Online Appendix to*

The Transmission of Monetary Policy Shocks

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This version: 19 December 2019

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*For Online Publication Only

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A Derivations

A.1 Aggregate Expectation Revisions

Recall from Section 3 that at $\underline{t}$ both agents and the central bank receive signals about the economy, and as a result of that, update their expectations. Specifically, at opening time $\underline{t}$ each agent i observes a private noisy signal of the state of the economy x_t

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

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

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

where ξ_t is the vector of structural shocks.

Given the signals, agents update their expectations using

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

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

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

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

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

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

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

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

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

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

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

$$
\begin{aligned}
F_{i,\bar{t}}x_t - F_{i,\underline{t}}x_t &= K_2\left[\tilde{s}_{cb,\bar{t}} - F_{i,\underline{t}}x_t\right] \\
&= K_2(x_t + \tilde{\nu}_{cb,\bar{t}}) - K_2\left[K_1(x_t + \nu_{i,\bar{t}}) + (1-K_1)F_{i,\overline{t-1}}x_t\right] \\
&= K_2(1-K_1)x_t + K_2\tilde{\nu}_{cb,\bar{t}} - K_2K_1\nu_{i,\bar{t}} - K_2(1-K_1)F_{i,\overline{t-1}}x_t \\
&= K_2(1-K_1)\rho\left[x_{t-1} - F_{i,\overline{t-1}}x_{t-1}\right] + K_2\left[(1-K_1)\xi_t + \tilde{\nu}_{cb,\bar{t}} - K_1\nu_{i,\bar{t}}\right].
\end{aligned}
\tag{A.10}
$$

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

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

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

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

The characteristics of the common noise $\tilde{\nu}_{cb,\bar{t}}$ are derived from the Taylor rule in Eq. (3), and the signal extraction problem of the central bank in Eq. (A.6). Specifically:

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

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

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

where

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

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

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

Eq. (6) follows by taking the average of Eq. (A.17) over the agents i.

A.2 Bias in OLS Regression

Recall Eq. (6):

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

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

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

The negative sign of the last two terms determine the negative bias of the estimator.

B Bayesian Local Projections

In this section we provide the gist of our Bayesian approach to local projections. A more comprehensive treatment of the method is reported in Miranda-Agrippino and Ricco (2015).

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

$$
y_{t+1} = By_t + \varepsilon_{t+1} \qquad \varepsilon_t \sim \mathcal{N}(0, \Sigma_\varepsilon)\ , \qquad \text{(B.1)}
$$

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 innovations.[1] Conversely, LPs estimate the IRFs directly from a set of linear regressions of the form

$$
y_{t+h} = B^{(h)}y_t + \varepsilon_{t+h}^{(h)}\ , \qquad \varepsilon_{t+h}^{(h)} \sim \mathcal{N}\left(0, \Sigma_\varepsilon^{(h)}\right) \qquad \forall\ h = 1, \ldots, H\ . \qquad \text{(B.2)}
$$

[1]To simplify the notation, we omit deterministic components from Eq. (B.1), and consider a simple VAR(1). However, this is equivalent to a VAR(p) written in VAR(1) companion form.

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

$$\text{IRF}_h^{\text{VAR}} = B^h A_0^{-1} \ , \tag{B.3}$$
$$\text{IRF}_h^{\text{LP}} \ = B^{(h)} A_0^{-1} \ , \tag{B.4}$$

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

$$B^{(h)} \longleftrightarrow B^{(\text{VAR},h)} = B^h \ , \tag{B.5}$$
$$\varepsilon_{t+h}^{(h)} \longleftrightarrow \varepsilon_{t+h}^{(\text{VAR},h)} \ = \sum_{j=1}^{h} B^{h-j} \varepsilon_{t+h} \ . \tag{B.6}$$

Three observations are in order. First, conditional on the underlying data generating process being the linear model in Eq. (B.1), and abstracting from estimation uncertainty, the IRFs computed with the two methods should coincide. Second, as shown by Eq. (B.6), conditional on the linear model being correctly specified, LPs are bound to have higher estimation variance due to (strongly) autocorrelated residuals.[2] Third, given that for $h = 1$ VARs and LPs coincide, the identification problem is identical for the two methods. In other words, given an external instrument or a set of theory-based assumptions, the way in which the A_0 matrix is derived from either VARs or LPs coincides.

The map in Eq. (B.5-B.6) provides a natural bridge between the two empirical specifications, which we exploit to inform the priors for our method.[3] For the coefficients of Eq. (B.2) 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

$$\Sigma_{\varepsilon}^{(h)} \mid \lambda^{(h)} \sim \mathcal{IW}\left(\Psi_0^{(h)}, d_0^{(h)}\right) \ ,$$
$$\beta^{(h)} \mid \Sigma_{\varepsilon}^{(h)}, \lambda^{(h)} \sim \mathcal{N}\left(\beta_0^{(h)}, \Sigma_{\varepsilon}^{(h)} \otimes \Omega_0^{(h)}\left(\lambda^{(h)}\right)\right) \ , \tag{B.7}$$

where $\beta^{(h)}$ is the vector containing all the local projection coefficients at horizon h –

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

[3]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.

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. (B.1) this writes

$$\beta_0^{(h)} = vec\left(B_{T_0}^h\right), \tag{B.8}$$

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). Intuitively, the prior gives weight to the belief that a VAR can describe the behaviour of economic time series, at least first approximation.[4]

The posterior distribution for the BLP coefficients can then be obtained by combining the priors in Eq. (B.7) 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.[5] 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

[4]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. Also, one could specify a hyperprior distribution for the first autocorrelation coefficients, as a generalisation of Litterman (1986), and conduct inference following the approach in Giannone et al. (2015). We explore these possibilities in Miranda-Agrippino and Ricco (2015).

[5]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.

MLE but with a HAC-corrected covariance matrix:

$$\begin{aligned}
&\Sigma_{\varepsilon,\text{HAC}}^{(h)} \mid \lambda^{(h)}, \text{y} \sim \mathcal{IW}\left(\Psi_{\text{HAC}}^{(h)}, d\right), \\
&\beta^{(h)} \mid \Sigma_{\varepsilon,\text{HAC}}^{(h)}, \lambda^{(h)}, \text{y} \sim \mathcal{N}\left(\tilde{\beta}^{(h)}, \Sigma_{\varepsilon,\text{HAC}}^{(h)} \otimes \Omega^{(h)}\right).
\end{aligned} \tag{B.9}$$

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

It is important to observe that BLP IRFs have been engineered to span the space between VARs and local projections. To see this, note that given the prior in Eq. (B.7), the posterior mean of BLP responses takes the form

$$B_{\text{BLP}}^{(h)} \propto \left(X'X + \left(\Omega_0^{(h)}\left(\lambda^{(h)}\right)\right)^{-1}\right)^{-1}\left((X'X)B_{\text{LP}}^{(h)} + \left(\Omega_0^{(h)}\left(\lambda^{(h)}\right)\right)^{-1} B_{\text{VAR}}^{h}\right), \tag{B.10}$$

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

$$\mathbb{V}ar\left(B_{\text{BLP}}^{(h)}\right) = \Sigma_{\varepsilon,\text{HAC}}^{(h)} \otimes \left(X'X + \left(\Omega_0^{(h)}\left(\lambda^{(h)}\right)\right)^{-1}\right)^{-1}. \tag{B.11}$$

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.

It is worth observing that, in general, BLP IRFs may not necessarily lie between VAR and LP IRFs for two reasons. First, the VAR prior for the BLP coefficients is drawn over a pre-sample whose properties may differ from the estimation sample. Second, note that Eq. (B.10) can be rewritten as

$$\begin{aligned}
B_{\text{BLP}}^{(h)} &\propto \left[\mathbb{I}_k + M^{-1}\right]^{-1} B_{\text{LP}}^{(h)} + \left[\mathbb{I}_k + M\right]^{-1} B_{\text{VAR}}^{h}, \\
&= QB_{\text{LP}}^{(h)} + (\mathbb{I}_k - Q)B_{\text{VAR}}^{h},
\end{aligned} \tag{B.12}$$

where $M \equiv X'X\Omega_0^{(h)}$ is a k-dimensional matrix, with $k = n(p+1)$. Each column of $B_{\text{BLP}}^{(h)}$ refers to a different equation in the system. Since Q is a full matrix, BLP IRFs for variable j at horizon h are not a simple weighed sum of the LP and VAR IRFs for variable j at horizon h with scalar weights at each horizon, and hence may not be in-between them.

The formulation of BLP allows us to address 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. 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 $\left[\beta^{(h)}, \Sigma_{\varepsilon,\mathrm{HAC}}^{(h)}\right]$ can then be drawn from their posterior, which is Normal-inverse-Wishart with HAC-corrected posterior scale.

C Data

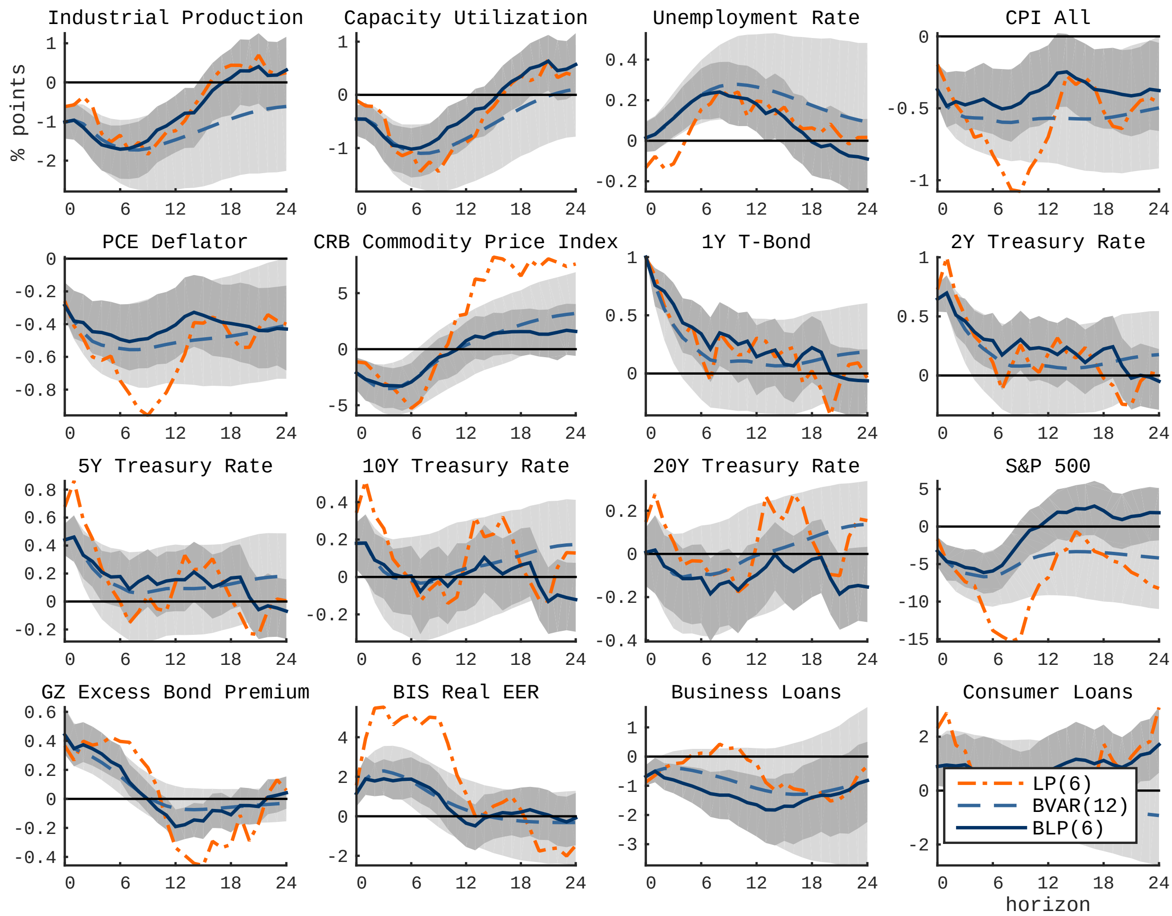
Table C.1: Variables Used

Code	Variable Name	Source	log	MODEL (1)	(2)	(3)	(4)
INDPRO	Industrial Production	FRED	●	●	●	●	●
CAPUTLB00004S	Capacity Utilization	FRED	●		●		●
UNRATE	Unemployment Rate	FRED		●	●	●	●
AWHMAN	Average Weekly Hours Mfg	FRED	●		●		
CES3000000008	Average Earnings Mfg	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	FRED	●		●		
DNDGRA3M086SBEA	Real Consumption: Nondurable	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 Treas)	GK			●		
CSHPI	Case Shiller House Price Index	DATASTREAM	●		●		
CFPROD	Expected Industrial Production	CE				●	
CFCPI	Expected Consumer Prices	CE				●	
CFURATE	Expected Unemployment Rate	CE				●	
CF3MRATE	Expected 3M Interest Rate	CE				●	

Models: (1) Baseline specification, Coibion (2012) VAR; (2) Specification of Figure 7; (3) Specification of Figure 9; (4) Specification of 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).

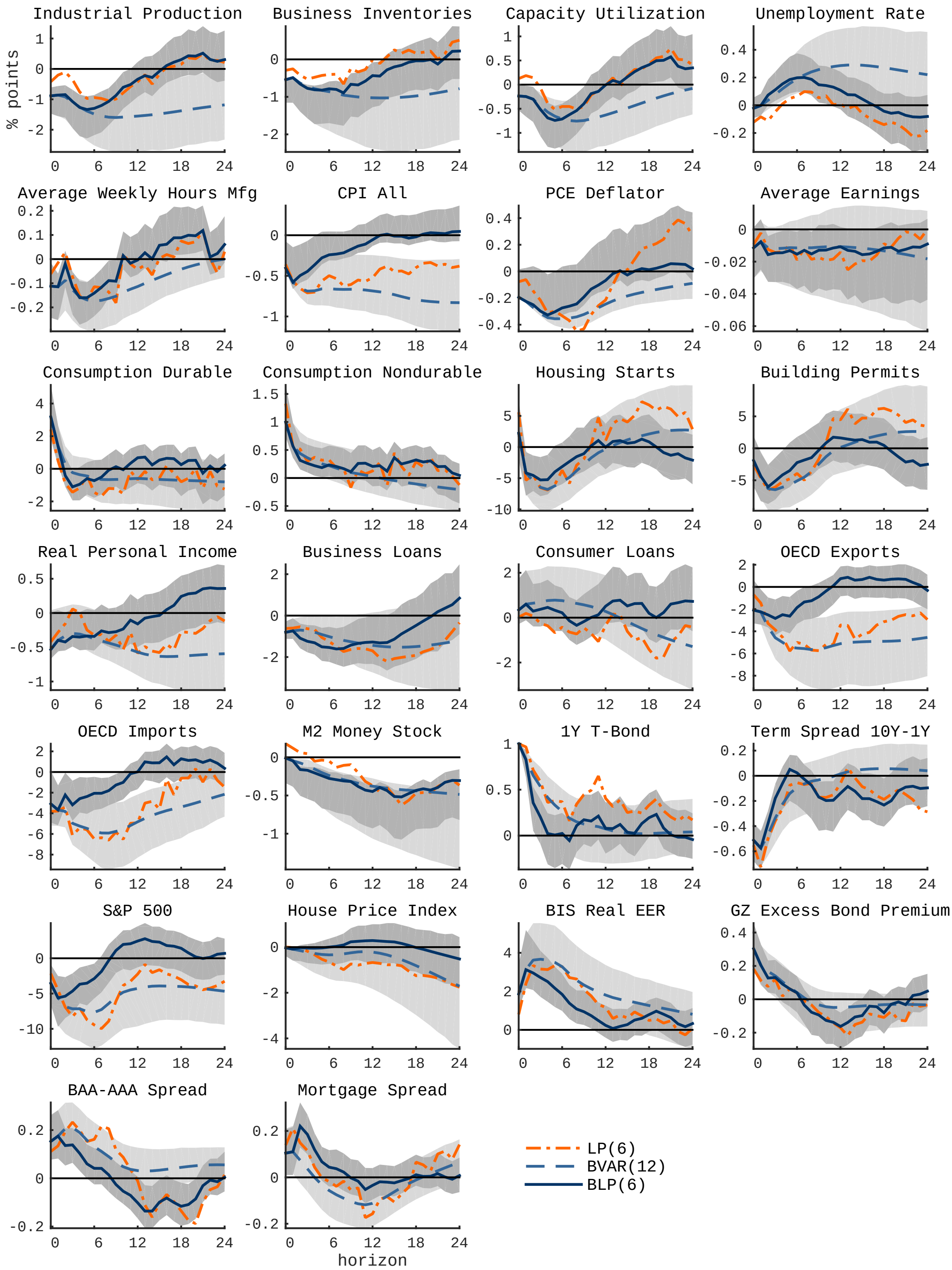
D Other Charts

Figure D.1: Interest Rate Channel, All Methods



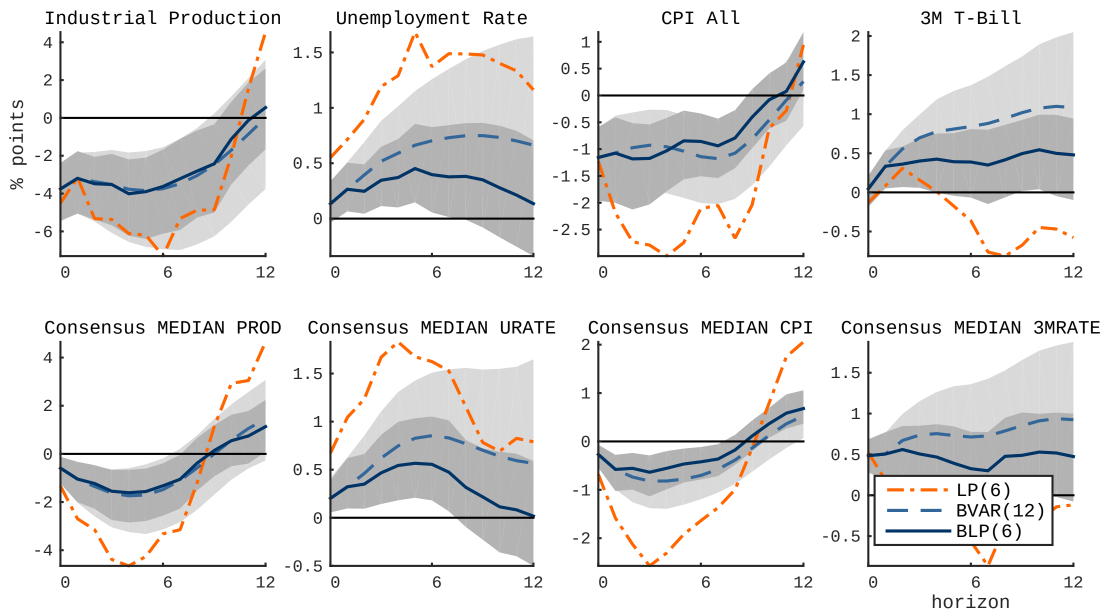
Note: BLP, VAR and LP responses to a contractionary monetary policy shock. Shock identified with the MPI_t series and normalised to induce a 100 basis point increase in the 1-year rate. Sample 1979:01 - 2014:12. $BLP(6)$ with $VAR(12)$ prior over 1973:01 - 1979:01. Shaded areas are 90% posterior coverage bands.

Figure D.2: All Variables. All Methods. Combination of Sets



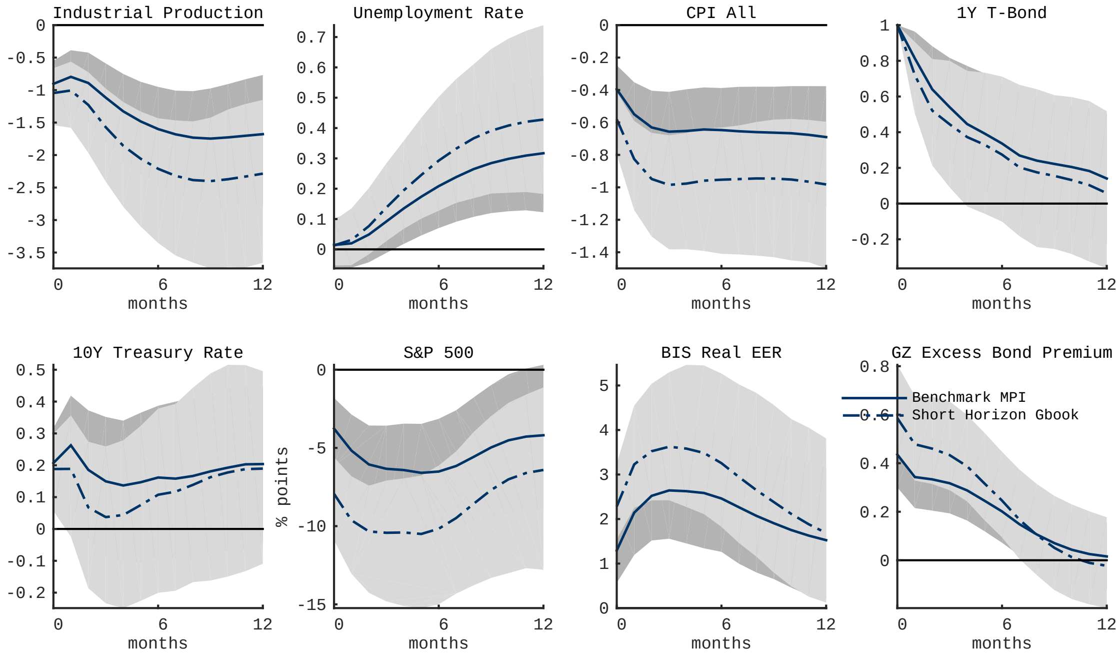
Note: BLP, VAR and LP responses to a contractionary monetary policy shock. Collection of responses from 4 smaller sets. Shock identified with the MPI_t series and normalised to induce a 100 basis point increase in the 1-year rate. Sample 1979:01 - 2014:12. $BLP(6)$ with $VAR(12)$ prior. Pre-sample varies depending on availability of the individual series. Shaded areas are 90% posterior coverage bands.

Figure D.3: Private Expectations. all Methods



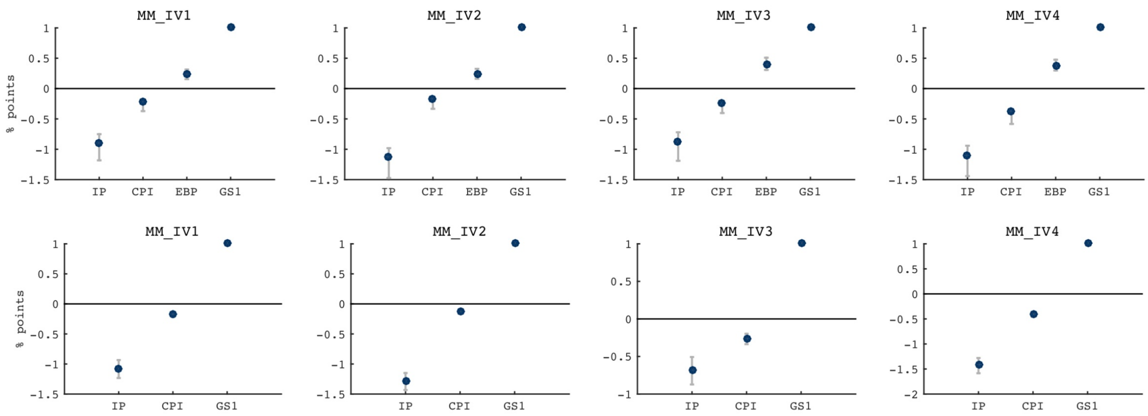
Note: BLP, VAR and LP responses to a contractionary monetary policy shock. Shock identified with the MPI_t series and normalised to induce a 100 basis point increase in the 1-year rate. Sample 1999:01 - 2014:12. $BLP(6)$ with $VAR(12)$ prior over 1993:01 - 1999:01. Shaded areas are 90% posterior coverage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

Figure D.4: Comparison of Instruments for MP Shocks



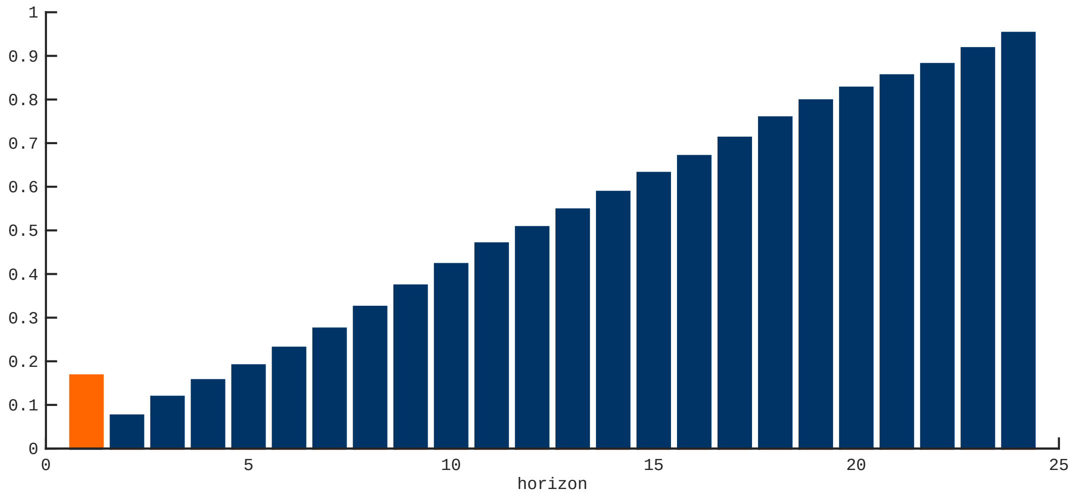
Note: Benchmark Monetary Policy Instrument (solid) vs instrument that only controls for Greenbook forecasts at short horizons (dash-dotted). Shock are normalised to induce a 100 basis point increase in the 1-year rate. Sample 1979:01 - 2014:12. Shaded areas are 90% posterior coverage bands.

Figure D.5: Comparison of Instruments for MP Shocks



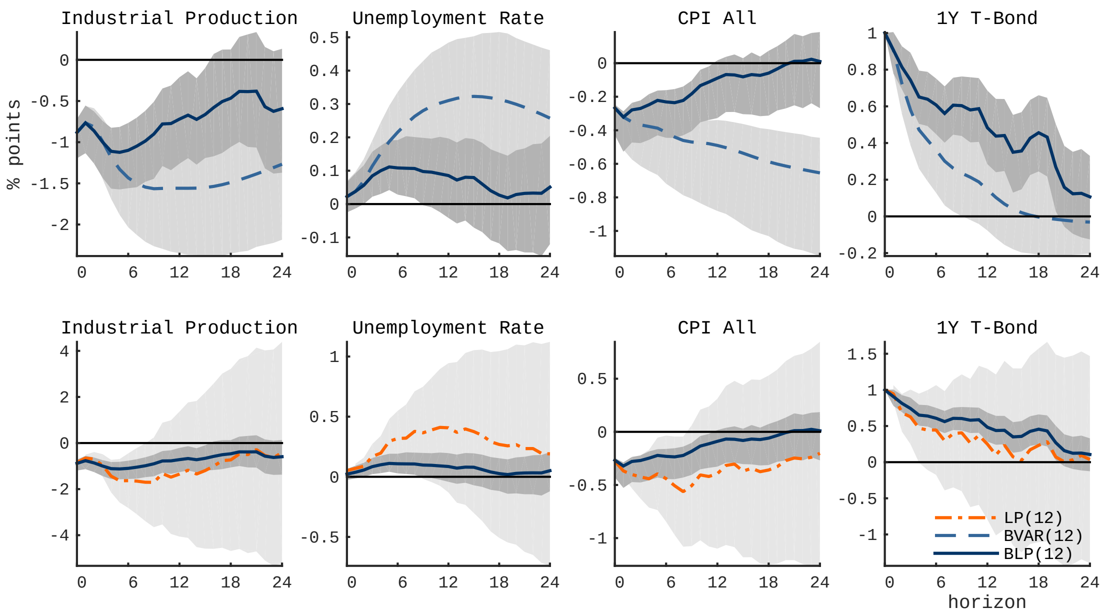
Note: Impact responses to monetary policy shocks across instruments and VARs. Top row: VAR includes IP, UNRATE, CPI, CRBPI, EBP, 1YRATE. Bottom row: VAR excludes EBP. Instruments: IV1= projection of FF4 at all HF dates on all Greenbok types (corresponds to our benchmark instrument, MPI); IV2= projection of FF4 at all HF dates on all Greenbok levels; IV3 = projection of FF4 at all HF dates on all Greenbok revisions; IV4: projection of FF4 at all HF dates on all Greenbok types at short horizons.

Figure D.6: Optimal BLP Prior Shrinkage at Projection Horizons



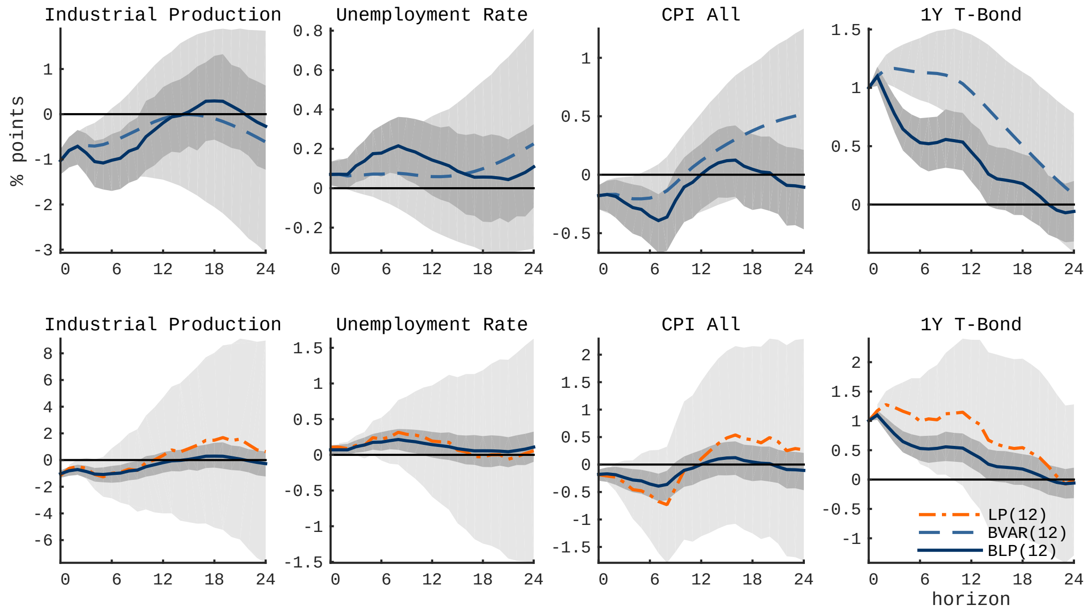
Note: Orange bar: optimal shrinkage of NIW prior for the VAR. Blue bars: optimal shrinkage of VAR prior for BLP coefficients at different horizons. Baseline set. Sample 1979:01 - 2014:12. $BLP(12)$ with $VAR(12)$ prior over 1969:01 - 1979:01.

Figure D.7: Methods Comparison: Random Walk Prior (no-presample) for BLP



Note: 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.

Figure D.8: Methods Comparison: Sample 1979-2014



Note: 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.

E Regressions of High-Frequency Surprises on Greenbook Forecasts

Notation:

- gPGDP, gRGDP, UNEMP denote Greenbook forecasts for the quarterly growth rate of the GDP deflator, the quarterly growth rate of real GDP, and the unemployment rate respectively.
- iPGDP, iRGDP, iUNEMP denote forecasts revisions between consecutive Greenbook publications for the quarterly growth rate of the GDP deflator, the quarterly growth rate of real GDP, and the unemployment rate respectively.
- B1 denotes forecast for the previous quarter, F0 denotes forecasts for the current quarter, F1, F2, F3 denote forecast for one, two and three quarters ahead respectively.

TABLE E.1 : FF4 – 1990:2009 – ALL HF DATES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
gRGDPB1	0.001	0.000	-0.000	0.005**				-0.000			-0.001				
	(0.28)	(0.07)	(-0.10)	(2.39)				(-0.05)			(-0.40)				
gRGDPF0	0.006	0.007	0.009		0.009***			0.009**			0.009*				
	(1.04)	(1.27)	(1.19)		(2.80)			(1.98)			(1.75)				
gRGDPF1	0.001	-0.000	-0.003			0.003		0.004			0.003				
	(0.14)	(-0.03)	(-0.27)			(0.77)		(0.56)			(0.30)				
gRGDPF2	-0.001	-0.004	-0.005				0.001	-0.008			-0.006				
	(-0.07)	(-0.45)	(-0.53)				(0.26)	(-1.16)			(-0.76)				
gRGDPF3	-0.004		-0.004					0.001			-0.004				
	(-0.56)		(-0.50)					(0.21)			(-0.53)				
gPGDPB1	-0.009	-0.012*	-0.007	-0.008*					-0.011*		-0.006				
	(-1.49)	(-1.94)	(-1.27)	(-1.94)					(-1.93)		(-1.30)				
gPGDPF0	0.012	0.010	0.015*		-0.000				0.004		0.009				
	(1.52)	(1.42)	(1.82)		(-0.01)				(0.75)		(1.37)				
gPGDPF1	-0.036**	-0.037**	-0.034**			-0.014**			-0.023**		-0.015				
	(-2.30)	(-2.52)	(-2.31)			(-2.24)			(-2.29)		(-1.40)				
gPGDPF2	0.040**	0.027**	0.042**				-0.008		0.019		0.021				
	(2.00)	(2.04)	(2.04)				(-1.45)		(1.45)		(1.35)				
gPGDPF3	-0.018		-0.028						-0.002		-0.019				
	(-0.96)		(-1.28)						(-0.13)		(-0.95)				
UNEMPF0	0.003	0.003	-0.065		0.001					-0.008	-0.039				
	(0.60)	(0.70)	(-0.64)		(0.19)					(-0.11)	(-0.60)				
iRGDPB1	-0.007	-0.009	-0.006	-0.010**								-0.001			0.000
	(-1.23)	(-1.62)	(-1.07)	(-2.04)								(-0.25)			(0.02)
iRGDPF0	0.000	-0.001	-0.002		0.005							0.007			0.007
	(0.06)	(-0.18)	(-0.25)		(0.99)							(1.51)			(1.32)
iRGDPF1	0.008	0.008	0.010			0.006						0.014*			0.014*
	(0.76)	(0.83)	(0.91)			(0.84)						(1.73)			(1.71)
iRGDPF2	0.010	0.001	0.013				-0.005					-0.011			-0.001
	(0.97)	(0.07)	(1.17)				(-0.56)					(-1.31)			(-0.09)
iPGDPB1	-0.004	-0.004	-0.009	-0.002									-0.002		-0.000
	(-0.45)	(-0.47)	(-0.88)	(-0.19)									(-0.17)		(-0.04)
iPGDPF0	-0.002	-0.002	-0.002		0.004								0.008		0.008
	(-0.18)	(-0.19)	(-0.19)		(0.49)								(0.92)		(0.96)
iPGDPF1	0.043**	0.046**	0.047**			0.018							0.015		0.016
	(2.04)	(2.40)	(2.41)			(1.46)							(1.23)		(1.09)
iPGDPF2	-0.021	-0.024	-0.019				0.023						0.021		0.012
	(-0.86)	(-1.02)	(-0.74)				(1.31)						(1.22)		(0.79)
iUNEMPB1	0.068		0.054	0.053										0.103	0.082
	(1.01)		(0.74)	(0.82)										(1.59)	(1.31)
iUNEMPF0	-0.015		0.026		0.009									0.035	-0.013
	(-0.31)		(0.34)		(0.34)									(0.96)	(-0.36)
iUNEMPF1	-0.098		-0.254**			-0.028								-0.174**	-0.134*
	(-1.30)		(-2.28)			(-1.00)								(-2.29)	(-1.87)
iUNEMPF2	0.104		0.212**				-0.023							0.092*	0.131**
	(1.63)		(2.59)				(-0.81)							(1.75)	(2.26)
UNEMPB1			-0.003	0.002						0.034	0.007				
			(-0.06)	(0.41)						(1.18)	(0.25)				
UNEMPF1			0.260*			-0.000				0.020	0.096				
			(1.77)			(-0.01)				(0.21)	(0.86)				
UNEMPF2			-0.210*				-0.003			-0.074	-0.041				
			(-1.66)				(-1.01)			(-0.69)	(-0.39)				
UNEMPF3			0.015							0.028	-0.024				
			(0.17)							(0.44)	(-0.30)				
constant	-0.011	-0.015	0.041	-0.022	-0.040	0.005	0.016	-0.029**	0.013	-0.016	0.017	-0.017***	-0.020***	-0.018***	-0.018***
	(-0.25)	(-0.35)	(0.62)	(-0.61)	(-1.09)	(0.15)	(0.44)	(-2.24)	(1.03)	(-0.64)	(0.30)	(-3.41)	(-3.75)	(-3.55)	(-3.23)
R^2	0.044	0.060	0.058	0.027	0.045	0.040	-0.004	0.054	0.036	0.020	0.046	0.014	-0.010	0.014	0.000
F	1.651	1.768	1.578	2.024	2.636	2.436	1.045	2.752	2.538	1.603	1.541	1.800	1.086	1.663	1.405
p	0.039	0.036	0.045	0.065	0.018	0.027	0.398	0.020	0.030	0.161	0.096	0.131	0.365	0.160	0.167
N	186	186	186	186	186	186	186	186	186	186	186	186	186	186	186

TABLE E.2 : FF4 – 1990:2009 – SCHEDULED FOMC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
gRGDPB1	-0.005**	-0.006**	-0.004	0.001				-0.005**			-0.006**				
	(-2.00)	(-2.02)	(-1.49)	(0.71)				(-2.55)			(-2.44)				
gRGDPF0	0.007	0.008*	0.008		0.006**			0.008**			0.009**				
	(1.49)	(1.80)	(1.42)		(2.31)			(2.23)			(2.01)				
gRGDPF1	0.002	0.001	-0.001			0.005		0.007			0.007				
	(0.32)	(0.15)	(-0.08)			(1.23)		(1.16)			(0.97)				
gRGDPF2	0.004	0.001	0.001				0.004	-0.003			0.001				
	(0.59)	(0.25)	(0.20)				(1.02)	(-0.48)			(0.19)				
gRGDPF3	-0.002		0.001					-0.002			-0.001				
	(-0.25)		(0.10)					(-0.35)			(-0.08)				
gPGDPB1	-0.006	-0.010*	-0.005	-0.007*					-0.006		-0.007				
	(-1.02)	(-1.76)	(-0.96)	(-1.78)					(-1.06)		(-1.60)				
gPGDPF0	0.013*	0.010	0.013*		0.003				0.004		0.007				
	(1.73)	(1.46)	(1.75)		(0.63)				(0.75)		(1.25)				
gPGDPF1	-0.009	-0.014	-0.009			-0.005			-0.012		-0.000				
	(-0.63)	(-1.10)	(-0.72)			(-0.97)			(-1.25)		(-0.00)				
gPGDPF2	0.022	0.010	0.023				-0.003		0.013		0.011				
	(1.03)	(0.83)	(1.04)				(-0.57)		(1.01)		(0.81)				
gPGDPF3	-0.024		-0.023						-0.007		-0.013				
	(-1.01)		(-0.86)						(-0.30)		(-0.59)				
UNEMPF0	-0.004	-0.003	0.108		-0.001					0.125**	0.068				
	(-1.09)	(-0.86)	(1.30)		(-0.23)					(2.32)	(1.29)				
iRGDPB1	-0.002	-0.005	-0.002	-0.008*								-0.006			-0.004
	(-0.43)	(-1.12)	(-0.41)	(-1.66)								(-1.38)			(-0.90)
iRGDPF0	0.001	-0.001	-0.000		0.009*							0.008*			0.007
	(0.18)	(-0.12)	(-0.02)		(1.91)							(1.74)			(1.47)
iRGDPF1	0.011	0.012	0.012			0.008						0.016*			0.014*
	(1.00)	(1.31)	(1.21)			(1.09)						(1.96)			(1.73)
iRGDPF2	0.003	-0.007	0.006				-0.007					-0.010			-0.001
	(0.36)	(-0.84)	(0.67)				(-0.69)					(-1.12)			(-0.09)
iPGDPB1	0.001	0.001	0.001	0.004									0.002		0.003
	(0.13)	(0.10)	(0.13)	(0.46)									(0.29)		(0.32)
iPGDPF0	-0.004	-0.002	-0.004		0.002								0.007		0.007
	(-0.38)	(-0.23)	(-0.41)		(0.21)								(0.79)		(0.87)
iPGDPF1	0.020	0.027	0.021			0.011							0.013		0.015
	(0.86)	(1.38)	(1.04)			(0.88)							(1.09)		(1.03)
iPGDPF2	0.007	-0.000	0.001				0.025						0.024		0.014
	(0.27)	(-0.01)	(0.06)				(1.39)						(1.40)		(0.89)
iUNEMPB1	0.074		0.117*	0.036										0.106*	0.081
	(1.17)		(1.85)	(0.56)										(1.79)	(1.46)
iUNEMPF0	0.032		-0.043		0.012									0.070**	0.019
	(0.87)		(-0.67)		(0.46)									(2.19)	(0.57)
iUNEMPF1	-0.167**		-0.183**			-0.020								-0.205***	-0.155**
	(-2.41)		(-1.98)			(-0.77)								(-2.66)	(-2.21)
iUNEMPF2	0.138**		0.174***				-0.023							0.097*	0.126**
	(2.48)		(2.69)				(-0.86)							(1.83)	(2.19)
UNEMPB1			-0.055	-0.002						-0.014	-0.021				
			(-1.13)	(-0.58)						(-0.66)	(-0.76)				
UNEMPF1			0.014			-0.001				-0.140*	-0.098				
			(0.13)			(-0.50)				(-1.74)	(-1.17)				
UNEMPF2			-0.179*				-0.003			-0.018	-0.007				
			(-1.81)				(-1.21)			(-0.21)	(-0.09)				
UNEMPF3			0.107							0.047	0.056				
			(1.55)							(0.94)	(0.87)				
constant	0.009	0.010	0.006	0.018	-0.023	-0.001	0.004	-0.019*	0.006	-0.005	-0.019	-0.006*	-0.010**	-0.007*	-0.006
	(0.23)	(0.28)	(0.11)	(0.62)	(-0.85)	(-0.04)	(0.13)	(-1.78)	(0.59)	(-0.24)	(-0.42)	(-1.68)	(-2.27)	(-1.93)	(-1.47)
R^2	0.113	0.099	0.111	0.000	0.070	0.070	0.011	0.097	0.002	0.047	0.099	0.072	-0.001	0.066	0.087
F	1.600	1.388	1.726	0.908	2.160	1.834	1.162	2.729	0.991	1.966	1.631	2.662	1.427	2.309	1.747
p	0.052	0.151	0.023	0.491	0.050	0.096	0.329	0.022	0.425	0.087	0.072	0.035	0.228	0.060	0.062
N	160	160	160	160	160	160	160	160	160	160	160	160	160	160	160

TABLE E.3: FF4 – 1994:2009 – SCHEDULED FOMC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
gRGDPB1	-0.004	-0.004	-0.003	0.003			
	(-1.24)	(-1.43)	(-0.98)	(1.24)			
gRGDPF0	0.007	0.007	0.007		0.006**		
	(1.22)	(1.31)	(1.03)		(2.50)		
gRGDPF1	0.002	0.002	0.001			0.006	
	(0.17)	(0.25)	(0.07)			(1.45)	
gRGDPF2	0.001	-0.001	-0.000				0.005
	(0.14)	(-0.18)	(-0.04)				(1.14)
gRGDPF3	0.001		0.003				
	(0.07)		(0.33)				
gPGDPB1	-0.009	-0.010*	-0.009	-0.009*			
	(-1.43)	(-1.71)	(-1.40)	(-1.70)			
gPGDPF0	0.015*	0.014*	0.014		0.006		
	(1.68)	(1.70)	(1.63)		(1.02)		
gPGDPF1	-0.011	-0.014	-0.012			-0.004	
	(-0.67)	(-0.98)	(-0.82)			(-0.51)	
gPGDPF2	0.010	0.004	0.011				-0.000
	(0.50)	(0.22)	(0.53)				(-0.02)
gPGDPF3	-0.011		-0.007				
	(-0.60)		(-0.36)				
UNEMPF0	-0.002	-0.002	0.088		0.001		
	(-0.52)	(-0.45)	(0.93)		(0.49)		
iRGDPB1	-0.003	-0.006	-0.002	-0.010*			
	(-0.54)	(-1.05)	(-0.28)	(-1.80)			
iRGDPF0	0.005	0.003	0.004		0.012**		
	(0.64)	(0.42)	(0.45)		(2.08)		
iRGDPF1	0.006	0.008	0.009			0.010	
	(0.59)	(0.83)	(0.82)			(1.36)	
iRGDPF2	0.002	-0.003	0.004				-0.005
	(0.21)	(-0.33)	(0.33)				(-0.48)
iPGDPB1	0.002	0.004	0.003	0.009			
	(0.19)	(0.35)	(0.31)	(0.86)			
iPGDPF0	-0.004	-0.003	-0.004		0.003		
	(-0.38)	(-0.29)	(-0.42)		(0.26)		
iPGDPF1	0.019	0.023	0.019			0.004	
	(0.67)	(0.93)	(0.71)			(0.30)	
iPGDPF2	0.018	0.017	0.012				0.021
	(0.67)	(0.66)	(0.43)				(1.02)
iUNEMPB1	0.075		0.104	0.065			
	(0.92)		(1.29)	(0.85)			
iUNEMPF0	0.068		-0.000		0.027		
	(1.52)		(-0.01)		(1.02)		
iUNEMPF1	-0.166**		-0.155			-0.011	
	(-2.03)		(-1.59)			(-0.37)	
iUNEMPF2	0.121*		0.141*				-0.023
	(1.80)		(1.77)				(-0.72)
UNEMPB1			-0.037	-0.001			
			(-0.66)	(-0.19)			
UNEMPF1			-0.021			-0.001	
			(-0.16)			(-0.42)	
UNEMPF2			-0.124				-0.002
			(-1.08)				(-0.64)
UNEMPF3			0.091				
			(1.10)				
constant	0.003	0.009	-0.007	0.011	-0.042	-0.007	-0.011
	(0.07)	(0.25)	(-0.10)	(0.42)	(-1.51)	(-0.20)	(-0.27)
R^2	0.111	0.113	0.092	0.015	0.108	0.076	0.003
F	1.369	1.365	1.646	0.910	2.274	1.664	0.886
p	0.145	0.168	0.040	0.490	0.041	0.136	0.508
N	128	128	128	128	128	128	128

Table E.1: Greenbook Forecasts, All Variables, 1990-2014

	(1) FF4	(2) FF4	(3) FF4	(4) FF4	(5) FF4s	(6) FF4s	(7) FF4s	(8) FF4s
gRGDPB1	-0.000			-0.002	-0.005***			-0.006**
	(-0.08)			(-0.56)	(-2.64)			(-2.58)
gRGDPF0	0.009**			0.009**	0.008**			0.009**
	(2.15)			(2.11)	(2.38)			(2.27)
gRGDPF1	0.004			0.002	0.007			0.005
	(0.58)			(0.23)	(1.21)			(0.86)
gRGDPF2	-0.008			-0.007	-0.003			0.001
	(-1.21)			(-0.86)	(-0.50)			(0.08)
gRGDPF3	0.002			-0.003	-0.002			0.000
	(0.32)			(-0.46)	(-0.33)			(0.01)
gPGDPB1		-0.011*		-0.006		-0.006		-0.006
		(-1.95)		(-1.35)		(-1.07)		(-1.53)
gPGDPF0		0.003		0.008		0.003		0.006
		(0.67)		(1.31)		(0.68)		(1.22)
gPGDPF1		-0.021**		-0.013		-0.010		-0.001
		(-2.31)		(-1.45)		(-1.23)		(-0.15)
gPGDPF2		0.013		0.014		0.008		0.007
		(1.42)		(1.37)		(0.99)		(0.82)
gPGDPF3		0.002		-0.013		-0.003		-0.009
		(0.13)		(-0.88)		(-0.16)		(-0.58)
UNEMPB1			0.034	0.006			-0.009	-0.012
			(1.39)	(0.27)			(-0.53)	(-0.57)
UNEMPF0			-0.002	-0.029			0.115**	0.068
			(-0.03)	(-0.50)			(2.45)	(1.50)
UNEMPF1			0.008	0.079			-0.133*	-0.109
			(0.09)	(0.79)			(-1.90)	(-1.53)
UNEMPF2			-0.064	-0.030			-0.020	0.005
			(-0.71)	(-0.34)			(-0.31)	(0.07)
UNEMPF3			0.026	-0.027			0.048	0.049
			(0.47)	(-0.36)			(1.16)	(0.89)
_cons	-0.029**	0.014	-0.021	0.018	-0.019*	0.006	-0.011	-0.024
	(-2.32)	(1.29)	(-1.31)	(0.34)	(-1.82)	(0.76)	(-0.81)	(-0.59)
R^2	0.058	0.037	0.026	0.052	0.100	0.003	0.050	0.099
F	2.878	2.722	1.792	1.667	2.774	1.017	2.044	1.588
p	0.016	0.021	0.116	0.061	0.020	0.409	0.075	0.082
N	202	202	202	202	176	176	176	176

Note: The first four columns use all announcement dates, last four the dates of scheduled FOMC meetings only. Regressions estimated on the sample 1990:01-2014:12. t-stat in parentheses, * p<0.1, ** p<0.05, *** p<0.01

Table E.2: Greenbook Forecast Revisions, All Variables, 1990-2014

	(1) FF4	(2) FF4	(3) FF4	(4) FF4	(5) FF4s	(6) FF4s	(7) FF4s	(8) FF4s
iRGDPB1	-0.002			-0.000	-0.006			-0.004
	(-0.40)			(-0.06)	(-1.49)			(-0.96)
iRGDPF0	0.007			0.007	0.008*			0.007
	(1.46)			(1.37)	(1.76)			(1.56)
iRGDPF1	0.015*			0.014*	0.016**			0.014*
	(1.87)			(1.90)	(2.03)			(1.87)
iRGDPF2	-0.012			-0.003	-0.011			-0.002
	(-1.45)			(-0.31)	(-1.18)			(-0.25)
iPGDPB1		-0.002		-0.000		0.002		0.003
		(-0.22)		(-0.01)		(0.23)		(0.37)
iPGDPF0		0.009		0.009		0.007		0.007
		(1.01)		(1.12)		(0.79)		(0.96)
iPGDPF1		0.016		0.015		0.013		0.013
		(1.49)		(1.29)		(1.28)		(1.13)
iPGDPF2		0.017		0.011		0.019		0.012
		(1.21)		(0.85)		(1.37)		(0.95)
iUNEMPB1			0.078	0.069			0.086	0.075
			(1.35)	(1.18)			(1.63)	(1.42)
iUNEMPF0			0.039	-0.004			0.071**	0.027
			(1.21)	(-0.12)			(2.44)	(0.91)
iUNEMPF1			-0.166**	-0.123*			-0.192***	-0.144**
			(-2.36)	(-1.97)			(-2.69)	(-2.35)
iUNEMPF2			0.087*	0.119**			0.089*	0.113**
			(1.79)	(2.28)			(1.81)	(2.20)
_cons	-0.016***	-0.018***	-0.016***	-0.017***	-0.005	-0.009**	-0.007*	-0.005
	(-3.38)	(-3.74)	(-3.53)	(-3.20)	(-1.64)	(-2.28)	(-1.92)	(-1.44)
R^2	0.016	-0.007	0.014	0.005	0.074	-0.000	0.062	0.089
F	1.789	1.246	1.654	1.367	2.694	1.544	2.306	1.764
p	0.132	0.293	0.162	0.185	0.033	0.192	0.060	0.058
N	202	202	202	202	176	176	176	176

Note: The first four columns use all announcement dates, last four the dates of scheduled FOMC meetings only. Regressions estimated on the sample 1990:01-2014:12. t-stat in parentheses, * p<0.1, ** p<0.05, *** p<0.01

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