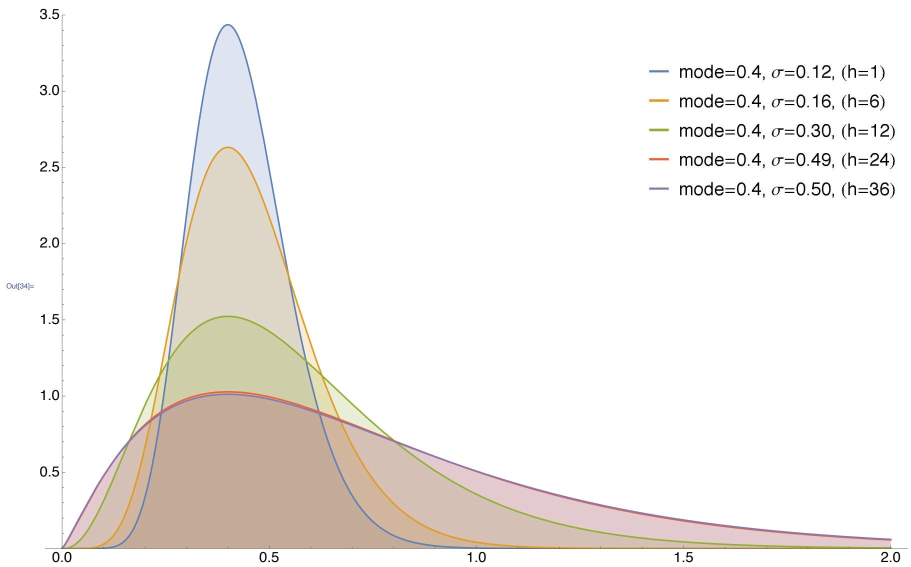
$$\mathrm{sd}(\lambda^{(h)}) = 0.1 + 0.4/[1 + \exp(-0.3(h - 12))] \ ,$$

and plotted in Figure B.1a. Figure B.1b illustrates the evolution of the hyperprior for $\lambda^{(h)}$ as a function of the horizon.

Figure B.1: Hyperprior for BLP-IRF Coefficients



(A) Standard deviation of the hyperprior as a Logistic function of h.



(B) Hyperprior Gamma distributions for a selection of horizons.

C Other Charts and Tables

Table C.1: Test for Information Frictions – 1994:2009

	$FF4_t$		$FF4_t^{GK}$		MPN_t	
lag 1	0.009		0.419		-0.059	
	[0.13]		[5.67]***		[-0.67]	
lag 2	-0.109		-0.290		0.206	
	[-1.48]		[-3.62]***		[2.61]**	
lag 3	0.040		0.092		0.560	
	[0.55]		[1.14]		[7.08]***	
lag 4	0.085		0.122		0.076	
	[1.16]		[1.47]		[0.83]	
$f_{1,t-1}$		-0.009		-0.010		-0.146
		[-1.35]		[-2.65]***		[-4.58]***
$f_{2,t-1}$		0.002		0.004		-0.011
		[0.75]		[1.71]*		[-0.76]
$f_{3,t-1}$		-0.003		-0.005		-0.041
		[-0.77]		[-1.38]		[-1.87]*
$f_{4,t-1}$		0.010		0.007		0.079
		[1.30]		[1.67]*		[2.53]**
$f_{5,t-1}$		0.005		0.000		0.028
		[0.68]		[-0.04]		[0.83]
$f_{6,t-1}$		-0.014		-0.007		0.018
		[-2.44]**		[-2.75]***		[0.91]
$f_{7,t-1}$		-0.014		-0.011		-0.061
		[-1.89]*		[-2.38]**		[-2.44]**
$f_{8,t-1}$		0.000		-0.001		-0.044
		[-0.10]		[-0.23]		[-1.88]*
$f_{9,t-1}$		-0.002		-0.001		-0.045
		[-0.43]		[-0.36]		[-1.79]*
$f_{10,t-1}$		0.004		0.001		-0.039
		[0.75]		[0.22]		[-2.48]**
r^2	0.002	0.132	0.168	0.210	0.282	0.269
F	1.083	1.957	10.205	3.339	16.531	3.532
p	0.366	0.035	0.000	0.000	0.000	0.000
N	183	189	183	189	159	165

Note: Regressions are estimated over the sample 1994:2009. From left to right, the monthly surprise in the fourth federal funds future ($FF4_t$), the instrument in Gertler and Karadi (2015) ($FF4_t^{GK}$), the narrative series of Romer and Romer (2004) (MPN_t). t-statistics are reported in square brackets, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Constant included. Regressions on factors include a lag of the dependent variable. Robust SE.

Table C.2: Variables Used

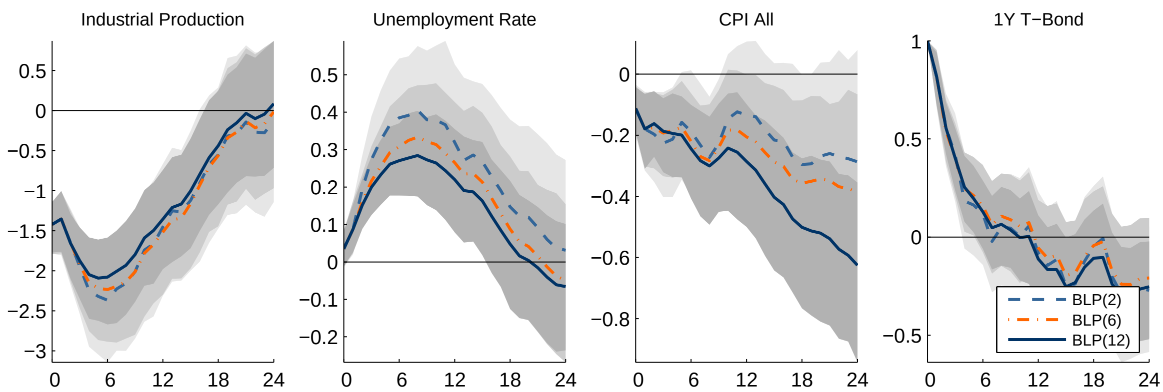
Code	Variable Name	Source	log	MODEL (1)	(2)	(3)	(4)
INDPRO	Industrial Production	FRED	•	•	•	•	•
CAPUTLB00004S	Capacity Utilization	FRED	•	•	•	•	•
UNRATE	Unemployment Rate	FRED		•	•	•	•
AWHMAN	Average Weekly Hours Mfg	FRED	•		•		
CES3000000008	Average Earnings Manufacturing	FRED	•		•		
CPIAUCSL	CPI All Items	FRED	•	•	•	•	•
PCEPI	PCE Deflator	FRED	•		•		•
HOUST	Housing Starts	FRED	•		•		
PERMIT	Building Permits	FRED	•		•		
BUSINVx	Business Inventories	FRED	•		•		
M2SL	M2 Money Stock	FRED	•		•		
BUSLOANS	Business Loans	FRED	•		•		•
DTCTHFNM	Consumer Loans	FRED	•		•		•
RPI	Real Personal Income	FRED	•		•		
DDURRA3M086SBEA	Real Consumption: Durable Goods	FRED	•		•		
DNDGRA3M086SBEA	Real Consumption: Nondurable Goods	FRED	•		•		
S&P 500	S&P 500	FRED	•		•		•
TB3MS	3M T-Bill	FRED				•	
CRBPI	Commodity Price Index	CRB	•	•	•		•
EBP	GZ Excess Bond Premium	FRB	•		•	•	•
DGS1	1Y Treasury Rate	FRED			•	•	•
DGS2	2Y Treasury Rate	FRED					•
DGS5	5Y Treasury Rate	FRED					•
DGS10	10Y Treasury Rate	FRED					•
DGS20	20Y Treasury Rate	FRED					•
YCSLOPE	Term (10Y-1Y Rate) Spread	FRED			•		
OECDEXP	Exports of Goods	OECD	•		•		
OECDIMP	Imports of Goods	OECD	•		•		
BISREER	Real Effective Exchange Rate	BIS	•		•		
BASPREAD	BAA-AAA Spread	FRED			•		
MTGSPREAD	Mortgage Spread (10Y Treasury)	GK			•		
CSHPI	Case Shiller House Price Index	DATASTREAM	•		•		
CFGDP	Expected Gross Domestic Product	CE				•	
CFPCE	Expected Personal Consumption	CE				•	
CFINV	Expected Business Investment	CE				•	
CFPROD	Expected Industrial Production	CE				•	
CFCPI	Expected Consumer Prices	CE				•	
CFURATE	Expected Unemployment Rate	CE				•	
CF3MRATE	Expected 3M Interest Rate	CE				•	

Models: (1) Baseline set for tests in Sections 3 and 4; (2) Channels of monetary transmission in Figure 9; (3) Expectation channel in Figure 11; (4) Interest rate channel in Figure 10. *Sources:* Federal Reserve Economic Data (FRED), Commodity Research Bureau (CRB), Federal Reserve Board (RFB), Organisation for Economic Co-operation and Development (OECD), Bank for International Settlements (BIS), Gertler and Karadi (2015) (GK), Thomson Reuters (DATASTREAM), Consensus Economics (CE).

Figure C.1: Informationally-robust instrument for monetary policy shocks: Crisis Episodes

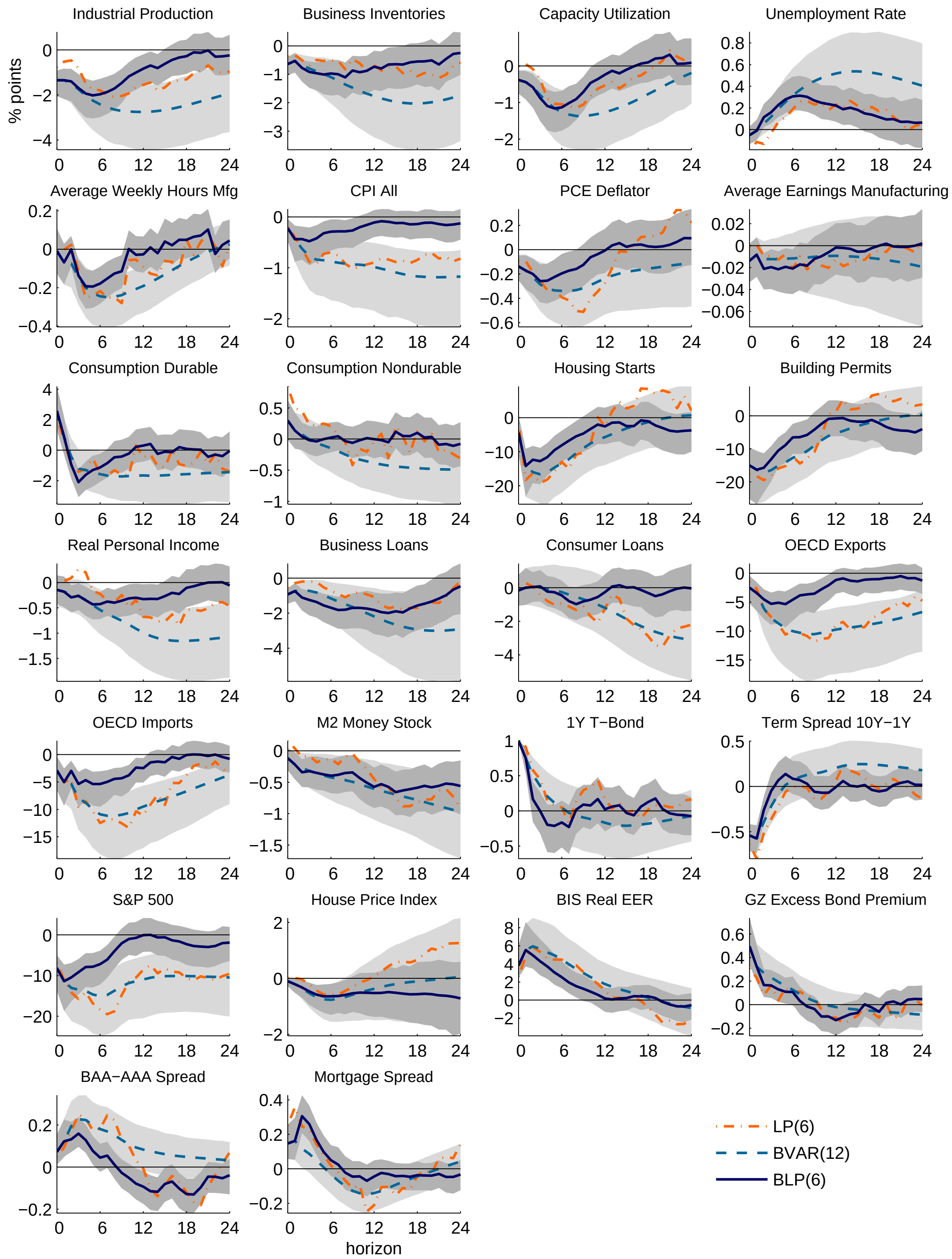
Note: market-based surprises conditional on private agents' information set $FF4_t$ (orange line), residual to Eq. (16) MPI_t, (blue, solid). Shaded areas denote NBER recessions. LEFT PANEL: 2001:01 - 2003:12. RIGHT PANEL: 2007:01 - 2009:12.

Figure C.2: BLP responses: Lag Length



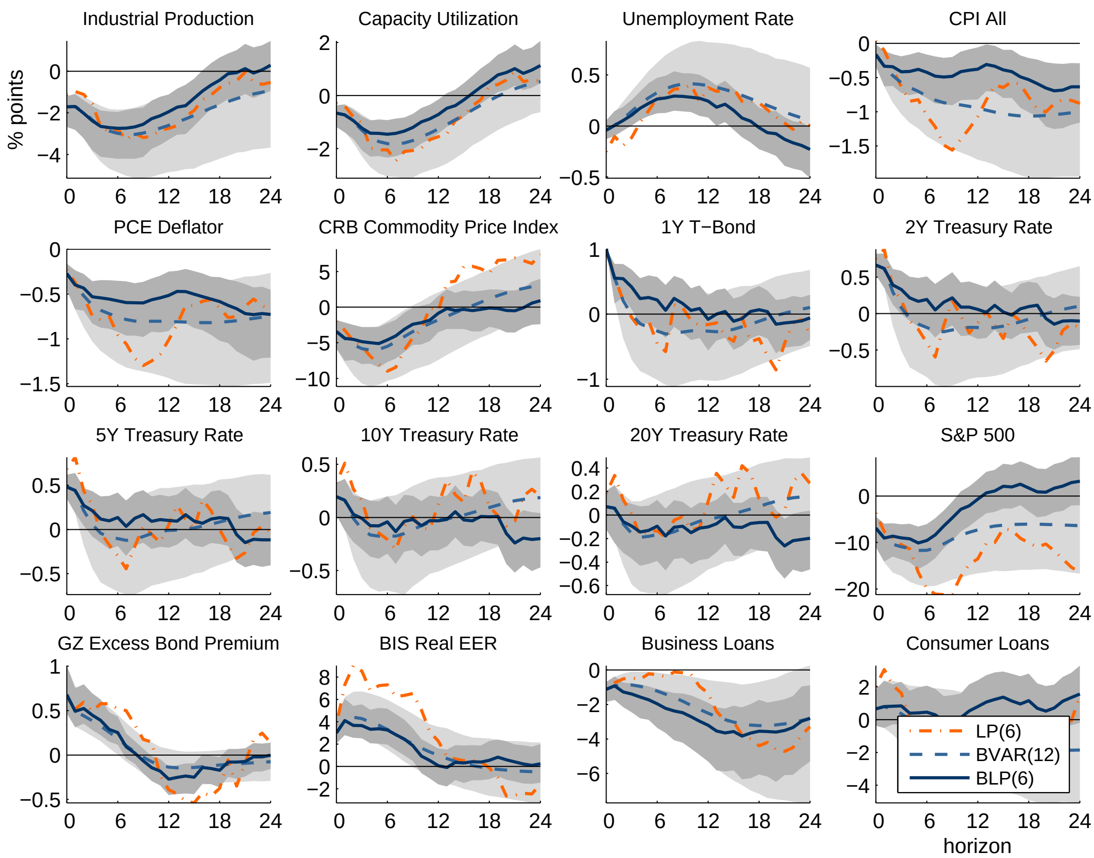
$BLP(2)$ (teal, dashed), $BLP(6)$ (orange, dash-dotted) and $BLP(12)$ (blue, solid) impulse responses. $VAR(12)$ prior. Shaded areas are 90% posterior coverage bands.

Figure C.3: IRFs to Monetary Policy Shock: all Variables, all Methods

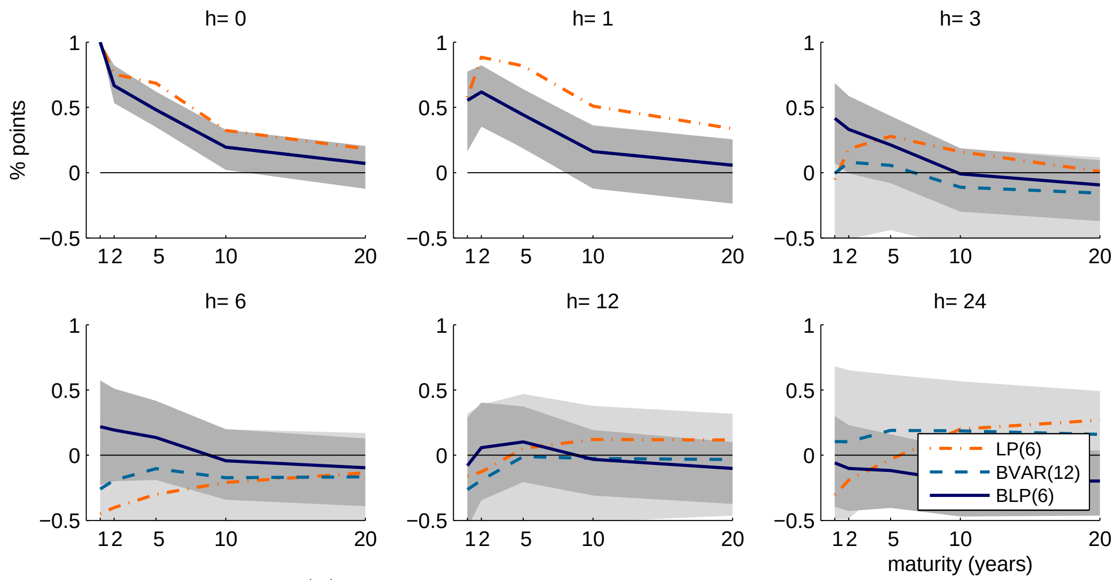


Note: BLP, VAR and LP responses to a contractionary monetary policy shock. Shock identified with the MPI_t series and normalised to induce a 100 basis point increase in the 1-year rate. Sample 1979:01 - 2014:12. $BLP(6)$ with $VAR(12)$ prior over 1969:01 - 1979:01. Shaded areas are 90% posterior coverage bands.

Figure C.4: IRFs to Monetary Policy Shock: Interest Rates, all Methods



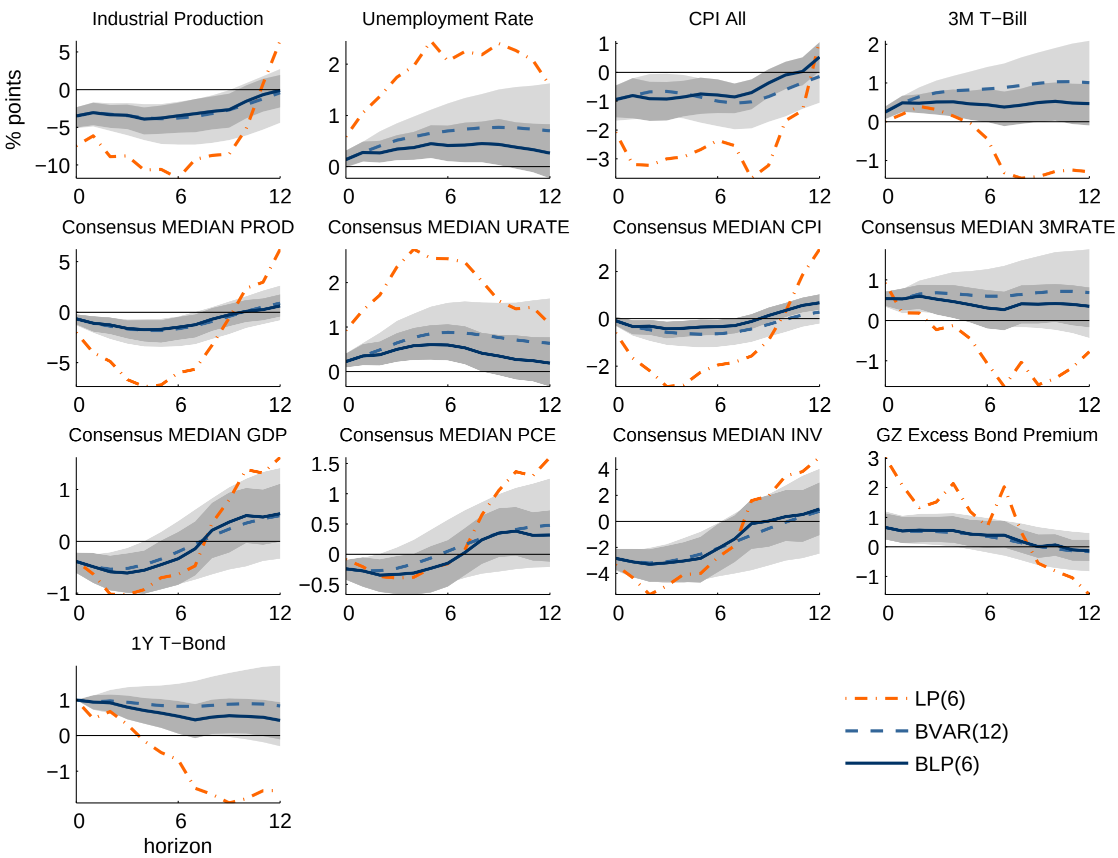
(a) Interest rates responses across horizons.



(b) Interest rates responses across maturities.

Note: BLP, VAR and LP responses to a contractionary monetary policy shock. Shock identified with the MPI_t series and normalised to induce a 100 basis point increase in the 1-year rate. Sample 1979:01 - 2014:12. $BLP(6)$ with $VAR(12)$ prior over 1969:01 - 1979:01. Shaded areas are 90% posterior coverage bands.

Figure C.5: IRFs to Monetary Policy Shock: Private Expectations, all Methods



Note: BLP, VAR and LP responses to a contractionary monetary policy shock. Shock identified with the MPI_t series and normalised to induce a 100 basis point increase in the 1-year rate. Sample 1999:01 - 2014:12. $BLP(6)$ with $VAR(12)$ prior over 1993:01 - 1999:01. Shaded areas are 90% posterior coverage bands.