The Transmission of Monetary Policy Shocks

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Abstract

In the presence of information frictions, commonly used instruments for the identification of monetary policy disturbances combine the true policy shock with information about the state of the economy to which the central bank endogenously reacts. This paper shows that information effects can give rise to the empirical puzzles reported in the literature, and proposes a new high-frequency identification of monetary policy shocks that accounts for informational rigidities. We employ this identification in a novel flexible econometric method robust to misspecifications that bridges between VARs and Local Projections, and assess the model dependence of our results. Findings show 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: C11; C14; E52; G14.

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

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[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,

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[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. A related paper, Miranda-Agrippino and Ricco (2017), proposes an in-depth analysis of the informational content of high-frequency surprises, their predictability, and many additional details. 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 and Ricco, 2017) 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.[5,6] This is the emerging feature of models of imperfect information. 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). We think of this as evidence of the 'signalling channel' discussed in Melosi (2017) – 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; Cloyne and Hürtgen, 2016), 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

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

[6]Looking at financial markets, Gourinchas and Tornell (2004), Piazzesi et al. (2015), Bacchetta et al. (2009) and Cieslak (2016) have connected systematic forecast errors in survey forecasts to puzzles in financial markets.

information set, as summarised by Greenbook forecasts.[7] We use this informationally-robust instrument to identify the shocks from the stochastic component of an autoregressive model (Stock and Watson, 2012, 2017; Mertens and Ravn, 2013). In a standardly specified VAR, our identification does not give rise to either output or price puzzles.

Transmission. Following Ramey (2016), we assess the model dependence of these results and their sensitivity to model misspecification. 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.[8] 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

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[7]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); Hamilton, Pruitt and Borger (2011); Gilchrist, López-Salido and Zakrajšek (2015); Campbell, Fisher, Justiniano and Melosi (2016); Caldara and Herbst (2016). Thapar (2008) and Barakchian and Crowe (2013) 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.

[8]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.

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 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. The expectational channel is also 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

In the presence of informational frictions, monetary policy shocks are best thought of as shifts to the policy rate that are both unforeseen by market participants, and not due to the central bank's concerns about either current or anticipated changes in the economic conditions. Building on the high-frequency identification of Gertler and Karadi (2015) and on Romer and Romer (2004)'s narrative approach, we propose a novel instrument for monetary policy shocks that takes into account both the slow absorption of information in the economy, and the signalling channel of monetary policy that arises from the asymmetry of information between the central bank and market participants.

We provide a microfoundation for our identification strategy using a simple model of noisy information, where both private agents and the central bank update their information sets and make decisions based on noisy signals about the state of the economy. Using the the model's predictions, we then test for the presence of informational frictions in our and other leading instruments for monetary policy shocks.

1.1 An Informationally-robust Instrument

We construct our instrument for monetary policy shocks as the component of market surprises triggered by policy announcements that is orthogonal to both central bank's economic projections, and to past market surprises. Operationally, we proceed in two steps. First, following Gertler and Karadi (2015), we build monthly market surprises as the sum of the daily series in Gürkaynak, Sack and Swanson (2005).[9] We think of these price revisions in interest rates futures as proxies for expectation revisions triggered by FOMC announcements. Second, we regress these monthly surprises onto (*i*) their lags, to control for the autocorrelation due to the slow absorption of information – the trademark of imperfect information –, and (*ii*) onto Greenbook forecasts and forecast revisions for real output growth, inflation and the unemployment rate, as in Romer and

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[9]Differently from Gertler and Karadi (2015), however, we use an unweighted monthly aggregate of daily surprises. With typically one meeting per month, this effectively amounts to assigning each surprise to the month the FOMC meeting falls into. We assign a zero to months without FOMC meetings. For months with more than one meeting, we sum the surprises within the month.

Romer (2004), to control for the central bank's private information, and hence for the signalling channel of monetary policy.

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

$$mps_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i mps_{t-i} +$$
$$+ \sum_{j=-1}^{3} \theta_j F_t^{cb} x_{q+j} + \sum_{j=-1}^{2} \vartheta_j \left[F_t^{cb} x_{q+j} - F_{t-1}^{cb} x_{q+j} \right] + MPI_t. \qquad (1)$$

mps_t denotes the market-based 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.[10,11]

The daily series used to construct the monthly monetary policy surprises (mps_t) are the intraday movements in the fourth federal funds futures contracts ($FF4_t$) 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 and 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 (see e.g. Gürkaynak et al., 2005).

In Figure 1 we plot the original monetary surprise mps_t ($FF4_t$, orange line) and our instrument for the monetary policy shock (MPI_t, blue line). Interestingly, the chart shows that significant discrepancies arise during times of economic distress (see also

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[10]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.

[11]Identification with external instruments entails regressing reduced-form innovations onto the instrument. Because our instrument is a residual generated regressor, OLS-based inference is asymptotically correct (Pagan, 1984).

FIGURE 1: INFORMATIONALLY-ROBUST INSTRUMENT FOR MONETARY POLICY
SHOKS
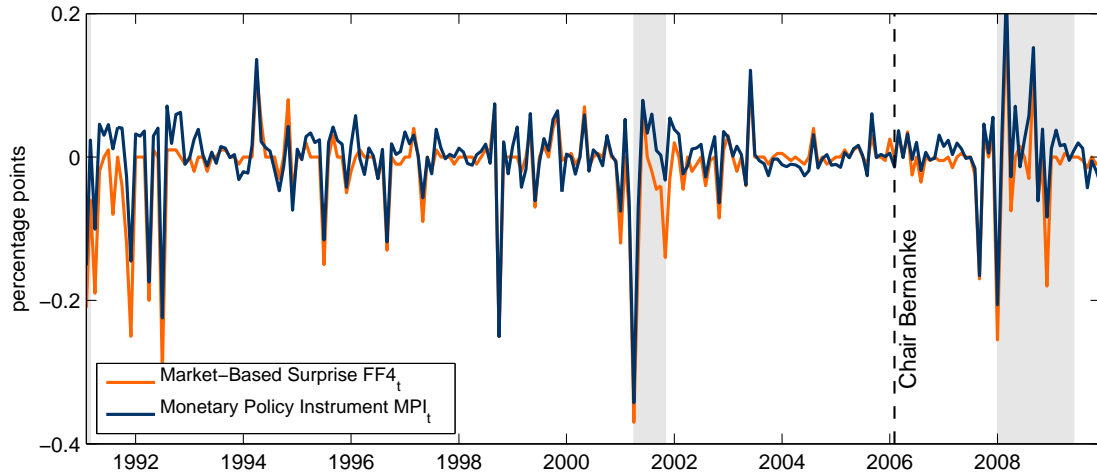
Note: market-based surprises conditional on private agents' information set $FF4_t$ (orange line), residual to Eq. (1) MPI_t (blue, solid). Shaded areas denote NBER recessions.

Figure C.1 in Appendix C). More importantly, however, the difference between these two series resides in their informational content. Indeed, as results in Section 1.3 show, the MPI_t series is the only one that survives the tests for informational frictions.

1.2 A Simple Noisy Information Model

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. This implies that revisions of expectations – and importantly movements in market prices – can be correlated over time, and contain information on both current and past structural shocks. Moreover, due to the asymmetry of information between policy makers and market participants, observable policy actions convey information about fundamentals. 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 funda-

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rate i_t announced
$\mathcal{I}_{i,\bar{t}} = \{i_t, \mathcal{I}_{i,\underline{t}}\}$
trade on $F_{\bar{t}}x_t - F_{\underline{t}}x_t$

$\overline{t-1}$
$\bar{t}$
$\cdots$

$\cdots$

$\underline{t}$
$\underline{t+1}$

signals $s_{i,\underline{t}} = x_t + \nu_{i,\underline{t}}$
$\mathcal{I}_{i,\underline{t}} = \{s_{i,\underline{t}}, \mathcal{I}_{i,\overline{t-1}}\}$
$F_{i,\underline{t}}x_t$
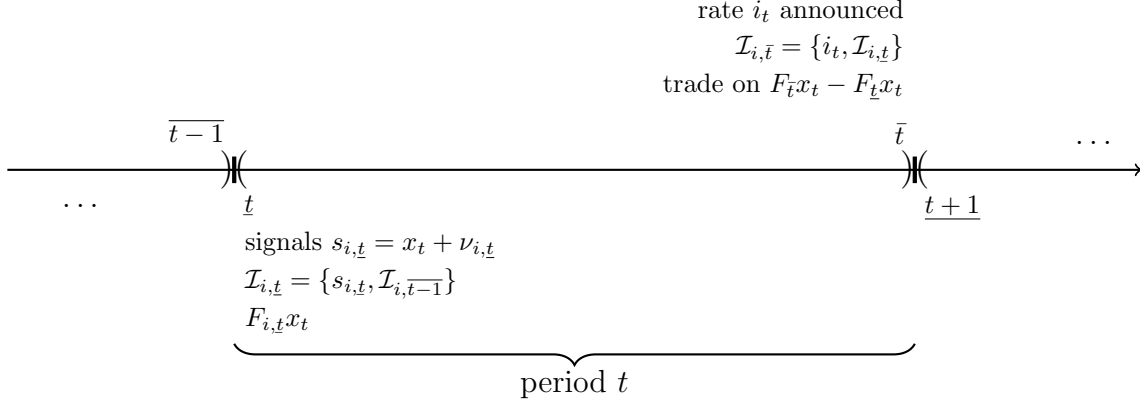
period t

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 $\bar{t}$.

mentals evolves following an autoregressive process

$$x_t = \rho x_{t-1} + \xi_t \qquad \xi_t \sim \mathcal{N}(0, \Sigma_\xi) \ . \tag{2}$$

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 noisy signals that they receive. We use $s_{i,\underline{t}}$ and $s_{cb,\underline{t}}$ to denote the signals received at time $\underline{t}$ by private agents and the central bank respectively. Similarly, we use $F_{i,\underline{t}}$ and $F_{cb,\underline{t}}$ to denote their respective conditional forecasts. The information flow is sketched in Figure 2.

Agents can trade securities (e.g. futures contracts) based on i_{t+h}, the realisation of the policy rate at time $t + h$. The price of a futures contract on i_{t+h} reflects their aggregate expectation about x_t, as follows

$$p_{\underline{t}}(i_{t+h}) = F_{\underline{t}}x_{t+h} + \mu_t \ , \tag{3}$$

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where μ_t is a stochastic component, 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 $\bar{t}$, and conditional on its own forecast $F_{cb,\underline{t}}x_t$, the central bank sets the interest rate for the current period using a Taylor rule

$$i_t = \phi_0 + \phi'_x F_{cb,\underline{t}}x_t + u_t + w_{t|t-1} \ , \tag{4}$$

where u_t denotes the monetary policy shock and K_{cb} is the central bank's Kalman gain.[12] Also, the central bank can announce – or leak – at time $t-1$ a deviation from the Taylor rule, $w_{t|t-1}$, that takes places at time t.[13] Having observed the current policy rate, agents update their forecasts, and trade at $\bar{t}$. Conditional on i_{t-1}, observing the interest rate is equivalent to receiving a public signal with common noise $\tilde{s}_{cb,\bar{t}}$ from the central bank. Because of this forecast update triggered by the policy announcement, the price of futures contracts is revised by an amount proportional to the average (in population) revision of expectations, that is

$$p_{\bar{t}}(i_{t+1}) - p_{\underline{t}}(i_{t+1}) \propto (F_{\bar{t}}x_{t+1} - F_{\underline{t}}x_{t+1}) \ , \tag{6}$$

where $F_{\underline{t}}x_{t+1}$ and $F_{\bar{t}}x_{t+1}$ are the average forecast updates that follow $s_{i,\underline{t}}$ and $\tilde{s}_{cb,\bar{t}}$. In Appendix A we provide a proof of the following lemma.

Lemma. *Following a central bank policy announcement, aggregate expectations revisions*

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[12]Interestingly, the interest rate smoothing in the monetary policy rule arises naturally from the signal extraction problem faced by the central bank. Indeed, it is possible to rewrite Eq. (4) as

$$i_t = [1 - (1 - K_{cb})\rho]\phi_0 + (1 - K_{cb})\rho i_{t-1} + K_{cb}\phi'_x s_{cb,\underline{t}} - (1 - K_{cb})\rho u_{t-1} + u_t \ . \tag{5}$$

The policy rate at any time t is a function of current and past signals, and of current and past monetary policy shocks.

[13]This announced deviation – that can be thought of as due to either implicit or explicit forward guidance – creates a wedge between Taylor rule residuals and monetary policy shocks. Additionally, Taylor rule deviations can also be autocorrelated and hence forecastable. In these cases, the monetary policy shocks would be different from the residuals of a regression of the policy rate on central bank's private forecasts. For the sake of simplicity, we abstract from such case in the model, while testing empirically for predictability and autocorrelation of residuals form an empirically estimated Taylor rule.

evolve as

$$F_{\bar{t}}x_t - F_{\underline{t}}x_t = (1 - K_2)(1 - K_1)\left[F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t\right]$$
$$+ K_2(1 - K_1)\xi_t + K_2\left[\nu_{cb,\underline{t}} - (1 - K_1)\rho\nu_{cb,\underline{t-1}}\right]$$
$$+ K_2(K_{cb}\phi'_x)^{-1}\left[u_t - \rho(K_1 - K_{cb})u_{t-1} + (1 - K_1)(1 - K_{cb})\rho^2 u_{t-2}\right], \quad (7)$$

where K_1 and K_2 denote the agents' Kalman gains employed in $F_{i,\underline{t}}$ and $F_{i,\bar{t}}$ respectively, K_{cb} is the central bank's Kalman gain, u_t is a monetary policy shock, and ν_{cb} is the central bank's observational noise.

Two emerging features of models of imperfect information that have important implications for the identification of monetary policy shocks are in evidence in Eq. (7). First, average expectation revisions (and thus high-frequency surprises) – a direct measure of the shocks under full information –, are orthogonal neither to their past, nor to past available information due to the slow absorption of new information over time. Second, observable policy actions can transfer information about economic fundamentals from the policy maker to market participants. Indeed, the second term in Eq. (7) that depends on the structural shocks ξ_t is the update of expectations due to the revisions of beliefs about the state of the economy that follow the policy announcement – i.e. the 'the signalling channel' (see Melosi, 2017; 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 policy rate increase, these two scenarios imply profoundly different evolutions for macroeconomic aggregates, and agents' expectations (see e.g. Campbell et al., 2012, and Section 5).[14]

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[14]It is also worth noticing that the third term in Eq. (7) is the aggregate noise contained in the policy announcement, due to the central bank's noisy observation of the state of the economy. This too

Eq. ([7](#)) provides us with testable predictions about market-based monetary surprises: in the presence of imperfect information they are (i) serially correlated, (ii) predictable using other macroeconomic variables, and (iii) correlated with the central bank's projections of relevant macroeconomic variables. We empirically document the testable implications of these three predictions in the reminder of this section.

1.3 Testing for Imperfect Information

Tables [1](#) and [2](#) report the tests for (i) serial correlation, (ii) correlation with the Fed's internal forecasts, and (iii) predictability with lagged state variables, for our and other commonly used instruments for monetary policy shocks. 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](#)); FF4-based market surprises calculated around scheduled FOMC meetings only ($FF4_t^{\dagger}$); 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.[15] All regressions displayed are estimated at monthly frequency on all available observations over the sample 1990:01 - 2009:12.[16]

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 MPI_t instrument is orthogonal to both sets of variables by construction. The null is strongly rejected for both the Greenbook forecasts themselves and their revision, and for all types of monthly market surprises.[17] The correlation with the central bank's private forecast is not driven by the un-scheduled meetings. The signalling channel, enabled by the information asymmetry, is a feature of all central banks' announcements. We note, however, that the bulk of predictability

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can be thought of as another exogenous policy shift (see Orphanides, [2003](#)).

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

[16]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](#)).

[17]Related results are in Barakchian and Crowe ([2013](#)), Gertler and Karadi ([2015](#)), Ramey ([2016](#)) and Miranda-Agrippino and Ricco ([2017](#)).

Table 1: Serial Correlation and Central Bank Signalling

	$FF4_t$		$FF4_t^\dagger$		$FF4_t^{GK}$		MPN_t
$AR(4)$	2.219		3.498		10.480		16.989
	[0.068]*		[0.009]***		[0.000]***		[0.000]***
R^2	0.021		0.047		0.142		0.237
N	230		202		230		207
Greenbook Forecast	2.287		2.413		3.377		–
	[0.011]**		[0.008]***		[0.000]***		
Greenbook Revision		2.702		4.667		3.719	–
		[0.007]***		[0.000]***		[0.000]***	
R^2	0.080	0.068	0.163	0.128	0.129	0.100	–
N	238	238	232	232	238	238	–

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 monthly surprise in the fourth federal funds future in scheduled meetings only ($FF4_t^\dagger$), the instrument in Gertler and Karadi (2015) ($FF4_t^{GK}$), the narrative series of Romer and Romer (2004) (MPN_t). 1990:2009. F-statistics with robust p-value in square brackets, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, robust SE.

resides in the forecast revisions between consecutive meetings. This is consistent with the characteristics of the signalling channel. In the first row of the table, we note that all four series are autocorrelated. 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.[18]

In Table 2 we project the different measures of monetary policy shocks (including our own) on a set of lagged macro-financial factors extracted from the collection of monthly variables assembled in McCracken and Ng (2015). The dataset that we 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 2 confirm the predictability of market-based monetary surprises using past information.[19] They also show that narrative accounts of

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[18] As pointed out in Coibion and Gorodnichenko (2012), the OLS coefficients in the autoregression 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.18).

[19] Miranda-Agrippino and Ricco (2017) shows that market-based monetary surprises are significantly

TABLE 2: PREDICTABILITY OF MONETARY POLICY INSTRUMENTS

	$FF4_t$		$FF4_t^\dagger$		$FF4_t^{GK}$		MPN_t		MPI_t	
$f_{1,t-1}$	-0.012	[-1.97]*	-0.006	[-1.14]	-0.011	[-2.74]***	-0.103	[-4.13]***	0.006	[0.98]
$f_{2,t-1}$	0.001	[0.38]	0.000	[0.13]	0.004	[1.79]*	-0.005	[-0.45]	0.005	[1.56]
$f_{3,t-1}$	0.002	[0.41]	0.007	[1.33]	-0.001	[-0.23]	-0.035	[-2.21]**	0.001	[0.29]
$f_{4,t-1}$	0.015	[2.09]**	0.008	[1.33]	0.008	[1.92]*	0.068	[2.71]***	0.005	[0.70]
$f_{5,t-1}$	0.002	[0.26]	-0.001	[-0.19]	0.001	[0.12]	0.017	[0.61]	0.008	[1.18]
$f_{6,t-1}$	-0.011	[-2.19]**	-0.006	[-1.72]*	-0.007	[-2.58]**	0.008	[0.57]	-0.008	[-1.63]
$f_{7,t-1}$	-0.010	[-1.69]*	-0.005	[-0.85]	-0.006	[-1.40]	-0.053	[-2.85]***	-0.004	[-0.54]
$f_{8,t-1}$	-0.001	[-0.35]	-0.001	[-0.49]	0.001	[0.32]	-0.042	[-2.38]**	-0.001	[-0.15]
$f_{9,t-1}$	-0.002	[-0.59]	-0.002	[-.42]	-0.002	[-0.53]	-0.037	[-1.65]	0.000	[0.07]
$f_{10,t-1}$	0.004	[0.75]	0.006	[1.18]	0.000	[-0.03]	-0.030	[-2.54]**	-0.003	[-0.70]
R^2	0.073		0.025		0.140		0.202		0.033	
F	2.230		1.788		3.572		3.372		2.225	
p	0.014		0.058		0.000		0.000		0.014	
N	236		224		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 monthly surprise in the fourth federal funds future in scheduled meetings only ($FF4_t^\dagger$), 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 1.1 (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.

'unanticipated' interest rate changes are similarly predictable by state variables which are a function of past structural shocks.[20]

Our results on the predictability of the narrative series are novel, and can be rationalised as follows. The construction of MPN_t amounts to running a regression motivated by an empirical Taylor rule, and using the residuals as a measure of the shocks u_t. If, however, the deviation from the rule is autocorrelated, the residuals of the projection of the policy rate onto central bank's forecasts are not the structural shock u_t – agents can try to forecast it using past information. Moreover, the projection residuals may also be contaminated by announced policy changes, as is the case e.g. for forward guidance.[21]

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predictable by lagged factors intended to summarise the pre-existing economic and financial conditions in the economy. The predictability holds across both financial instruments and countries.

[20]Factors are estimated using last vintage data which are likely to incorporate revisions to early releases. 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.

[21]See e.g. discussion of Eq. (4). 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 will also be endogenous to these variables. This again may show up as predictability

1.4 The Role of Different Identifying Assumptions

Our informationally robust instrument allows us to study the role that different informational assumptions have on the identification of monetary policy shocks. We compare responses to shocks estimated in a standard VAR while changing the external instrument used for the identification.[22] 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.[23] 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. We choose the 1-year nominal rate as our policy variable as in Gertler and Karadi (2015), and normalise the responses such that the shock increases the policy rate by 1% on impact. All variables are monthly. Impulse response functions are from a VAR(12) estimated in levels from 1979:01 to 2014:12.[24]

Figure 3 collects the results. The difference among the IRFs reported in the charts lies in the informational assumptions made in order to identify the shock, the VAR being the same in all cases. 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 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 solid blue lines indicate the effects of a monetary disturbance identified using our informationally robust instrument MPI_t.[25]

A few features are noteworthy. First, both the narrative and Gertler and Karadi

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with factors.

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

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

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, 2017; 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.

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

[24]Results on robustness to the sample are in Section 5.

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

FIGURE 3: RESPONSES TO MONETARY POLICY SHOCK UNDER DIFFERENT IDENTIFICATIONS
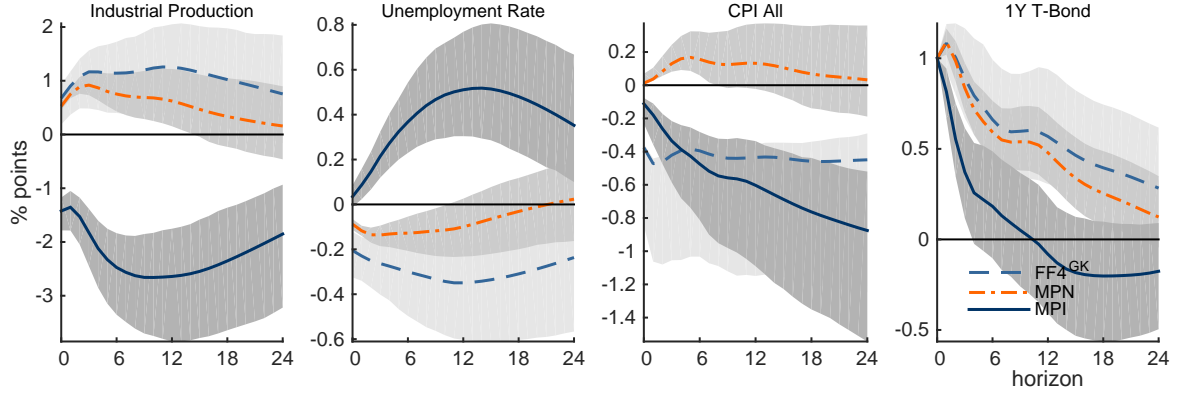
Note: Shock identified with Gertler and Karadi (2015)'s average monthly market surprise (teal, dashed), extended narrative measure of Romer and Romer (2004) (orange, dash-dotted), informationally robust MPI_t series (dark blue lines). The shock is normalised to induce a 100 basis point increase in the 1-year rate. Sample 1979:1 - 2014:12. Shaded areas are 90% posterior coverage bands.

TABLE 3: 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.

(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 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 and Ricco (2017). 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. 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, the heterogeneity of the responses in Figure 3 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 1.3). 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 3).

A potentially important concern relates to the role of unscheduled meetings, where the FOMC takes urgent decisions in moments of particular economic distress – as it happened for example during the Great Recession. These unexpected meetings that coalesce markets attention, may in fact be the ones responsible for the information channel. We assess this concern by showing in Figure 4 that none of the conclusions change if only surprises registered at scheduled FOMC meetings are used for the identification.

In the next section we explore the model dependence of these results.
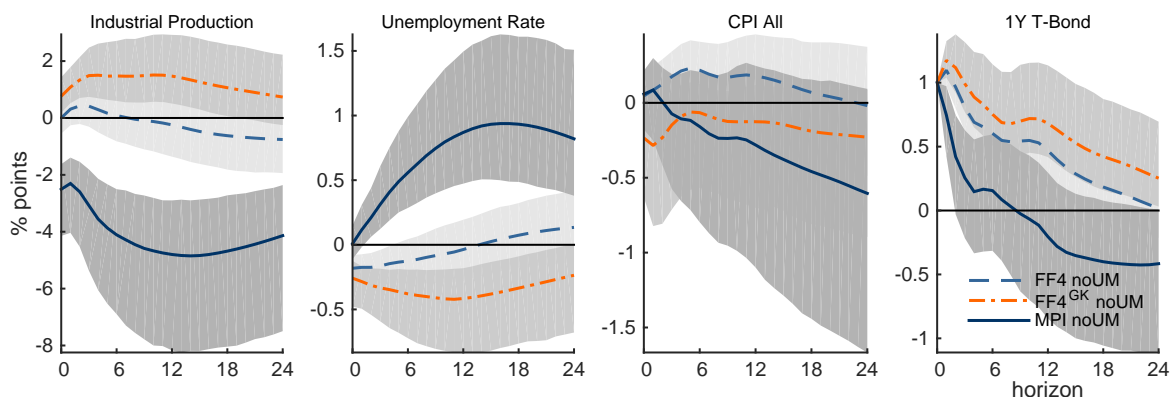
Note: Shock identified with Gertler and Karadi (2015)'s average monthly market surprise (teal, dashed), extended narrative measure of Romer and Romer (2004) (orange, dash-dotted), informationally robust MPI_t series (dark blue lines). The shock is normalised to induce a 100 basis point increase in the 1-year rate. Sample 1979:1 - 2014:12. Shaded areas are 90% posterior coverage bands.

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 – i.e. combinations of economically meaningful shocks –, and identifies the ones of interest using a variety of different schemes. Once the structural shocks are identified, the autoregressive coefficients of the model are employed to study the transmission of the exogenous disturbances over time. While considerable attention has been devoted to the identification of the shocks, the issues related to model specification have often been overlooked (see also discussion in Caldara and Herbst, 2016).

The standard approach in empirical monetary economics is to employ small VARs consisting of a policy indicator and a few macroeconomic variables of interest. However, it is well understood that such small VARs are likely to be misspecified.[26] In this case,

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[26]Misspecifications can arise 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. Second, the lag order of the underlying process may potentially be underestimated. Also, if the disturbances of the underlying data generating process are a moving average process, fitting

estimates of the parameters – transmission coefficients and covariance matrix alike – are inconsistent (Braun and Mittnik, 1993). In turn, this affects both the identification of the disturbances and the estimated impulse responses. These concerns have motivated the adoption of more flexible, 'non-parametric' empirical specifications, such as Jordà (2005)'s local projections (LP).

From a classical perspective, choosing between iterated VARs and direct methods such as LP 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 more prone to bias if the one-step-ahead model is misspecified.[27] We think of this as a standard trade-off in Bayesian estimation and propose a Bayesian approach to Local Projection (BLP) that optimally spans the model space between VAR-based and LP-based impulse responses (IRFs). Intuitively, BLP regularises LP responses using priors centred around an iterated VAR, while allowing the data structure to select the optimal degree of departure form the priors at each horizon. This approach has a dual interpretation in classic regularisation techniques.

2.1 Bayesian Local Projections

VARs recover impulse responses by iterating up to the relevant horizon the coefficients of a system of one-step ahead reduced-form equations

$$y_{t+1} = By_t + \varepsilon_{t+1} \qquad \varepsilon_t \sim \mathcal{N}(0, \Sigma_\varepsilon) \; , \tag{8}$$

where $y_t = (y_t^1, \ldots, y_t^n)'$ is a $(n \times 1)$ random vector of macroeconomic variables, B is an n-dimensional matrix of coefficients, and ε_t is an $(n \times 1)$ vector of reduced-form

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a low-order, or indeed any finite-order VAR may be inadequate. 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.

[27]In the forecasting literature, the distinction between direct LP IRFs and iterated VAR 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). Direct forecasts tend to have higher sample MSFEs than iterated forecasts, and become increasingly less desirable as the forecast horizon lengthens (see Marcellino et al., 2006). Also, LP asymptotic intervals are often less accurate than the bias-adjusted VAR bootstrapped intervals, notwithstanding their large average width (see Kilian and Kim, 2011).

innovations.[28] Conversely, LPs estimate the IRFs directly from a set of linear regressions of the form

$$y_{t+h} = B^{(h)}y_t + \varepsilon_{t+h}^{(h)} \ , \qquad \varepsilon_{t+h}^{(h)} \sim \mathcal{N}\left(0, \Sigma_{\varepsilon}^{(h)}\right) \qquad \forall \ h = 1, \ldots, H \ . \tag{9}$$

Being a combination of one-step-ahead forecast errors, the projection residuals $\varepsilon_{t+h}^{(h)}$ are serially correlated and heteroskedastic.

The horizon-h impulse response functions from the two methods are given by

$$\text{IRF}_h^{\text{VAR}} = B^h A_0^{-1} \ , \tag{10}$$

$$\text{IRF}_h^{\text{LP}} \ = B^{(h)} A_0^{-1} \ , \tag{11}$$

where A_0 identifies the mapping between the structural shocks u_t and the reduced-form one-step-ahead forecast errors, i.e. $\varepsilon_t = A_0^{-1} u_t$. Assuming the VAR to be the true description of the data generating process, the coefficients and residuals of an iterated VAR can be readily mapped into those of LP, yielding

$$B^{(h)} \longleftrightarrow B^{(\text{VAR},h)} = B^h \ , \tag{12}$$

$$\varepsilon_{t+h}^{(h)} \longleftrightarrow \varepsilon_{t+h}^{(\text{VAR},h)} \ = \sum_{j=1}^{h} B^{h-j} \varepsilon_{t+h} \ . \tag{13}$$

Three observations are in order. First, conditional on the underlying data generating process being the linear model in Eq. (8), and abstracting from estimation uncertainty, the IRFs computed with the two methods should coincide. Second, as shown by Eq. (13), conditional on the linear model being correctly specified, LPs are bound to have higher estimation variance due to (strongly) autocorrelated residuals.[29] 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

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[28]To provide the gist of our approach and simplify the notation, we omit deterministic components from Eq. (8), and consider a simple VAR(1). However, this is equivalent to a VAR(p) written in VAR(1) companion form. A detailed description of the method is reported in Appendix B.

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

assumptions, the way in which the A_0 matrix is derived from either VARs or LPs coincides.

The map in Eq. (12-13) provides a natural bridge between the two empirical specifications, which we exploit to inform the priors for our method.[30] For the coefficients of Eq. (9) at each horizon h, and leaving temporarily aside concerns about the structure of the projection residuals, we specify standard conjugate Normal-inverse Wishart informative priors of the form

$$\Sigma_\varepsilon^{(h)} \mid \lambda^{(h)} \sim \mathcal{IW}\left(\Psi_0^{(h)}, d_0^{(h)}\right),$$
$$\beta^{(h)} \mid \Sigma_\varepsilon^{(h)}, \lambda^{(h)} \sim \mathcal{N}\left(\beta_0^{(h)}, \Sigma_\varepsilon^{(h)} \otimes \Omega_0^{(h)}\left(\lambda^{(h)}\right)\right), \tag{14}$$

where $\beta^{(h)}$ is the vector containing all the local projection coefficients at horizon h – i.e. $\beta^{(h)} \equiv vec\left(B^{(h)}\right)$. $\lambda^{(h)}$ is the hyperparameter that regulates the variance of the coefficients in $\beta^{(h)}$, and thus effectively determines the overall tightness of the priors. The prior mean $\beta_0^{(h)}$ is informed by the iterated coefficients of a similarly specified VAR estimated over a pre-sample. For the model in Eq. (8) this writes

$$\beta_0^{(h)} = vec\left(B_{T_0}^h\right), \tag{15}$$

where $B_{T_0}^h$ is the h-th power of the autoregressive coefficients estimated over a pre-sample T_0, that is then discarded. As it is standard in Bayesian econometrics modelling, we fix $d_0^{(h)}$ equal to the number of variables minus 2, such that the prior mean of $\Sigma_\varepsilon^{(h)}$ exists, and the remaining hyperparameters in $\Psi_0^{(h)}$ and $\Omega_0^{(h)}$ using sample information (see e.g. Kadiyala and Karlsson, 1997; Banbura et al., 2010). Appendix B provides all the details. Intuitively, the prior gives weight to the belief that a VAR can describe the behaviour of economic time series, at least first approximation.[31]

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[30]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.

[31]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 Appendix B. Also, one could

The posterior distribution for the BLP coefficients can then be obtained by combining the priors in Eq. (14) with the likelihood of the data conditional on the parameters, where the autocorrelation of the projection residuals is not taken into account. This modelling choice has three 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. However, there is a third implication that is the price to pay for the first two: 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 misspecified posterior distribution. This implies that if one were to draw inference about $\beta^{(h)}$ – i.e. the horizon-h responses –, from the misspecified posterior distribution, 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.[32] Hence, similarly to the frequentist 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:

$$\Sigma_{\varepsilon,\text{HAC}}^{(h)} \mid \lambda^{(h)}, \text{y} \sim \mathcal{IW}\left(\Psi_{\text{HAC}}^{(h)}, d\right),$$

$$\beta^{(h)} \mid \Sigma_{\varepsilon,\text{HAC}}^{(h)}, \lambda^{(h)}, \text{y} \sim \mathcal{N}\left(\tilde{\beta}^{(h)}, \Sigma_{\varepsilon,\text{HAC}}^{(h)} \otimes \Omega^{(h)}\right). \tag{16}$$

This allows us to remain agnostic about the source of model misspecification as in Jordà (2005).

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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).

[32]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.

It is important to observe that BLP IRFs have been engineered to span the space between VARs and local projections. This allows us to assess the model dependence of the results under the discipline provided by the data. To see this, note that given the prior in Eq. (14), the posterior mean of BLP responses takes the form

$$B_{\text{BLP}}^{(h)} \propto \left(X'X + \left(\Omega_0^{(h)} \left(\lambda^{(h)} \right) \right)^{-1} \right)^{-1} \left((X'X) B_{\text{LP}}^{(h)} + \left(\Omega_0^{(h)} \left(\lambda^{(h)} \right) \right)^{-1} B_{\text{VAR}}^{h} \right), \quad (17)$$

where $X \equiv (x_{h+2}, \ldots, x_T)'$, and $x_t \equiv (1, y'_{t-h}, \ldots, y'_{t-(h+1)})'$, while the posterior variance of BLP coefficients is equal to

$$\mathbb{V}ar \left(B_{\text{BLP}}^{(h)} \right) = \Sigma_{\varepsilon,\text{HAC}}^{(h)} \otimes \left(X'X + \left(\Omega_0^{(h)} \left(\lambda^{(h)} \right) \right)^{-1} \right)^{-1}. \quad (18)$$

At each horizon h, the relative weight of VAR and LP responses is set by $\Omega_0^{(h)} \left(\lambda^{(h)} \right)$ 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.

Hence, this formulation allows us to solve the the bias-variance trade-off by estimating IRFs that are an optimal combination of LP and VAR-based IRFs at each horizon. In fact, extending the argument in Giannone, Lenza and Primiceri (2015), we treat $\lambda^{(h)}$ as an additional model parameter for which we specify a Gamma prior probability distribution, and estimate it at each horizon as the maximiser of the posterior likelihood in the spirit of hierarchical modelling. This allows us to effectively balance bias and estimation variance at all horizons, and therefore solve the trade-off in a fully data-driven way.[33] Since the marginal likelihood is available in closed-form, we can estimate $\lambda^{(h)}$ at each horizon as the maximiser of the posterior likelihood (see Giannone et al., 2015, for details). This step requires a numerical optimisation. Conditional on a value of $\lambda^{(h)}$, the BLP coefficients $\left[\beta^{(h)}, \Sigma_{\varepsilon,\text{HAC}}^{(h)} \right]$ can then be drawn from their posterior, which is Normal-inverse-Wishart with HAC-corrected posterior scale.

[33]See Appendix B for details.

3 VAR, LP, and BLP

We start our empirical exploration by comparing the IRFs estimated using VAR, LP, and BLP in Figure 5. The matrix of contemporaneous transmission coefficients A_0 is the same in the three cases, and is estimated using our informationally robust series MPI_t as an external instrument.The contractionary 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 variables used are the same as in Section 1. It should be stressed that the information set considered is likely to be misspecified due to the small number of variables considered. Unless otherwise stated, we set the number of lags in both VAR and LP to 12 and use the observations between 1969:01 and 1979:01 as a pre-sample to centre the prior for the BLP coefficients. The estimation sample goes from 1979:01 to 2014:12. For the hyperparameters $\lambda^{(h)}$ we specify Gamma hyperpriors with mode equal to 0.4 and a standard deviation that is a Logistic function of the forecast horizon.[34]

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 5 is qualitative similar. This is not necessarily the case, as results in Sections 4 and 5 show.

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[34]A detailed description of the method is in Appendix B. See Table C.2 in Appendix C for details on series included. The resilience of BLP responses to the chosen lag length is plotted in Figure C.2 in Appendix C. Results are also robust to the lag length of the VAR prior (not shown).
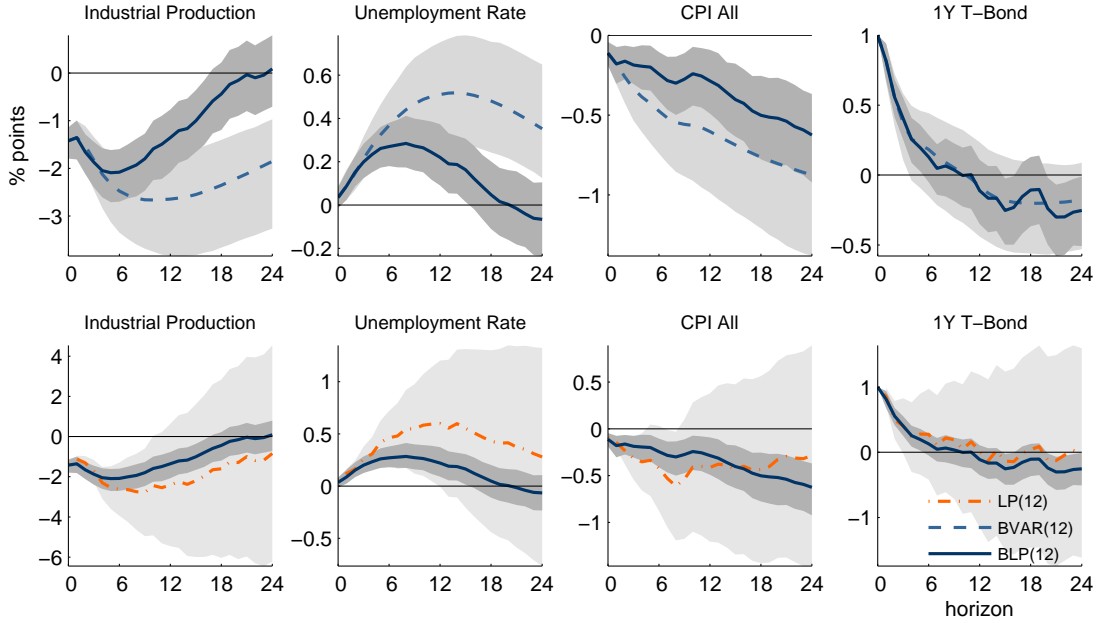
TOP ROW: VAR (teal, dashed) and BLP (blue, solid) impulse responses. BOTTOM ROW: LP (orange, dash-dotted) and BLP (blue, solid) impulse responses. Shaded areas are 90% posterior coverage bands.

VAR responses are, by construction, the smoothest. Based on the same one-step-ahead model iterated forward, VAR responses naturally also have tighter bands than LP do – Eq. (13). 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 iterative structure, rather then being genuine features of the data. The blue bars in Figure 6 display the optimal prior shrinkage hyperparameters that maximise $p(\lambda^{(h)}|y^{(h)})$, $y^{(h)} = vec(Y^{(h)})$, $Y^{(h)} \equiv (y_{p+1+h}, \dots, y_T)'$ for $h = 2, \dots, 24$ in the BLP responses in Figure 5. The VAR prior is optimally loosened as the horizon increases, suggesting that the data tend to progressively deviate from the VAR responses. In particular, we observe that while the policy rate response is similar across the two methods, BLP peak responses for the other variables are registered significantly earlier

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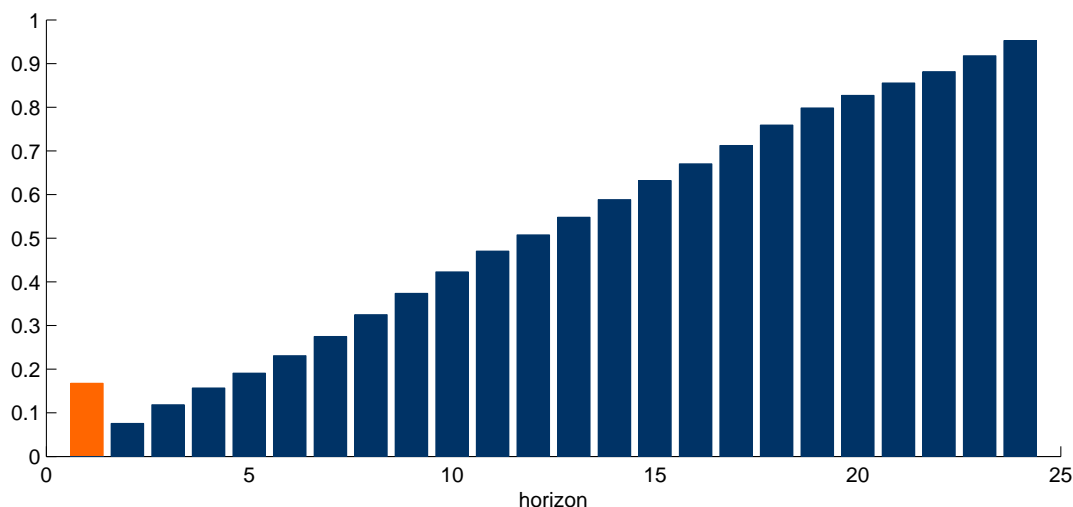
Note: The orange bar is the optimal shrinkage of the Litterman (1986) prior for the VAR coefficients at $h = 1$. Blue bars are for the optimal tightness of the VAR prior for BLP coefficients for $h > 1$.

than VAR peaks, and are often realised within the first year after the shock.

While useful to explore the differences across methods, these exercises lack an observable counterpart agains which the accuracy of the IRFs can be measured. To address this issue, in Appendix B we assess the performances of the different methods by using simulated data from an estimated version of the Justiniano et al. (2010)'s DSGE model. Results show that BLPs perform better than VAR IRFs, and can be as accurate as LPs on average, but with significant gains in terms of estimation uncertainty.

In Section 5 we explore how the iterative nature of VAR responses can at times contribute to the emergence of puzzles which are absent in BLP responses.

4   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).[35] As before, monetary policy shocks are identified by using the MPI_t instrument defined in Section 1.1. Results, in the form of dynamic responses and obtained using the BLP approach, are presented in Figures 7 to 9. 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.[36]

In line with results shown in previous sections, a contractionary monetary policy shock is unequivocally and significantly recessionary also in a larger model (Figure 7). 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), 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

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[35]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.

[36]We set the number of LP lags to 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.

FIGURE 7: THE EFFECTS OF MONETARY POLICY SHOCKS
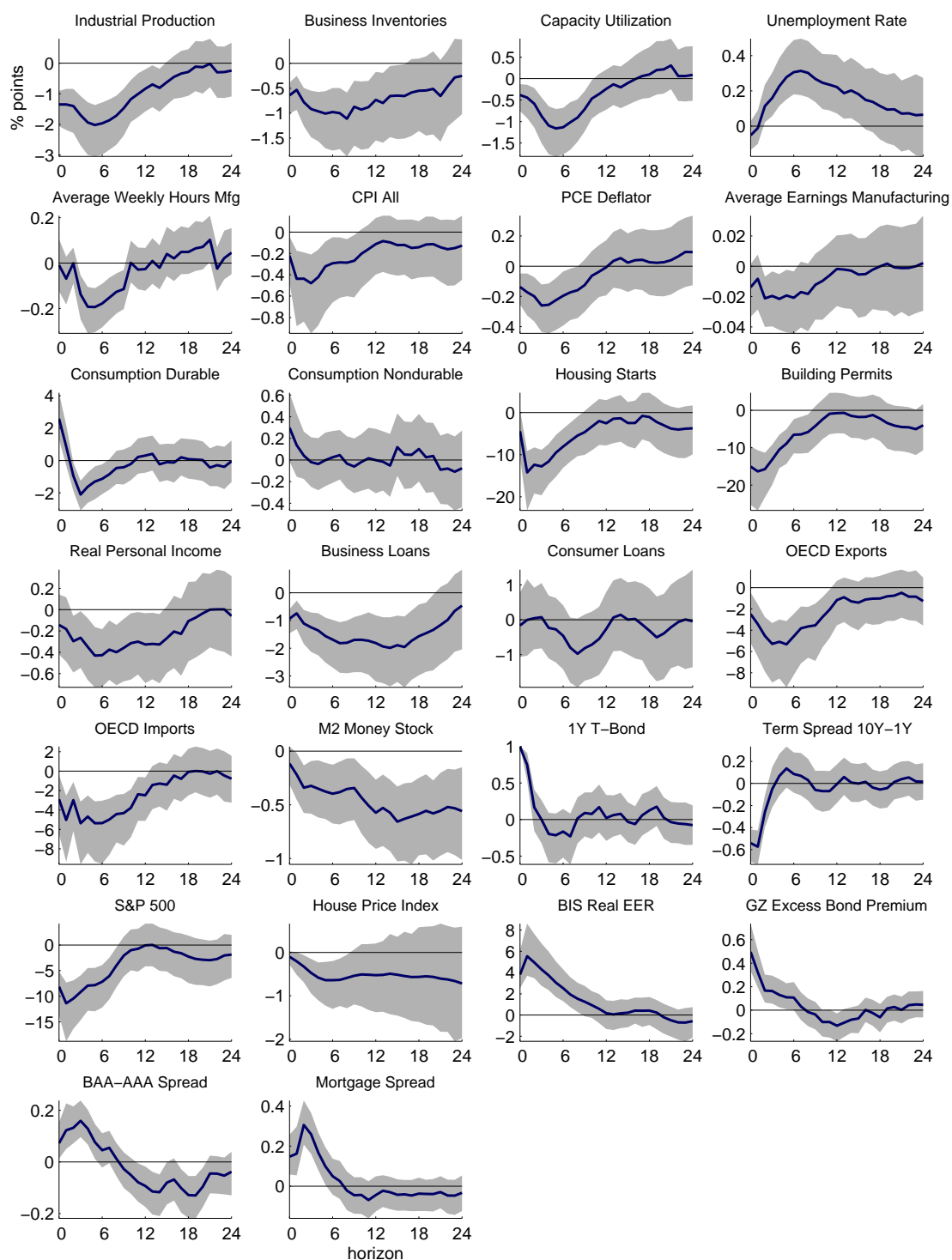
Note: BLP responses to a contractionary monetary policy shock. Shock identified with the $MPShock$ series and normalisedto induce a 100 basis point increase in the 1-year rate. Sample 1979:01 - 2014:12. $BLP(6)$ with $VAR(12)$ prior over 1969:01 - 1979:01. Shaded areas are 90% posterior coverage bands. VAR and LP responses in Figure C.3.

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. 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 8. 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 7 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' hy-

Figure 8: Yield Curve Response to MP Shocks
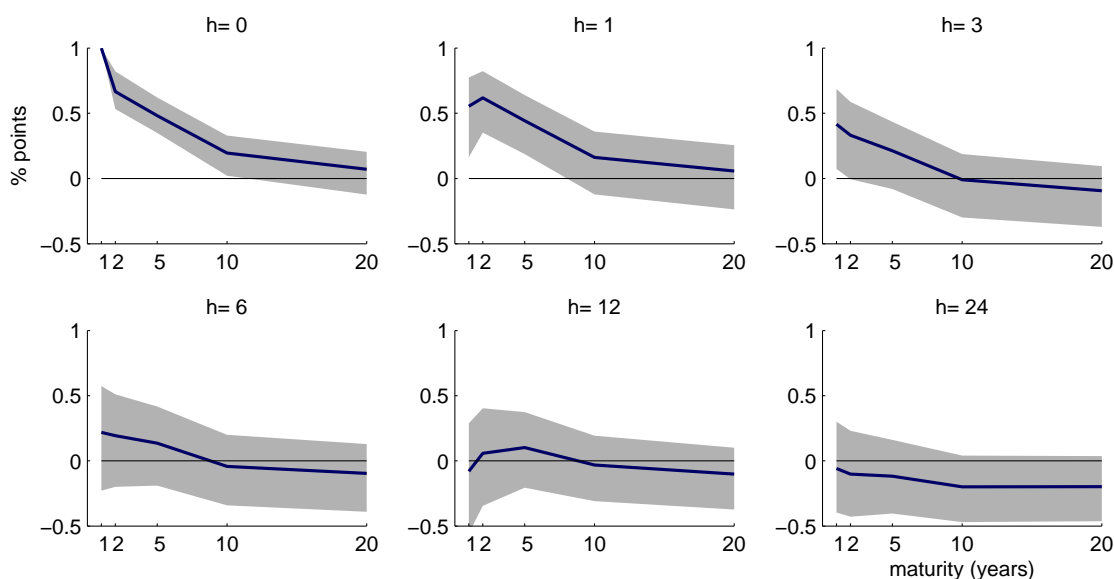
Note: BLP responses to a contractionary monetary policy shock. Shock identified with the *MPShock* series and normalised to induce a 100 basis point increase in the 1-year rate. Sample 1979:01 - 2014:12. $BLP(6)$ with $VAR(12)$ prior over 1969:01 - 1979:01. Shaded areas are 90% posterior coverage bands. VAR and LP responses in Figure C.4.

pothesis 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 (the excess bond premium of Gilchrist and Zakrajšek, 2012) 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.[37]

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 iterative nature of the VAR approach forces on the estimated IRFs (see also discussion in Section 2 and Figure C.3 in Appendix C for a direct comparison). Figure 7 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.

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[37]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.

FIGURE 9: RESPONSE OF EXPECTATIONS TO MP SHOCKS
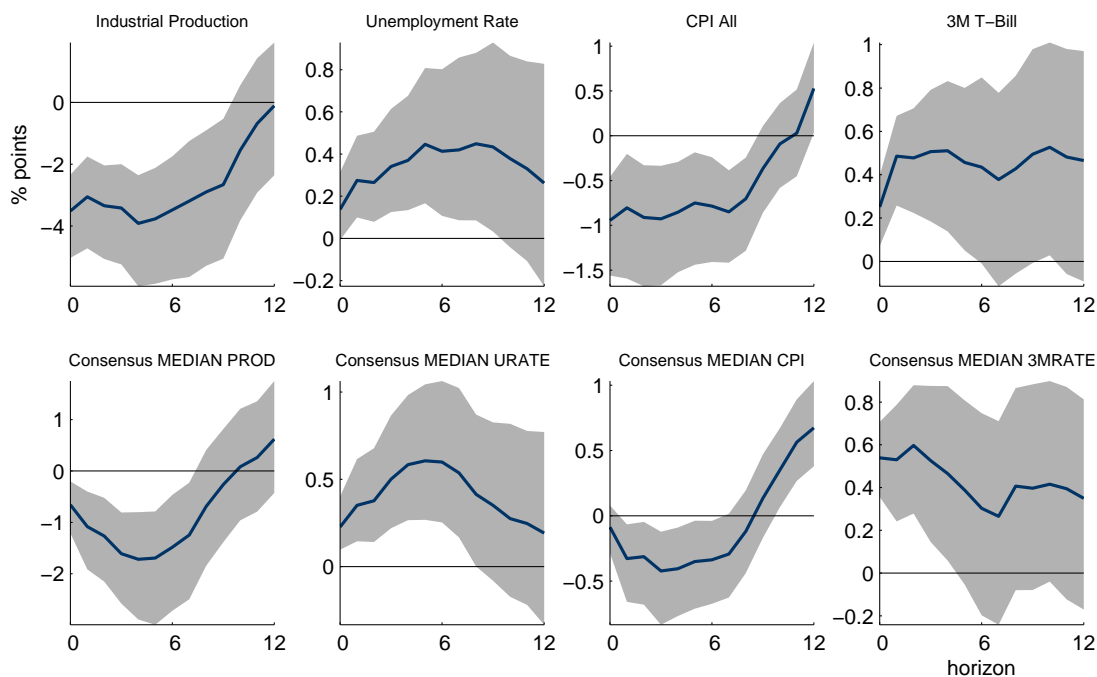
Note: BLP responses to a contractionary monetary policy shock. Shock identified with the *MPShock* series and normalised to induce a 100 basis point increase in the 1-year rate. Sample 1999:01 - 2014:12. $BLP(6)$ with $VAR(12)$ prior over 1993:01 - 1999:01. Shaded areas are 90% posterior coverage bands. VAR and LP responses in Figure C.5.

Finally, we turn to the responses of private sector expectations, in Figure 9. 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 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.[38] 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

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[38]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.

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.[39]

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 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).

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[39]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).

FIGURE 10: VAR, BLP AND LP RESPONSES ACROSS SUBSAMPLES
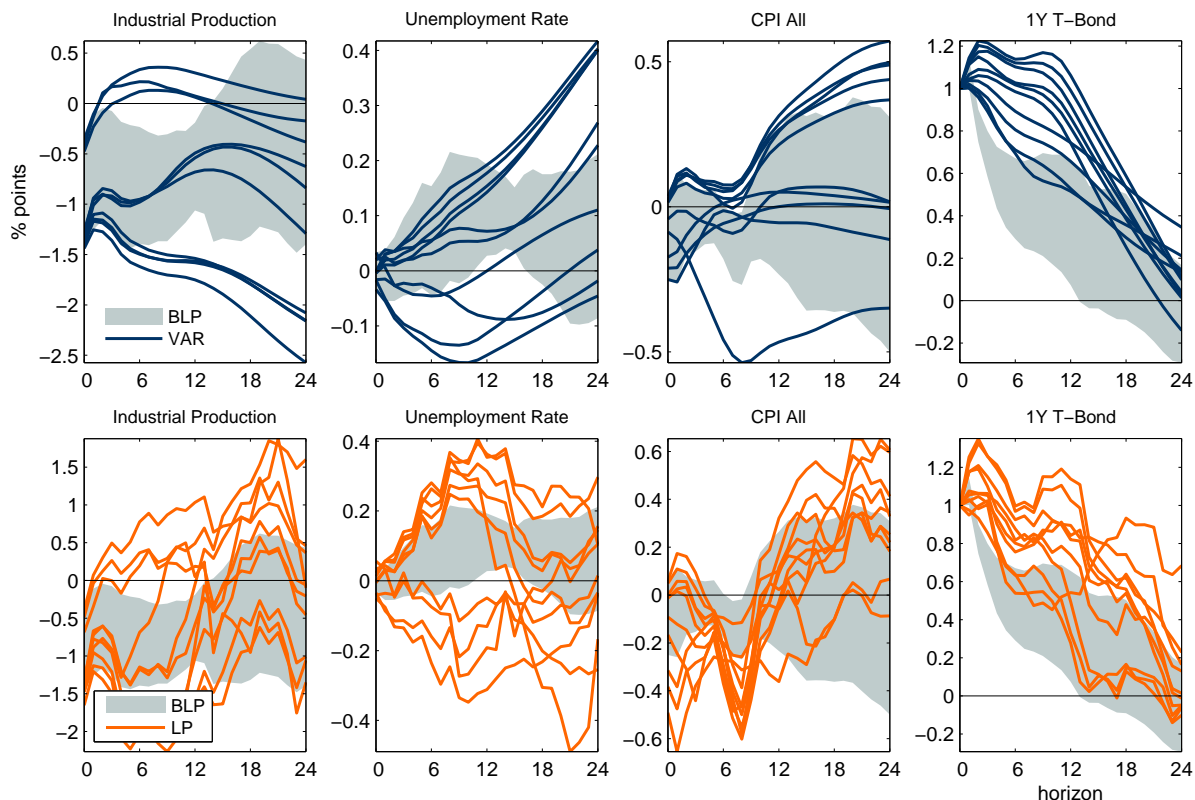
Note: TOP ROW: VAR(12) (blue, solid), and BLP(12) (grey, area) responses. BOTTOM ROW: LP(12) (orange, solid), and BLP(12) (grey, area) responses. Subsamples 1981:2005, 1982:2006, ..., 1990:2014.

5   Puzzles Revisited: Models and Subsamples

In Section 1 we showed that accounting for information frictions helps rationalising many of the puzzles reported in the literature. In this section we document how much of the lack of stability reported in previous studies can be explained by the use of severely mis-specified models for the estimation of the dynamic responses. To this end, we compare responses to shocks estimated by using the same (informationally-robust) instrument and changing the empirical specification and the samples. All other features are kept fixed and in line with the ones adopted in the previous sections. Figure 10 compares the responses obtained using VAR, LP and BLP over a set of 24-year subsamples from 1981 to 2014, using our novel instrument. This specification is helpful to assess how different

methods cope with short samples and potentially severely misspecified information sets.
[40] In fact, 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 economy, hence amplifying the information set mis-
specification of the system.[41] 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
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 (Figure 11), we test the behaviour of BLP focusing on three
specific subsamples: the Great Moderation period (1983-2007, top row), the sample in
Gertler and Karadi (2015) – 1990-2012, middle row, and one spanning the years 1994-
2007 as in Caldara and Herbst (2016), bottom row. The first two samples have been

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[40]For each subsample, the previous 10 years are used to calibrate the BLP prior. Hence, this exercise
also gives insights of the robustness of BLP to the choice of the pre-sample used for the initialisation.

[41]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 11: VAR, BLP AND LP RESPONSES: SELECTED SUBSAMPLES
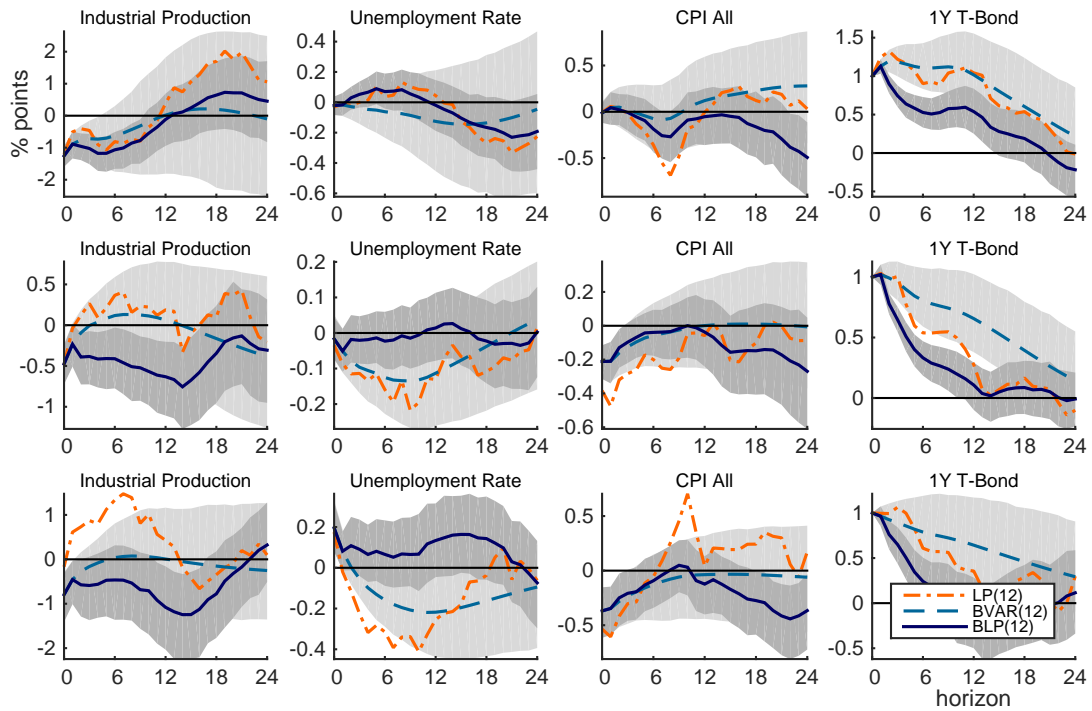
Note: $BLP(12)$ with VAR(12) prior (blue, solid), VAR(12) (teal, dotted) and $LP(12)$ (orange, dash-dotted) responses to a contractionary monetary policy shock. TOP ROW: estimation sample 1990:01 - 2012:12, pre-sample 1969:01 - 1979:12. MIDDLE ROW: estimation sample 1983:01 - 2007:12, pre-sample 1969:01 - 1982:12. BOTTOM ROW: estimation sample 1994:01 - 2007:12, pre-sample 1969:01 - 1979:12.

recognised as being particularly problematic because of either output or price puzzles (see e.g. Ramey, 2016). The last subsample refers to a period of particularly tranquil monetary policy. In all 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.

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.

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A Derivations - For Online Publication

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

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

We assume the k-dimensional vector of macroeconomic fundamentals to evolve following an AR(1)

$$x_t = \rho x_{t-1} + \xi_t \qquad \xi_t \sim \mathcal{N}(0, \Sigma_\xi) , \qquad (A.2)$$

where ξ_t is the vector of structural shocks.

Given the signals, agents update their expectations using

$$F_{i,\underline{t}} x_t \quad = K_1 s_{i,\underline{t}} + (1 - K_1) F_{i,\overline{t-1}} x_t , \qquad (A.3)$$

$$F_{i,\underline{t}} x_{t+h} = \rho^h F_{i,\underline{t}} x_t \qquad \forall h > 0 , \qquad (A.4)$$

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

$$s_{cb,\underline{t}} = x_t + \nu_{cb,\underline{t}} , \qquad \nu_{cb,\underline{t}} \sim \mathcal{N}(0, \sigma_{cb,\nu}) . \qquad (A.5)$$

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

$$F_{cb,\underline{t}} x_t \quad = K_{cb} s_{cb,\underline{t}} + (1 - K_{cb}) F_{cb,\overline{t-1}} x_t , \qquad (A.6)$$

$$F_{cb,\underline{t}} x_{t+h} = \rho^h F_{cb,\underline{t}} x_t \qquad \forall h > 0 , \qquad (A.7)$$

where K_{cb} is the central 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

$$F_{i,\bar{t}}x_t \quad = K_2 \tilde{s}_{cb,\bar{t}} + (1 - K_2)F_{i,\underline{t}}x_t \ , \tag{A.8}$$

$$F_{i,\bar{t}}x_{t+h} = \rho^h F_{i,\bar{t}}x_t \qquad \forall h > 0 \ , \tag{A.9}$$

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.8) with Eq. (A.3), and using Eq. (A.2) and Eq. (A.9) we find

$$\begin{aligned}
F_{i,\bar{t}}x_t - F_{i,\underline{t}}x_t &= K_2 \left[\tilde{s}_{cb,\bar{t}} - F_{i,\underline{t}}x_t \right] \\
&= K_2(x_t + \tilde{\nu}_{cb,\bar{t}}) - K_2 \left[K_1(x_t + \nu_{i,\bar{t}}) + (1 - K_1)F_{i,\overline{t-1}}x_t \right] \\
&= K_2(1 - K_1)x_t + K_2\tilde{\nu}_{cb,\bar{t}} - K_2 K_1 \nu_{i,\bar{t}} - K_2(1 - K_1)F_{i,\overline{t-1}}x_t \\
&= K_2(1 - K_1)\rho \left[x_{t-1} - F_{i,\overline{t-1}}x_{t-1} \right] + K_2 \left[(1 - K_1)\xi_t + \tilde{\nu}_{cb,\bar{t}} - K_1\nu_{i,\bar{t}} \right]. \tag{A.10}
\end{aligned}$$

To find an expression for the forecast error $\left(x_{t-1} - F_{i,\overline{t-1}}x_{t-1} \right)$ in Eq. (A.10), first note that Eq. (A.8) implies

$$x_t - F_{i,\bar{t}}x_t = K_2^{-1}(1 - K_2)\left(F_{i,\bar{t}}x_t - F_{i,\underline{t}}x_t \right) - \tilde{\nu}_{cb,\bar{t}}. \tag{A.11}$$

Then Eq. (A.11) one period earlier can be written as

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

Substituting Eq. (A.12) into Eq. (A.10) yields

$$\begin{aligned}
F_{i,\bar{t}}x_t - F_{i,\underline{t}}x_t =& (1 - K_2)(1 - K_1)\left[F_{i,\overline{t-1}}x_t - F_{i,\underline{t-1}}x_t \right] \\
&+ K_2 \left[(1 - K_1)\xi_t + \left(\tilde{\nu}_{cb,\bar{t}} - (1 - K_1)\rho\tilde{\nu}_{cb,\overline{t-1}} \right) - K_1\nu_{i,\bar{t}} \right] \ . \tag{A.13}
\end{aligned}$$

The characteristics of the common noise $\tilde{\nu}_{cb,\bar{t}}$ are derived from the Taylor rule in Eq. (4), and

the signal extraction problem of the central bank in Eq. (A.6). Specifically:

$$
\begin{aligned}
i_t &= \phi_0 + \phi_x' F_{cb,\underline{t}} x_t + u_t \\
&= \phi_0 + \phi_x' \left[K_{cb} s_{cb,\underline{t}} + (1 - K_{cb}) F_{cb,\overline{t-1}} x_t \right] + u_t \\
&= \phi_0 + \phi_x' \left[K_{cb} s_{cb,\underline{t}} + (1 - K_{cb}) \rho F_{cb,\overline{t-1}} x_{t-1} \right] + u_t \\
&= \phi_0 + K_{cb} \phi_x' s_{cb,\underline{t}} + (1 - K_{cb}) \rho (i_{t-1} - \phi_0 - u_{t-1}) + u_t \\
&= \left[1 - (1 - K_{cb}) \rho \right] \phi_0 + (1 - K_{cb}) \rho i_{t-1} + K_{cb} \phi_x' s_{cb,\underline{t}} - (1 - K_{cb}) \rho u_{t-1} + u_t , \qquad \text{(A.14)}
\end{aligned}
$$

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

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

where

$$
\tilde{\nu}_{cb,\underline{t}} = \nu_{cb,\underline{t}} + \left(K_{cb} \phi_x' \right)^{-1} \left[u_t - (1 - K_{cb}) \rho u_{t-1} \right] . \qquad \text{(A.16)}
$$

Plugging Eq. (A.16) into Eq. (A.13) yields

$$
\begin{aligned}
F_{i,\overline{t}} x_t - F_{i,\underline{t}} x_t =& (1 - K_2)(1 - K_1) \left[F_{i,\overline{t-1}} x_t - F_{i,\underline{t-1}} x_t \right] \\
&+ K_2 (1 - K_1) \xi_t + K_2 \left[\left(\nu_{cb,\overline{t}} - (1 - K_1) \rho \nu_{cb,\overline{t-1}} \right) - K_1 \nu_{i,\overline{t}} \right] \\
&+ K_2 \left(K_{cb} \phi_x' \right)^{-1} \left[u_t - (K_1 - K_{cb}) \rho u_{t-1} - \rho (1 - K_1)(1 - K_{cb}) \rho^2 u_{t-2} \right] .
\end{aligned}
$$
$$\text{(A.17)}$$

Eq. (7) follows by taking the average of Eq. (A.17) over the agents i.

A.2 Bias in OLS Regression

Recall Eq. (7):

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

For simplicity, let us consider the vector x_t to be univariate. Suppose one runs a regression of the form (e.g. top panel of Table 1)

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

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

$$
\begin{aligned}
\hat{\beta}^{OLS} =& \frac{\mathbb{E}\left[(F_{\bar{t}}x_t - F_{\underline{t}}x_t)(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)\right]}{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)^2\right]} \\
=& (1-K_2)(1-K_1) - K_2(1-K_1)\rho\frac{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)\nu_{cb,t-1}\right]}{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)^2\right]} \\
& - K_2(K_{cb}\phi_x')^{-1}(K_1-K_{cb})\rho\frac{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)u_{t-1}\right]}{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)^2\right]} + \mathcal{O}(\rho^3) \\
=& (1-K_2)(1-K_1) - K_2(1-K_1)\rho\frac{\mathbb{E}\left[\rho F_{\overline{t-1}}x_{t-1}\nu_{cb,t-1}\right]}{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)^2\right]} \\
& - K_2(K_{cb}\phi_x')^{-1}(K_1-K_{cb})\rho\frac{\mathbb{E}\left[\rho F_{\overline{t-1}}x_{t-1}u_{t-1}\right]}{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)^2\right]} + \mathcal{O}(\rho^3) \\
=& (1-K_2)(1-K_1) - K_2(1-K_1)\rho^2\frac{\Sigma_{\nu_{cb}}}{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)^2\right]} \\
& - K_2(K_{cb}\phi_x')^{-1}(K_1-K_{cb})\rho^2\frac{\Sigma_u}{\mathbb{E}\left[(F_{\overline{t-1}}x_t - F_{\underline{t-1}}x_t)^2\right]} + \mathcal{O}(\rho^3) \ . \qquad \text{(A.18)}
\end{aligned}
$$

The size of the last term in Eq. (A.18) 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 Priors for BLP - For Online Publication

B.1 Informative Priors for LP

Horizon-h IRFs estimated with the Local Projection method (LP, Jordà, 2005), are the coefficients in $B_1^{(h)}$ estimated from the linear regression

$$y_{t+h} = C^{(h)} + B_1^{(h)}y_t + \ldots + B_{\tilde{p}}^{(h)}y_{t-(\tilde{p}+1)} + \varepsilon_{t+h}^{(h)} \, , \tag{B.1}$$

$$\varepsilon_{t+h}^{(h)} \sim \mathcal{N}(0, \Sigma_\varepsilon^{(h)}) \qquad \forall \ h = 1, \ldots, H \, ,$$

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

For the coefficients of Eq. (B.1) at each horizon h we specify standard conjugate Normal-inverse Wishart priors

$$\Sigma_\varepsilon^{(h)} \mid \gamma \sim \mathcal{IW}\left(\Psi_0^{(h)}, d_0^{(h)}\right) \, ,$$

$$\beta^{(h)} \mid \Sigma_\varepsilon^{(h)}, \gamma \sim \mathcal{N}\left(\beta_0^{(h)}, \Sigma_\varepsilon^{(h)} \otimes \Omega_0^{(h)}(\gamma)\right) \, , \tag{B.2}$$

where $\beta^{(h)} \equiv vec(b^{(h)}) = vec\left(\left[C^{(h)}, B_1^{(h)}, \ldots, B_{\tilde{p}}^{(h)}\right]'\right)$. We use γ to denote the generic vector collecting all the priors' hyperparameters.

As in Kadiyala and Karlsson (1997), we set $d_0^{(h)} = n + 2$, to guarantee the existence of the prior mean for $\Sigma_\varepsilon^{(h)}$, equal to $\Psi_0^{(h)}/(d_0^{(h)} - n - 1)$. As is standard, we use sample information to fix some of the entries in Eq. (B.2). We set $\Psi_0^{(h)}$ 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 HAC-corrected variances of univariate local projection residuals. Similarly, we set $\Omega_0^{(h)}$ to be

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

where ϵ is a very small number (diffuse prior on the intercepts). The hyperparameter $\lambda^{(h)}$

controls the overall tightness of the priors at each horizon h, i.e. $\gamma \equiv \lambda^{(h)}$.

This specification implies the following moments for the IRF coefficients

$$\mathbb{E}\left[B_{ij}^{(h)} \mid \Sigma_\varepsilon^{(h)}\right] = B_{0,ij}^{(h)} \ , \tag{B.3}$$

$$\mathbb{V}ar\left[B_{ij}^{(h)} \mid \Sigma_\varepsilon^{(h)}\right] = (\lambda^{(h)})^2 \frac{(\sigma_i^{(h)})^2}{(\sigma_j^{(h)})^2} \ , \tag{B.4}$$

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

We set $\beta_0^{(h)}$ to be equal to the horizon-h IRFs resulting from a VAR(p) estimated on a pre-sample T_0 that is then discarded:

$$\beta_0^{(h)} = vec(B_{T_0}^h), \tag{B.5}$$

where $B_{T_0}^h$ is the h-th power of the VAR coefficients estimated over T_0 using standard priors (Litterman, 1986).

Having not explicitly modelled the autocorrelation of $\varepsilon_{t+h}^{(h)}$ has two important implications. First, the priors are conjugate. Second, the Kronecker structure of the standard macroeconomic priors is preserved. This makes the estimation both analytically and computationally tractable. Conditional on the data, the posterior distribution takes the following form

$$\Sigma_\varepsilon^{(h)} \mid \gamma^{(h)}, \mathrm{y} \sim \mathcal{IW}\left(\Psi^{(h)}, d\right)$$

$$\beta^{(h)} \mid \Sigma_\varepsilon^{(h)}, \gamma^{(h)}, \mathrm{y} \sim \mathcal{N}\left(\tilde{\beta}^{(h)}, \Sigma_\varepsilon^{(h)} \otimes \Omega^{(h)}\right) \ , \tag{B.6}$$

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

Because $\varepsilon_{t+h}^{(h)}$ are a combination of past forecast errors, Eq. (B.6) 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 one in Eq. (B.6). We follow Müller (2013) and, in line with the classical practice, construct posterior coverage bands for the BLP responses using an artificial Gaussian 'sandwich' posterior that is centred at the MLE

FIGURE B.1: BLP RESPONSES: VAR VS RW PRIOR
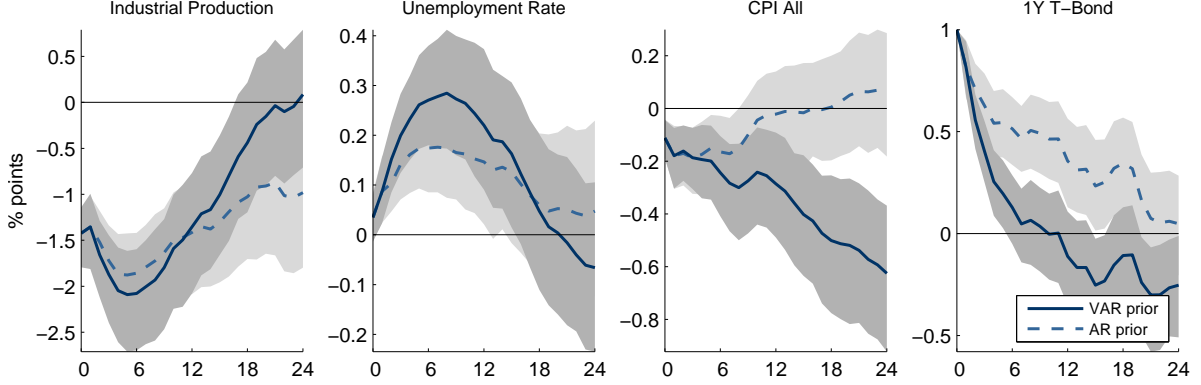
Note: BLP(12) with *RW* prior (teal, dashed), and BLP(12) with VAR(12) prior (blue, solid). 1979:2014. Pre-Sample 1969:1979.

but with a HAC-corrected covariance matrix. Specifically, we replace Eq. (B.6) with

$$
\Sigma^{(h)}_{\varepsilon,\text{HAC}} \mid \gamma^{(h)}, \mathrm{y} \sim \mathcal{IW}\left(\Psi^{(h)}_{\text{HAC}}, d\right) ,
$$

$$
\beta^{(h)} \mid \Sigma^{(h)}_{\varepsilon,\text{HAC}}, \gamma^{(h)}, \mathrm{y} \sim \mathcal{N}\left(\tilde{\beta}^{(h)}, \Sigma^{(h)}_{\varepsilon,\text{HAC}} \otimes \Omega^{(h)}\right) . \tag{B.7}
$$

We explore the role of our choice for the prior mean in Figure B.1. 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 5. 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.

B.2 Optimal Prior Tightness

The hyperparameter $\lambda^{(h)}$ controls the informativeness of the priors. Following Giannone, Lenza and Primiceri (2015), we treat $\lambda^{(h)}$ as an additional model parameter for which we specify a hyperprior $p(\lambda^{(h)})$, and estimate it at each h in the spirit of hierarchical modelling. Specifically,

we maximise

$$p(\lambda^{(h)}|y^{(h)}) = p(y^{(h)}|\lambda^{(h)}) \cdot p(\lambda^{(h)}) \ , \tag{B.8}$$

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

$$p(y^{(h)}|\lambda^{(h)}) = \int p(y^{(h)}|\lambda^{(h)}, \theta) p(\theta|\lambda^{(h)}) d\theta \ \forall h \ , \tag{B.9}$$

and $p(\theta|\lambda^{(h)})$ is the prior distribution of the remaining model's parameters conditional on $\lambda^{(h)}$. $y^{(h)} = vec(Y^{(h)})$ where $Y^{(h)} \equiv (y_{p+1+h}, \ldots, y_T)'$. Under a flat hyperprior, the procedure corresponds to maximising the marginal data density (or marginal likelihood, ML).

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

$$p(y^{(h)}|\lambda^{(h)}) \propto \underbrace{\left| \left(V^{\text{posterior}}_{\varepsilon^{(h)}} \right)^{-1} V^{\text{prior}}_{\varepsilon^{(h)}} \right|^{\frac{T-(\tilde{p}+h)+d}{2}}}_{\text{Fit}} \underbrace{\prod_{t=\tilde{p}+1}^{T-h} \left| V_{t+h|t} \right|^{-\frac{1}{2}}}_{\text{Penalty}} \qquad \forall h \ , \tag{B.10}$$

where $V^{\text{posterior}}_{\varepsilon^{(h)}}$ and $V^{\text{prior}}_{\varepsilon^{(h)}}$ are the posterior and prior mean of $\Sigma^{(h)}_{\varepsilon}$, and

$$V_{t+h|t} = \mathbb{E}_{\Sigma^{(h)}_{\varepsilon}} \left[\mathbb{V}ar(y_{t+h}|y^t, \Sigma^{(h)}_{\varepsilon}) \right]$$

is the variance (conditional on $\Sigma^{(h)}_{\varepsilon}$) of the h-step-ahead forecast of y_t, averaged across all possible a priori realisations of $\Sigma^{(h)}_{\varepsilon}$. The first term in Eq. (B.10) relates to the model's in-sample fit, and it increases when $V^{\text{posterior}}_{\varepsilon^{(h)}}$ falls relative to $V^{\text{prior}}_{\varepsilon^{(h)}}$. 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). Hence, the ML criterion favours hyperparameters values that generate both smaller forecast errors, and low forecast error variance, therefore balancing the trade-off between model fit and variance.

We choose $p(\lambda^{(h)})$, $p = 1, \ldots, H$ from a family of Gamma distributions. We specify the Gamma hyperprior to be more diffuse the larger h, consistent with the idea that misspecifications compound as the horizon grows. This is accomplished by choosing the scale and shape parameters of the Gamma distribution such 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

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

and plotted in Figure B.2a. Figure B.2b illustrates the evolution of the hyperprior for $\lambda^{(h)}$ as a function of the horizon.

B.3   DSGE Simulations

In this section we propose some controlled Monte Carlo experiments. We simulate artificial data sets from a dynamic stochastic general equilibrium (DSGE) model and assess the performances of LPs, VARs and BLP in misspecified settings. The DSGE that we use to simulate the data is identical to the one used in Giannone et al. (2015), that is derived from the model proposed in Justiniano et al. (2010) by assuming that that the behaviour of the private sector is predetermined with respect to the monetary policy shock. This allows for a recursive identification of monetary policy shocks. Since medium-scale DSGE models are known to produce reasonably good fit of the data (see e.g. Smets and Wouters, 2007), data simulated from them provide a sensible benchmark to assess the performance of the different empirical methods.

We simulate 500 artificial time series with 200 data points each for seven variables: output (Y), consumption (C), investment (I), hours worked (H), wages (W), prices (P), and the short-term interest rate (R). We use 75 points to initialise the BLP prior. For each data set, we estimate the impulse responses to a monetary policy shock obtained with BLP, a VAR with standard macroeconomic priors, and the standard Local Projections. The DSGE is parameterised using the posterior mode of the unknown coefficients, estimated using U.S. data on output growth, consumption growth, investment growth, hours, wage inflation, price inflation, and the federal funds rate, as in Justiniano et al. (2010). It is possible to show that this DSGE has a 7-variable VAR(5) representation.

In a first exercise, the misspecification amounts to (i) the use of 1 lag instead of 5, and (ii) omitting the price level variable which is important for the monetary transmission. Results from this specification are in Figures B.3a and B.3b. Figure B.3a compares the true IRFs obtained from the DSGE (red, dash dotted lines) with the average across replications of the median responses, and distribution of the median responses for LPs (top row, orange lines), BVAR (medium row, teal lines), and BLP (bottom row, blue lines). Figure B.3b on the other

hand plots the average optimal prior tightness, together with its distribution, again across the 500 replications.

In Figures B.4a and B.4b the degree of misspecification is exacerbated, and only 3 variables are included, again with 1 lag. The gains in terms of estimation uncertainty of BLP with respect to LP have already been discussed in Section 3. As expected, the VAR is the most affected by the misspecification. With the exception of consumption, the exclusion of the price level variable makes VAR IRFs deviate significantly from the true ones (grey areas are 90% quantiles of the distribution of the IRFs across simulations). The relatively poor performance of the VAR is confirmed by the large optimal prior tightness shown in Figure B.3b. Abstracting from estimation uncertainty, the average behaviour of BLP and LP is comparable. The difference between BLP and the VAR responses is starker in Figure B.4a.
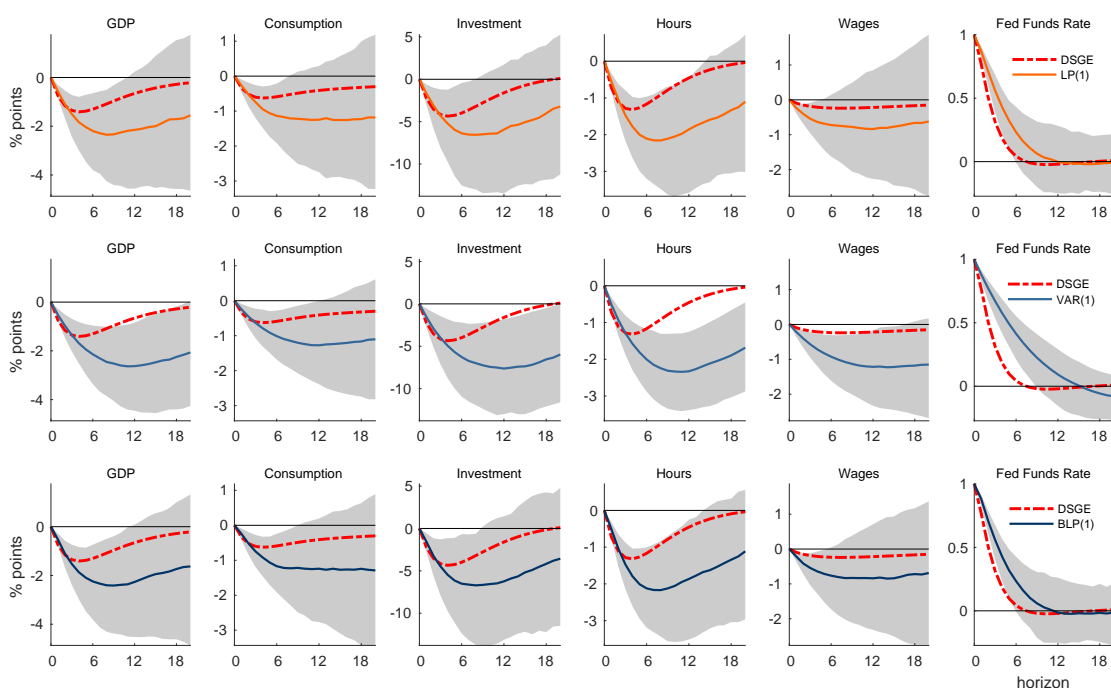
FIGURE B.2: HYPERPRIOR FOR BLP-IRF COEFFICIENTS
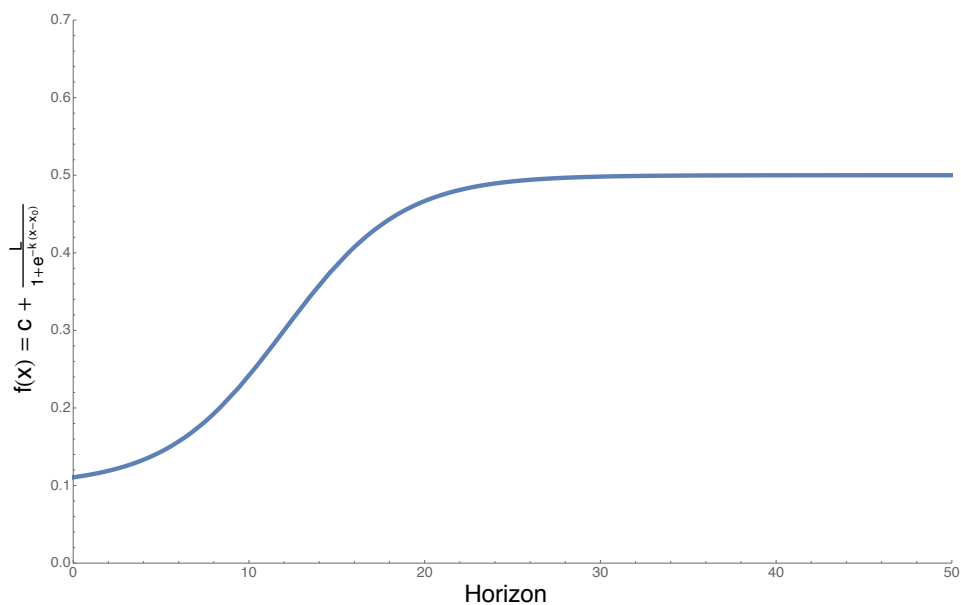
(A) Standard deviation of the hyperprior as a Logistic function of h.
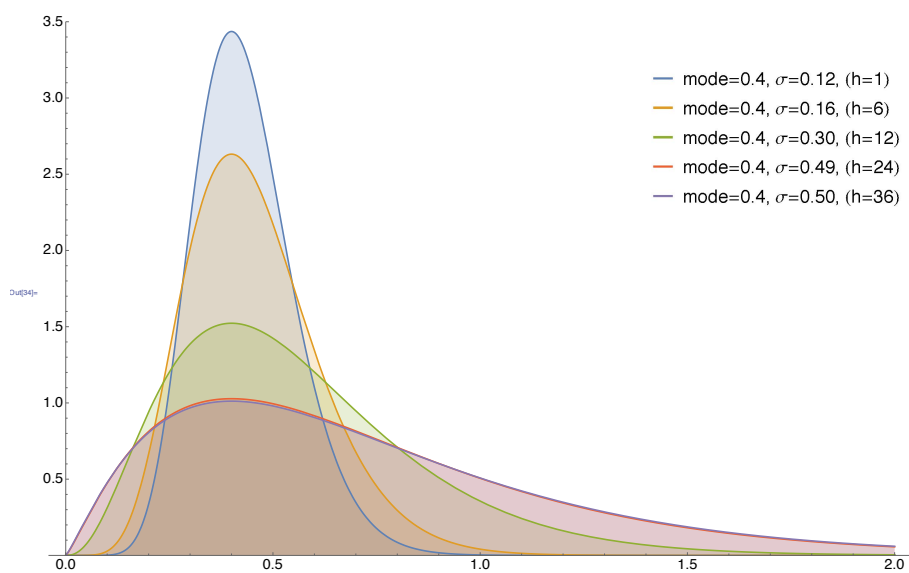
(B) Hyperprior Gamma distributions for a selection of horizons.

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FIGURE B.3: TRUE MODEL: $n = 7$, $p = 5$. ESTIMATED MODELS: $n = 6$, $p = 1$
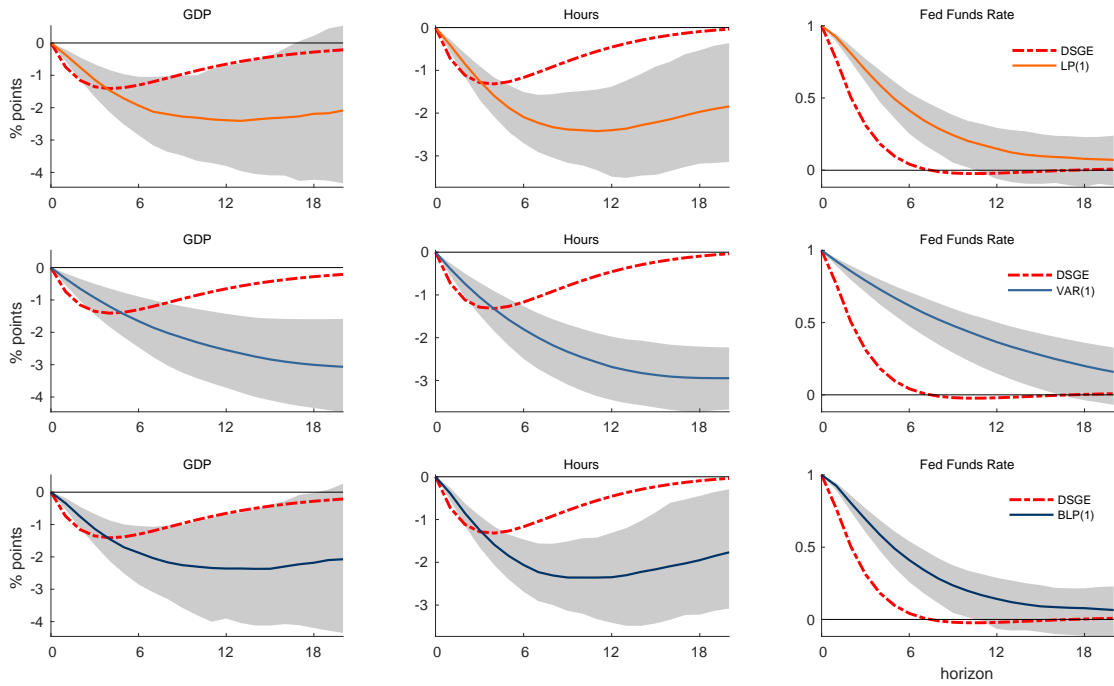

(A) IRFs. DSGE responses (red, dash-dotted lines) against average (across simulations) LP (top row, orange lines), VAR (middle row, teal lines), and BLP responses (bottom row, blue lines). Grey areas are 95% quantiles of the distribution of IRFs across simulations for each method.
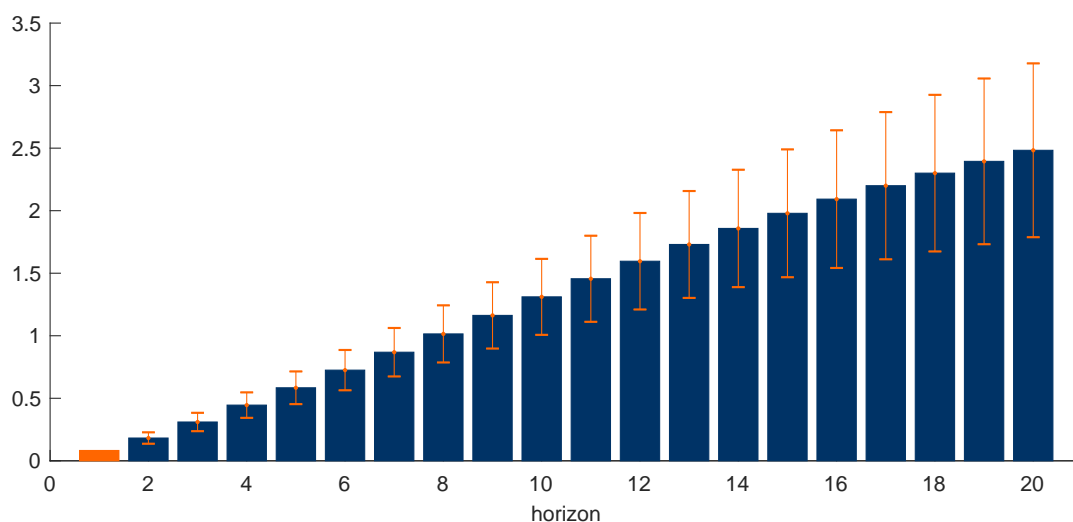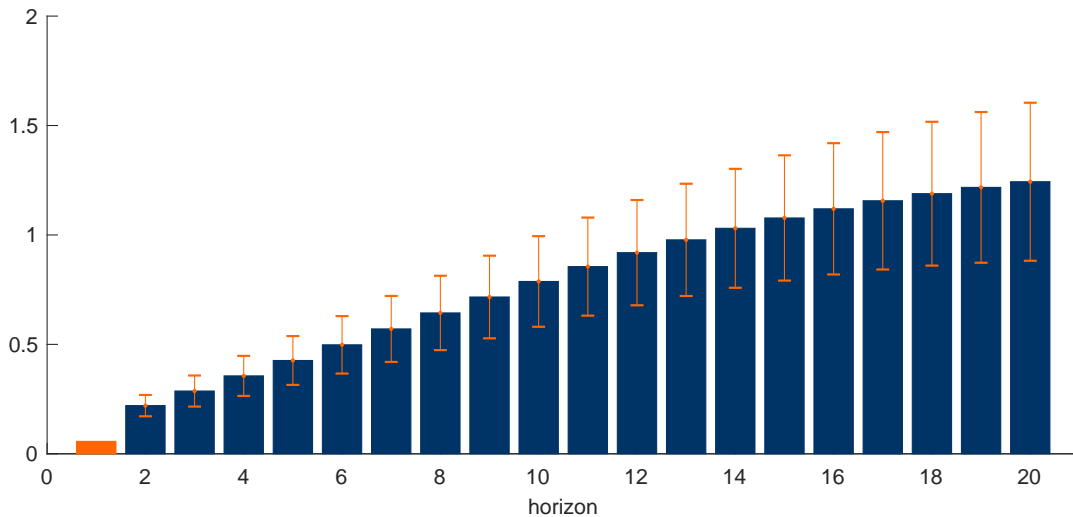

(B) Optimal Prior Tightness. Average BLP prior tightness over 500 simulations (blue bars) and distribution across simulations (orange lines).

FIGURE B.4: TRUE MODEL: $n = 7$, $p = 5$. ESTIMATED MODELS: $n = 3$, $p = 1$

(A) IRFs. DSGE responses (red, dash-dotted lines) against average (across simulations) LP (top row, orange lines), VAR (middle row, teal lines), and BLP responses (bottom row, blue lines). Grey areas are 95% quantiles of the distribution of IRFs across simulations for each method.

(B) Optimal Prior Tightness. Average BLP prior tightness over 500 simulations (blue bars) and distribution across simulations (orange lines).

TABLE C.1: TEST FOR INFORMATION FRICTIONS – 1994:2009

|	$FF4_t$		$FF4_t^{GK}$		MPN_t	
lag 1	0.009 [0.13]		0.419 [5.67]***		-0.059 [-0.67]	
lag 2	-0.109 [-1.48]		-0.290 [-3.62]***		0.206 [2.61]**	
lag 3	0.040 [0.55]		0.092 [1.14]		0.560 [7.08]***	
lag 4	0.085 [1.16]		0.122 [1.47]		0.076 [0.83]	
$f_{1,t-1}$		-0.009 [-1.35]		-0.010 [-2.65]***		-0.146 [-4.58]***
$f_{2,t-1}$		0.002 [0.75]		0.004 [1.71]*		-0.011 [-0.76]
$f_{3,t-1}$		-0.003 [-0.77]		-0.005 [-1.38]		-0.041 [-1.87]*
$f_{4,t-1}$		0.010 [1.30]		0.007 [1.67]*		0.079 [2.53]**
$f_{5,t-1}$		0.005 [0.68]		0.000 [-0.04]		0.028 [0.83]
$f_{6,t-1}$		-0.014 [-2.44]**		-0.007 [-2.75]***		0.018 [0.91]
$f_{7,t-1}$		-0.014 [-1.89]*		-0.011 [-2.38]**		-0.061 [-2.44]**
$f_{8,t-1}$		0.000 [-0.10]		-0.001 [-0.23]		-0.044 [-1.88]*
$f_{9,t-1}$		-0.002 [-0.43]		-0.001 [-0.36]		-0.045 [-1.79]*
$f_{10,t-1}$		0.004 [0.75]		0.001 [0.22]		-0.039 [-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	(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 5; (2) Channels of monetary transmission in Figure 7; (3) Expectation channel in Figure 9; (4) Interest rate channel in Figure 8. *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).
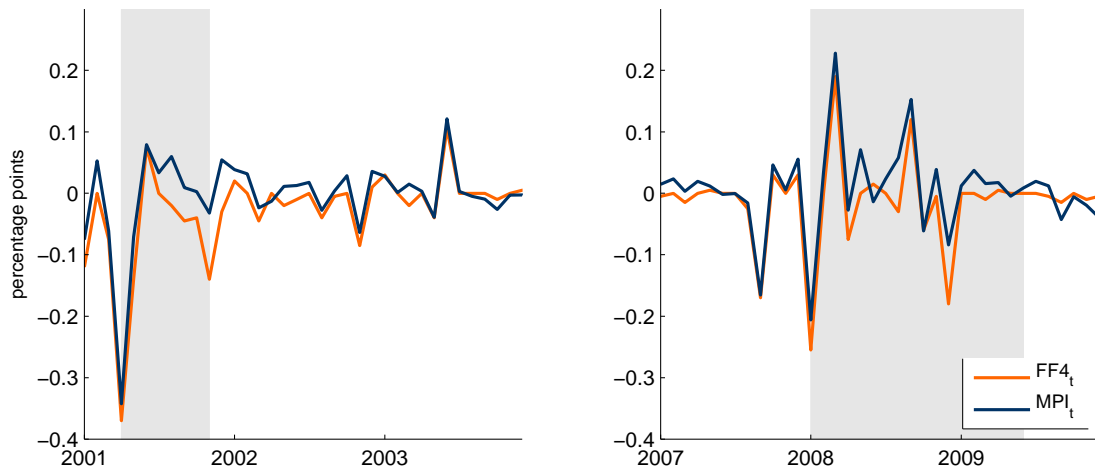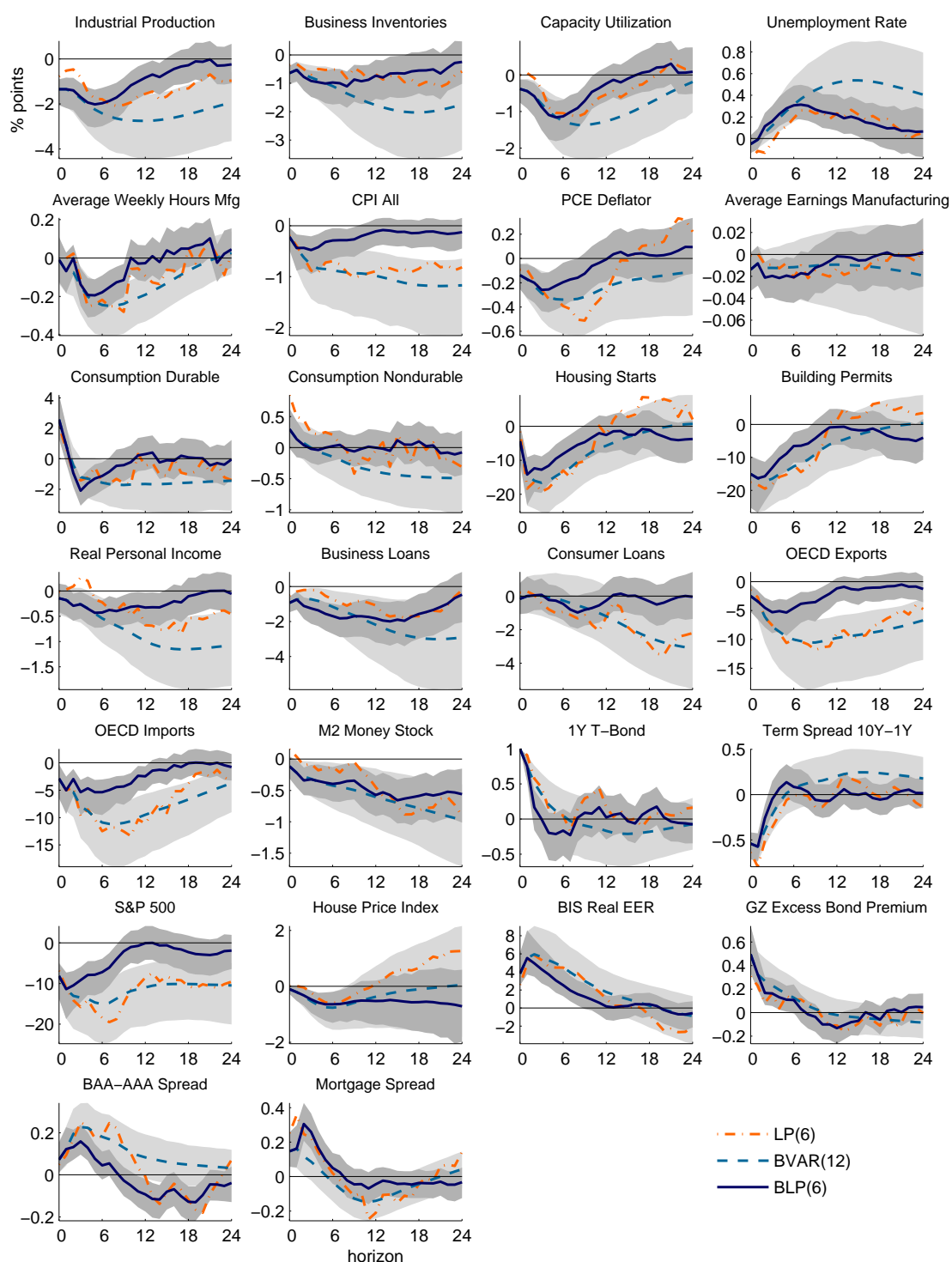
Note: market-based surprises conditional on private agents' information set $FF4_t$ (orange line), residual to Eq. (1) MPI_t, (blue, solid). Shaded areas denote NBER recessions. LEFT PANEL: 2001:01 - 2003:12. RIGHT PANEL: 2007:01 - 2009:12.

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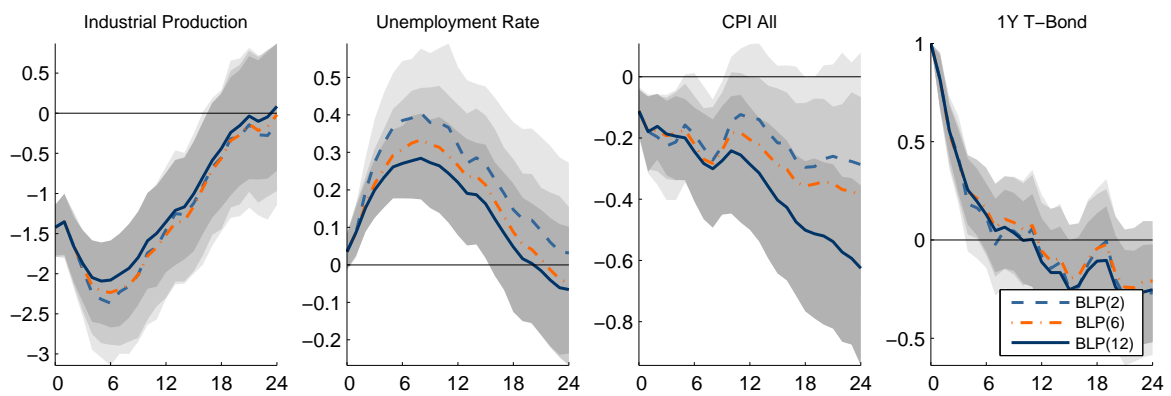
$BLP(2)$ (teal, dashed), $BLP(6)$ (orange, dash-dotted) and $BLP(12)$ (blue, solid) impulse responses. $VAR(12)$ prior. Shaded areas are 90% posterior coverage bands.

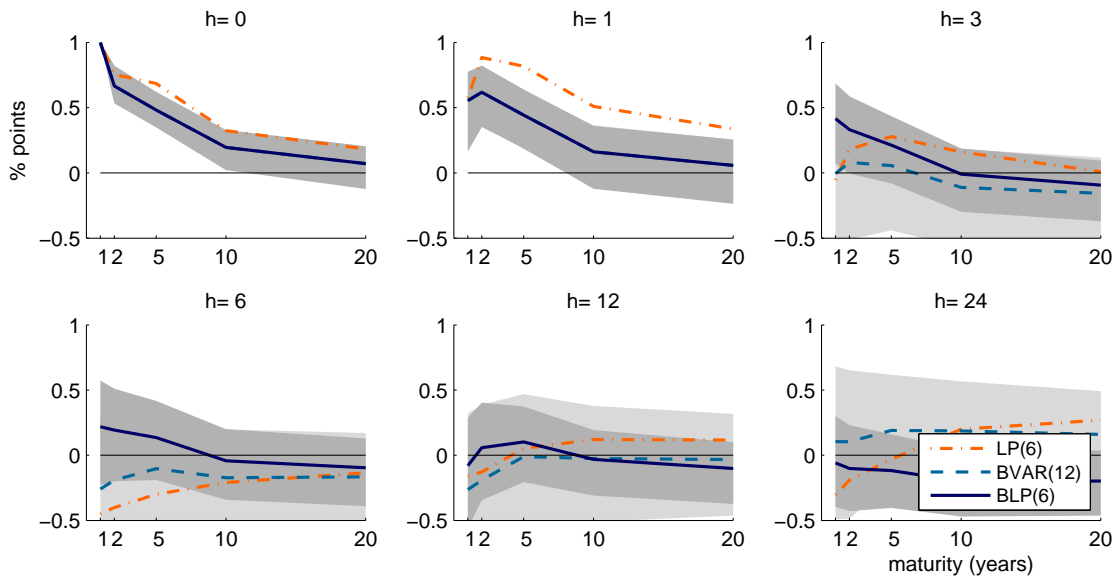FIGURE C.3: IRFs TO MONETARY POLICY SHOCK: ALL VARIABLES, ALL METHODS

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.
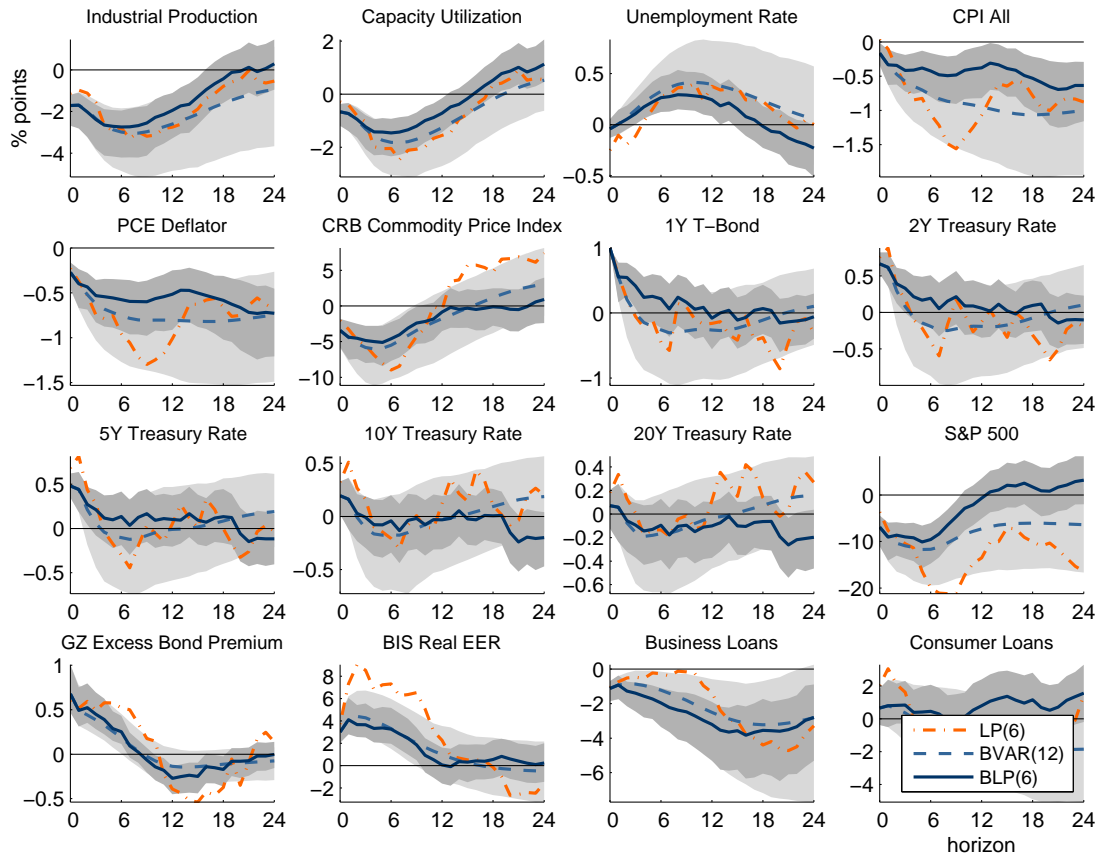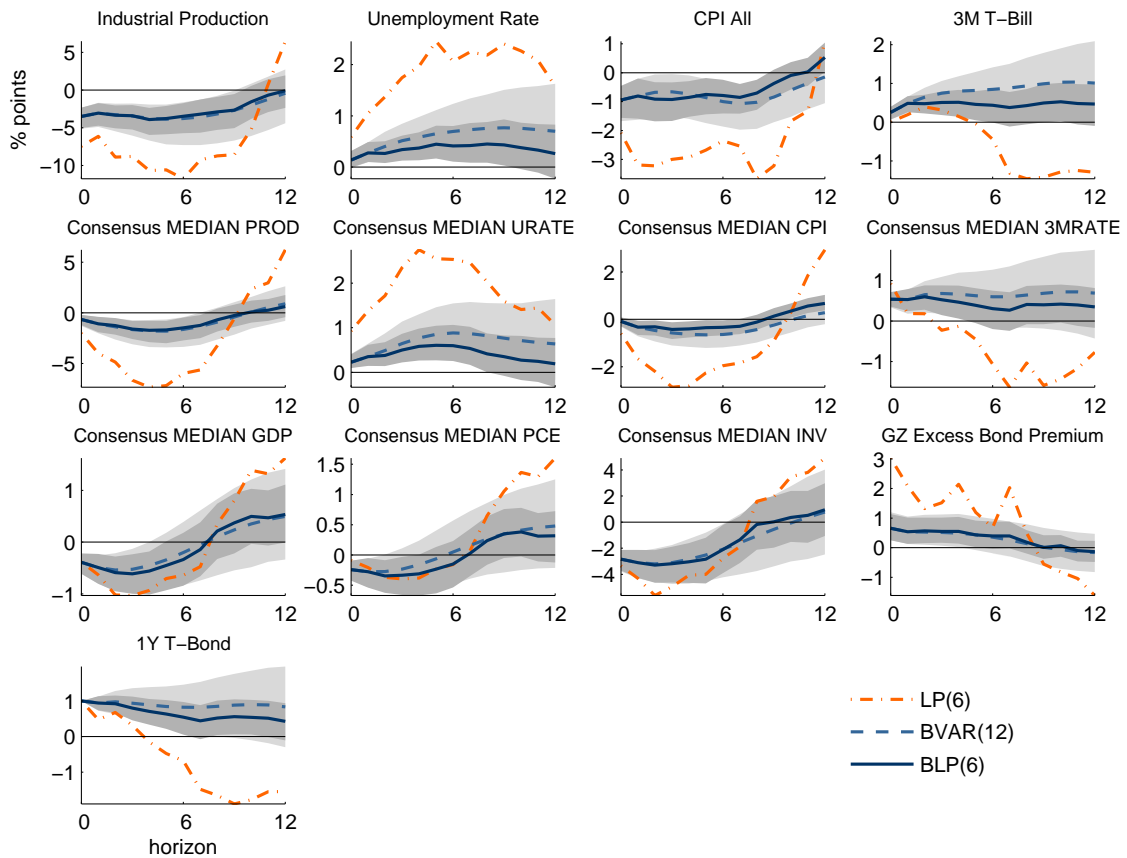
(A) Interest rates responses across horizons.

(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.

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.