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# Online Monitoring of Policy Optimality*

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**Abstract**

We present a method for online evaluation of the optimality of the current stance of monetary policy given the most up to date data available. The framework combines estimates of the causal effects of monetary policy tools on inflation and the unemployment gap with forecasts for these target variables. The forecasts are generated with a nowcasting model, incorporating new data as it becomes available, while using entropy tilting to anchor the long end of the forecast at long run survey expectations. In a retrospective analysis of the Fed's monetary policy decisions in the lead up to the Great Recession we find that we can reject the optimality of the policy stance as early as the beginning of February 2008. This early detection stems from the timely nowcasting of the deteriorating unemployment outlook.

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# 1 Introduction

The early detection of optimization failures in the stance of monetary policy is of crucial importance for policy makers. This is not only of interest within the central bank itself, but for governments and other policy makers, foreign and domestic alike, other market participants, and the general population. The prevalence of discussions, both in private and public, on how a central bank will, or should, respond to recent macroeconomic developments is a clear indicator of this. Since economic data relevant to the policy decisions is released every week, we present a framework for online monitoring of the stance of policy that incorporates the information contained in the constant inflow of new data. The framework allows us to update the assessment of the adequacy of the stance of policy at a frequency much higher than the frequency of the policy decisions.

This monitoring framework, which we refer to as the real-time OPP, will take the form of the OPP statistic of Barnichon and Mesters (2023). This statistic depends on the causal effects of policy instruments on the target variables along with conditional expectations of the target variables given a choice for the policy instruments. The real-time aspect of the proposed framework has to do with the conditional paths of the target variables. At the end of each week, we will update the conditional expectations of the paths of the target variables given all information available up to and including that week.[1] This means that we will systematically incorporate any economic data that is released in a particular week so that the calculation of the real-time OPP can be done at the end of each week using the most up-to-date information available. This will give us a timely indicator of whether the current stance of policy is optimal or not.

The fact that we test optimality of the stance of policy at the end of each week rather than testing the optimality of specific policy decisions, which happen at a frequency much lower than weekly, warrants some discussion. While the policy maker could, in theory, decide on policy each week, there are significant prohibitive costs to doing so. The real-time OPP

[1]In theory a smaller time increment could be chosen but for practical (computational) purposes the present paper considers updating the information set weekly.

should therefore be viewed as a thought experiment that supposes that the policy maker could adjust its policy at no cost in each week as a reaction to newly released information. In that setting, the real-time OPP gives the answer to the question if and how the policy maker should adjust its policy stance in light of new data. An alternative interpretation is that the sequence of test statistics between two consecutive policy decisions informs us how we should expect the policy maker to adjust their policy stance at the upcoming decision if they were to set policy optimally.

Building on the OPP statistic has the clear benefit that we do not need to know the true underlying structure of the economy. Instead, the statistic builds on the gradient of a loss function with respect to policy shocks. In the present paper, we will assume that the economy follows a linear model and therefore if the policy stance is optimal then the gradient of the loss function must be equal to zero. Therefore, knowing the value of the gradient is enough to determine whether the policy stance is optimal or not and, as we are assuming a linear model, setting the gradient equal to zero would give the optimal policy.

As alluded to previously, the gradient depends on two objects. The first are the deviations from targets of the forecasts, conditional on a policy decision, of inflation and unemployment, calculated over a horizon capturing the nature of the policy decision. The second are the causal effects of the policy tools on inflation and unemployment. It is important to note that knowledge of neither of these objects depends on knowing the true structural model of the economy. In fact, both components can be known without relying on any structural model at all.

The actual test statistic is a rescaling of the gradient by the inverse Hessian matrix of the loss function. The test statistic thus still only depends on the conditional forecasts and the causal effects. However, given the linearity of the underlying model and a quadratic loss function, the statistic now has a direct interpretation as the distance from the optimal policy path in the direction of an identified policy shock. That is, the value of the statistic equals the adjustment that would correct the optimization failure. Furthermore, the uncertainty inherent in the estimates of both the causal effects and the conditional expectations will serve to facilitate the use of the test statistic in a manner similar to a hypothesis test. The combined uncertainty allows us to calculate confidence bounds around the test statistic and thus allow us to make statements about a particular policy stance not being optimal at some confidence level.

In order to implement the framework we need estimates of the causal effects of the policy tools on the target variables, inflation and unemployment. This involves the estimation of structural impulse response functions (see, e.g., Ramey, 2016). Here we will use external instruments to identify the causal effects (see, e.g., Mertens and Ravn, 2013; Stock and Watson, 2018; Montiel Olea, Stock and Watson, 2021) where the external instruments are estimated from high-frequency price changes in assets around the time of monetary policy decisions (see, e.g., Altavilla et al., 2019; Kuttner, 2001; Gürkaynak, 2005; Swanson, 2017). More specifically, we will use penalized local projections along with external instruments for the estimation (see, Jordà, 2005; Barnichon and Brownlees, 2019).

Additionally we will need the conditional expectations for the paths of inflation and unemployment that incorporate the real-time inflow of data. Given the mixed frequency nature of the inflow of data that is to be incorporated into the evaluation, a nowcasting approach lends itself naturally to generating forecasts of the variables of interest. However, as the horizon over which monetary policy decisions are made extends well beyond what is usually considered in the nowcasting literature, we will augment the long end of the forecasts with long-run forecasts from the Survey of Professional Forecasters using relative entropy. We will now discuss this procedure in more detail.

The systematic incorporation of real-time releases of data to predict the present, near future or recent past state of some economic variable has been labeled nowcasting (for surveys, see, e.g., Banbura, Giannone and Reichlin, 2011 or Banbura et al., 2013). Its usual setting is to employ large datasets that consist of time series that are often measured at different frequencies and published at different times to predict an aggregate measure of economic activity such as GDP or other variables which are published with a lag. This setting poses some obvious problems when it comes to modeling as it requires consideration of mixed frequencies, jagged edges of data sets, missing values, along with other irregularities.

A natural candidate to solve these problems is a dynamic factor model. These models can be cast in state-space form and thus inference is straightforward by using the Kalman filter which easily handles the real-time data issues described above. Since the seminal papers of Giannone, Reichlin and Small (2008) and Aruoba, Diebold and Scotti (2009), who indeed use a dynamic factor model for nowcasting, this has been the standard model of choice when it comes to nowcasting by policy institutions and other forecasters as discussed in the surveys of Stock and Watson (2017), Luciani (2017), and Bok et al. (2018).

More recently, Cimadomo et al. (2022) show that Bayesian VAR models, as initially presented in Litterman (1979) and Doan, Litterman and Sims (1984) and first extended to high-dimensional setting in Banbura, Giannone and Reichlin (2010), work well for real-time nowcasting and thus also for real-time policy analysis. Banbura, Giannone and Lenza (2015) note that these models also have a state-space representation. Therefore, a VAR model using real-time data, with all the associated problems, can be efficiently analyzed using the Kalman filter. The remaining issue is how to make inference on the model parameters in light of these data irregularities. The approach taken in the present paper follows the Cube-Root BVAR (CR-BVAR) approach of Cimadomo et al. (2022) which seeks to find a high frequency representation of a standard model that is estimated on a balanced quarterly dataset in order to nowcast GDP. The model is estimated at the lower frequency and then mapped to the corresponding higher frequency model. Once this mapping is complete, standard Kalman filter techniques can be applied to handle mixed frequencies, jagged dataset edges, and missing observations.

The use of a VAR model also allows for a rich interdependence among the model variables. This is particularly important for the present paper since, as opposed to the vast majority of the nowcasting literature, we seek to use a model that can jointly nowcast both the inflation rate and the unemployment rate. Allowing for interdependence between the variables will also be important for longer run forecasts. This makes the use of the Bayesian VAR model that can handle higher frequency data the preferred approach in the present paper.

While the vast majority of the nowcasting literature has focused on GDP, there are some that explore nowcasting inflation and the unemployment rate, the policy variables of interest in the present setting. Using a factor model, Lenza and Warmedinger (2011) use monthly, weekly and daily data to nowcast euro area inflation by using univariate autoregressive models to fill in missing data. Madugno (2013), however, uses a dynamic factor model that mixes daily, weekly, and monthly data to nowcast U.S. headline CPI inflation using a unified framework exploiting a large panel of variables including financial variables, while Monteforte and Moretti (2013) use a dynamic factor model to generate a measure of core inflation which is used with a mixed data sampling (MIDAS) regression model based on Ghysels, Santa-Clara and Valkanov (2004, 2005) to nowcast euro area inflation. An alternative approach is presented in Knotek II and Zaman (2017) who rather than using a large number of time series chose a small number of variables at different frequencies to nowcast headline and core CPI and PCE inflation rates using a combination of univariate and multivariate regression methods imposing time-varying weights on disaggregate and aggregate variables.

The U.S. unemployment rate is surely one of the most studied time series around. When it comes to nowcasting, one of the most widely used indicators which is available at a higher frequency than the unemployment rate is the weekly published initial claims (see, e.g., Montgomery et al., 1998). Most commonly, these nowcasting models rely on one of two approaches. The first uses some transformation or selective sample of the high frequency data combined with standard regression techniques. Examples of this are D'Amuri and Marcucci (2017), McLaren and Shanbhogue (2011), and Vicente, López-Menéndez and Pérez (2015) for U.S., UK and Spanish unemployment respectively, The second approach uses MIDAS regressions that exploit the mixed frequency nature of the data as in Smith (2016) for UK unemployment and Maas (2020) for U.S. unemployment. Several of these papers explore the use of a Google Trends index along with initial claims. However, Nagao, Takeda and Tanaka (2019) point out several issues with the Google Trends data, such as repeated changes in its specification, which greatly complicate its use in real-time forecasting exercises. For that reason, we will not explore the use of internet search data in the present text.

The horizon which policy makers take into consideration when formulating their decisions ranges well beyond that of the nowcasting literature. And while Faust and Wright (2013) and Del Negro and Schorfheide (2013) show that longer horizon inflation forecasts do benefit from conditioning on starting points through nowcasts, the fact remains that model misspecification caused by using atheoretical models for forecasting can seriously distort the long horizon forecasts of the variables under consideration. This is due to the fact that the unrestricted long-run forecasts of VAR models converge to what is essentially the unconditional mean of the model variables as estimated in the sample or what is referred to as " the implied trend" of the model variables in Kozicki and Tinsley (1998). These unconditional means can be drastically different from what professional economists believe the long-run values of the variables should or will be since these unconditional means are based on historical data and thus do not take into account any changes in the structure of the economy or in the relationships between the variables. This is not only a problem for the long run forecast but, as emphasized in Clark and McCracken (2008), Clements and Hendry (1999), Kozicki and Tinsley (2001*a*), and Kozicki and Tinsley (2001*b*), the forecasts are increasingly affected by the trend of the model once beyond 5 quarters. The forecast errors in the medium term are therefore mostly determined by a poor estimate of the trend.

In order to address this issue, we begin by noting that surveys conducted among professional forecasters include questions about their long-run forecasts for a variety of variables. These forecasts provide reasonable proxies for the underlying trends as discussed in, e.g., Faust and Wright (2013), Kozicki and Tinsley (1998), and Wright (2013). They incorporate a bigger information set than the samples the models are estimated on and can adjust much quicker to new information that affects the long run values of the variables, such as exogenous shocks or underlying shifts in the economy. We will incorporate forecasts based on answers in the Survey of Professional Forecasters (SPF) with the CR-BVAR forecasts using relative entropy, an increasingly popular methodology since its first use in economic forecasting by Robertson, Tallman and Whiteman (2005). The flexibility of the approach is illustrated in Krüger, Clark and Ravazzolo (2017) who use it to condition one-step-ahead

VAR forecasts to match short-run survey forecasts, Altavilla, Giacomini and Ragusa (2017) who use it to shift parts of yield curve forecasts from term structure models such that they match survey expectations, and Tallman and Zaman (2020) who use the methodology to tilt both the shortest end and the long end of VAR forecasts to match SPF responses. It should be noted that this approach can be seen as a variant of the theory-coherent forecasting framework of Giacomini and Ragusa (2014) where the long-run forecasts from surveys can be seen as long-run equilibrium values that the atheoretical VAR model forecasts are corrected towards. Finally, both Tallman and Zaman (2020) and Aastveit et al. (2017) find that tilting benefits all the models they examine in the post-crisis period as they incorporate the structural changes associated with that period of time more rapidly.

Alternatives to using relative entropy to influence the long-term forecasts could be to use a steady-state BVAR as developed in Villani (2009). It can be shown that using prior beliefs that incorporate information from surveys, systematically improve the accuracy of forecasts for many U.S. macroeconomic variables. Another option for BVAR models that use variables in levels is to use the natural conjugate prior of Giannone, Lenza and Primiceri (2019) to affect the joint long-run behavior of the variables. A final option would be to model the variables in deviations from trends that are based on either univariate methods or long run survey projections as in Clark and McCracken (2010), Kozicki and Tinsley (2001*a*), Kozicki and Tinsley (2001*b*), or Zaman (2013). The fundamental difference between our chosen method of relative entropy and the previously mentioned ones is that, while the alternatives all incorporate the long run conditions into the estimation procedure, our approach can impose them post estimation.

The remainder of the paper is structured as follows. Section 2 presents the methodology used for the online monitoring, including the nowcasting model, the entropy tilting, causal effects estimation and how to calculate the OPP statistic, while Section 3 discusses the data used in the empirical application. Section 4 discusses the nowcasting and forecasting performance of the framework and Section 5 presents the results of the tests for optimality. Section 6 expands on the discussion on the test results in the lead up to the Fed Funds rate hitting the zero lower bound while Section 7 explores the drivers of changes in the nowcasts and the OPP statistic. Finally, Section 8 concludes.

# 2 Real-time OPP statistic

We begin this section by presenting the real-time version of the Optimal Policy Perturbation (OPP) statistic of Barnichon and Mesters (2023). We present the policy problem and the economic environment and show how we arrive at a test statistic that can be used, in real-time, to test the optimality of the contemporaneous stance of the policy. As with the OPP statistic, the real-time OPP will depend on conditional paths of the variables the Fed seeks to stabilize and the causal effects of monetary policy instruments on said variables. The section proceeds to discuss how to implement the test statistic in a real-time environment, how to systematically incorporate the inflow of new data into the conditional paths of the target variables and how to estimate the causal effects before presenting how to account for uncertainty in the testing proceedure. The section concludes with a summary of the real-time OPP testing procedure.

## 2.1 Policy problem, economic framework, and test statistic

In any given week $w$, the Fed seeks to conduct monetary policy to minimize the expected deviations of the paths of its target variables from the policy targets. Denote these paths by $Y_{t(w)} = (y'_{t(w)}, y'_{t(w)+1}, \ldots)'$, where, for the purposes of the present paper, $y_{t(w)} = (\pi_{t(w)} - \pi^\star, UGAP_{t(w)})'$, and $\pi_{t(w)} - \pi^\star$ denotes the deviation of the Fed's target measure of inflation from target at time $t(w)$ and $UGAP_{t(w)}$ is the deviation of the unemployment rate from the NAIRU at time $t(w)$. Here, $t(w)$ denotes the quarter to which week $w$ belongs. The expectation regarding the future path of $Y_{t(w)}$ based on the information set $\mathcal{F}_w$ at time $w$ is captured by $\mathbb{E}_w(Y_{t(w)}) = \mathbb{E}(Y_{t(w)}|\mathcal{F}_w)$.

The Fed aims to set its policy to minimize the expected loss function

$$\mathcal{L}_w = \frac{1}{2}\mathbb{E}_w Y'_{t(w)} \mathcal{W} Y_{t(w)} \tag{1}$$

where $\mathcal{W} = \text{diag}(\beta \otimes \lambda)$ where $\lambda = (\lambda_\pi, \lambda_{UR})'$ captures the different weights the Fed places on stabilizing inflation and unemployment and $\beta = (\beta_0, \beta_1, \ldots)'$ is the time discount factor.

In the present paper, we will assume that the only policy instruments at the Fed's disposal to minimize the loss function are the Fed Funds rate and the slope of the expected path of the policy rate. Limiting the evaluation to these two policy tools and thus ignoring other possible tools is why the present discussion is perhaps more akin to the sub-set version of the OPP statistic of Barnichon and Mesters (2023) who also present a more general framework with $M_p$ number of possible policy tools. Nonetheless, we make this assumption as it will save on the already heavy notation and the results on the optimality of the stance of the Fed funds rate and the slope of the expected path of the policy rate are unaffected.[2] Denote the expected path of policy by $P^e_{t(w)} = \mathbb{E}_w(p'_{t(w)}, p'_{t(w)+1}, \ldots)'$ where $p_{t(w)} = (FFR_{t(w)}, \Delta_{t(w)})'$ where $FFR_{t(w)}$ is the Fed Funds rate and $\Delta_{t(w)}$ is the slope of the expected path of the policy rate.

As in Barnichon and Mesters (2023) we will assume that, at the quarterly frequency, the underlying economy can be characterized by a generic linear model where the non-policy block of the economy at time $t(w)$ is given by

$$\begin{aligned}
\mathcal{A}_{yy}\mathbb{E}_w Y_{t(w)} - \mathcal{A}_{yz}\mathbb{E}_w Z_{t(w)} - \mathcal{A}_{yp} P^e_{t(w)} &= \mathcal{B}_{y\Lambda}\Lambda_{-t(w)} + \mathcal{B}_{y\xi}\mathbb{E}_w \Xi_{t(w)} \\
\mathcal{A}_{zz}\mathbb{E}_w Z_{t(w)} - \mathcal{A}_{zy}\mathbb{E}_w Y_{t(w)} - \mathcal{A}_{zp} P^e_{t(w)} &= \mathcal{B}_{z\Lambda}\Lambda_{-t(w)} + \mathcal{B}_{z\xi}\mathbb{E}_w \Xi_{t(w)}
\end{aligned} \tag{2}$$

where $Z_{t(w)} = (z'_{t(w)}, z'_{t(w)+1}, \ldots)'$ is the path of other endogenous variables that affect the target variables in $Y_{t(w)}$, $\Lambda_{-t(w)} = (y'_{t(w)-1}, z'_{t(w)-1}, p'_{t(w)-1}, y'_{t(w)-2}, \ldots)'$ contains the initial conditions defined by the past path of the variables $y_{t(w)}, z_{t(w)}$ and $p_{t(w)}$, and $\Xi_{t(w)} =$

[2] It would, of course, be possible to start from an environment with $M_p$ possible policy tools in the real-time OPP framework and then restrict the number of policy tools to arrive at a sub-set real-time OPP statistic. We refrain from this in order to lighten the notation as this will not affect the main results.

$(\xi'_{t(w)}, \xi'_{t(w)+1}, \ldots)'$ is the path of structural shocks. Finally, the linear maps $\mathcal{A}_{..}$ and $\mathcal{B}_{..}$ are assumed to be conformable.

This model is very general and if we consider small fluctuations around a steady-state, the linearity of the framework can be justified. In fact, this model can accommodate a large class of models used in structural macroeconomics, ranging from the standard New-Keynesian models (see, e.g., Smets and Wouters, 2007), to the more modern heterogeneous agents New-Keynesian models (see, e.g., Auclert et al., 2021). A further feature is that once we have taken the expectations $\mathbb{E}_w \Xi_{t(w)}$, we can interpret the expected path of the structural shocks as shocks to the economy's fundamentals that are released at time $t$. As $\Xi_{t(w)}$ includes the future path of the structural shocks, $\mathbb{E}_w \Xi_{t(w)}$ will capture both unanticipated contemporaneous shocks as well as news shocks that are released at time $t(w)$ but take effect at some future date (see, e.g., Chahrour and Jurado, 2018).

We define the optimal policy $P^{e,opt}_{t(w)}$ as the policy path chosen by a planner solving the problem

$$\min_{Y_{t(w)}, Z_{t(w)}, P_{t(w)}} \mathcal{L}_w \quad \text{s.t. } (2) \tag{3}$$

For the policy decision we will assume that it consists of two parts, the policy rule which captures the response to all available time-$t(w)$ measurable variables and an exogenous component. We assume a generic model for the policy block of the form

$$\mathcal{A}_{pp} P^e_{t(w)} - \mathcal{A}_{py} \mathbb{E}_w Y_{t(w)} - \mathcal{A}_{pz} \mathbb{E}_w Z_{t(w)} = \mathcal{B}_{p\Lambda} \Lambda_{-t(w)} + \mathcal{B}_{p\xi} \mathbb{E}_w \Xi_{t(w)} + \varepsilon^e_{t(w)} \tag{4}$$

where $\varepsilon^e_{t(w)} = \mathbb{E}_w \varepsilon_{t(w)}$ are shocks to the expected policy paths with $\varepsilon_{t(w)} = (\epsilon'_{t(w)}, \epsilon'_{t(w)+1}, \ldots)'$ where $\epsilon_{t(w)} = (\epsilon'_{FFR,t(w)}, \epsilon'_{\Delta,t(w)})'$. Note that taking the expectation of $\varepsilon_{t(w)}$ transforms the shocks into policy news shocks at time $t(w)$ which are assumed to be uncorrelated with the initial conditions and all other structural shocks.

We summarize the parameters of the policy rule as $\phi = \{\mathcal{A}_{pp}, \mathcal{A}_{py}, \mathcal{A}_{pz}, \mathcal{B}_{p\Lambda}, \mathcal{B}_{p\xi}\}$ and define a policy choice as $P^e_{t(w)}$ which is determined by the pair $(\phi, \varepsilon^e_{t(w)})$. The Fed's proposed expected policy path is denoted by $P^{e0}_{t(w)}$, determined by the pair $(\phi^0, \varepsilon^{e0}_{t(w)})$. Our interest lies in testing if $P^{e0}_{t(w)} = P^{e,opt}_{t(w)}$.

If we assume that the optimal policy $P^{e,opt}_{t(w)}$ is unique and that the rule $\phi^0$ leads to a unique and determinate equilibrium, Barnichon and Mesters (2023) show that

$$P^{e0}_{t(w)} = P^{e,opt}_{t(w)} \quad \Longleftrightarrow \quad \nabla_{\varepsilon_{t(w)}} \mathcal{L}_w |_{P^{e0}_{t(w)}} = \mathcal{R}^{0\prime} \mathcal{W} \mathbb{E}_w Y^0_{t(w)} = 0 \tag{5}$$

where $\mathbb{E}_w Y^0_{t(w)}$ is the allocation given $P^{e0}_{t(w)}$ and $\mathcal{R}^0$ measures the causal effects of the policy shocks to the target variables under the rule $\phi^0$. This implies that in order to detect a non-optimal policy stance, we only need to know the two statistics that make up the gradient of the loss function, $\mathcal{R}^0$ and $\mathbb{E}_w Y^0_{t(w)}$, in addition to the weighting matrix $\mathcal{W}$.

Following Barnichon and Mesters (2023), we will work with a rescaled version of the gradient. The benefit of the rescaling is that the test statistic will now have a clear economic interpretation as the distance that policy needs to be adjusted by to bring the policy stance to its optimal stance. Specifically, we will rescale the gradient by the inverse Hessian matrix and arrive at a real-time version of the OPP statistic of Barnichon and Mesters (2023):

$$\delta^\star_w = -(\mathcal{R}^{0\prime} \mathcal{W} \mathcal{R}^0)^{-1} \mathcal{R}^{0\prime} \mathcal{W} \mathbb{E}_w Y^0_{t(w)} \tag{6}$$

which, under the current set up, has the property that $\delta^\star_w = 0$ if and only if $P^{e0}_{t(w)} = P^{e,opt}_{t(w)}$ and, furthermore, $P^{e0}_{t(w)} + \delta^\star_w = P^{e,opt}_{t(w)}$. Testing whether policy is optimally set thus boils down to testing whether $\delta^\star_w$ is statistically different from zero.

The OPP statistic relies primarily on two objects, the expected path of the target variables $\mathbb{E}_w Y^0_{t(w)}$, and the matrix of causal effects $\mathcal{R}^0$. As we assume that the true structure of the economy (2) and (4) is not known, we need a way to estimate or approximate the causal effects and the expected paths. The remainder of this section discusses how we obtain these two objects and how to operationalize the test statistic.

Starting with the matrix of causal effects $\mathcal{R}^0$, we note that under the rule $\phi^0$ the proposed policy will lead to a unique equilibrium and therefore we can write the model of (2) and (4) as

$$
\begin{bmatrix} \mathbb{E}_w Y_{t(w)} \\ \mathbb{E}_w Z_{t(w)} \\ P^e_{t(w)} \end{bmatrix} = \begin{bmatrix} \mathcal{A}_{yy} & -\mathcal{A}_{yz} & -\mathcal{A}_{yp} \\ -\mathcal{A}_{zy} & \mathcal{A}_{zz} & -\mathcal{A}_{zp} \\ -\mathcal{A}_{py} & -\mathcal{A}_{pz} & \mathcal{A}_{pp} \end{bmatrix}^{-1} \begin{bmatrix} \mathcal{B}_{y\Lambda} & \mathcal{B}_{y\xi} & 0 \\ \mathcal{B}_{z\Lambda} & \mathcal{B}_{z\xi} & 0 \\ \mathcal{B}_{p\Lambda} & \mathcal{B}_{p\xi} & I \end{bmatrix} \begin{bmatrix} \Lambda_{-t(w)} \\ \mathbb{E}_w \Xi_{t(w)} \\ \varepsilon^e_{t(w)} \end{bmatrix}
$$

$$
= \begin{bmatrix} \mathcal{C}^0_{y\Lambda} & \mathcal{C}^0_{y\xi} & \mathcal{R}^0 \\ \mathcal{C}^0_{z\Lambda} & \mathcal{C}^0_{z\xi} & \mathcal{C}^0_{z\varepsilon} \\ \mathcal{C}^0_{p\Lambda} & \mathcal{C}^0_{p\xi} & \mathcal{C}^0_{z\varepsilon} \end{bmatrix} \begin{bmatrix} \Lambda_{-t(w)} \\ \mathbb{E}_w \Xi_{t(w)} \\ \varepsilon^e_{t(w)} \end{bmatrix} \tag{7}
$$

Note that using the first equation of the system, under $P^{e0}_{t(w)}$ we can write

$$
Y^0_{t(w)} = \mathcal{R}^0 \varepsilon^{e0}_{t(w)} + \underbrace{\mathcal{C}^0_{y\Lambda} \Lambda_{-t(w)} + \mathcal{C}^0_{y\xi} \mathbb{E}_w \Xi_{t(w)} + Y^0_{t(w)} - \mathbb{E}_w Y^0_{t(w)}}_{\Upsilon^0_{t(w)}} \tag{8}
$$

where $\Upsilon^0_{t(w)}$ is a linear combination of the model's structural shocks, its initial conditions and any future errors $Y^0_{t(w)} - \mathbb{E}_w Y^0_{t(w)}$ and $\mathbb{E}(\varepsilon^{e0}_{t(w)} \Upsilon^0_{t(w)}) = 0$ follows from the assumption that the time $t(w)$ policy news shocks $\varepsilon^{e0}_{t(w)}$ are orthogonal to the initial conditions and the other structural shocks. Therefore, if one has a measure of the policy news shocks, one could estimate the causal effects $\mathcal{R}^0$ using local projections as we will do in a later section.

Going back to the model as presented in (7), note that we can rearrange the rows of the model without any loss of generality. Define $x_{t(w)} = (y'_{t(w)}, z'_{t(W)}, p'_{t(w)})'$, and rewrite equation

(7) as

$$
\begin{aligned}
\begin{bmatrix} \mathbb{E}_w x_{t(w)} \\ \mathbb{E}_w x_{t(w)+1} \\ \mathbb{E}_w x_{t(w)+2} \\ \vdots \end{bmatrix}
&= \begin{bmatrix} \mathcal{C}^0_{0\Lambda} & \mathcal{C}^0_{0\xi} & \mathcal{C}^0_{0\varepsilon} \\ \mathcal{C}^0_{1\Lambda} & \mathcal{C}^0_{1\xi} & \mathcal{C}^0_{1\varepsilon} \\ \mathcal{C}^0_{2\Lambda} & \mathcal{C}^0_{2\xi} & \mathcal{C}^0_{2\varepsilon} \\ \vdots & \vdots & \vdots \end{bmatrix}
\begin{bmatrix} \Lambda_{-t(w)} \\ \mathbb{E}_w \Xi_{t(w)} \\ \varepsilon^e_{t(w)} \end{bmatrix} \\
&= \begin{bmatrix} \mathcal{C}^0_{0\Lambda}\Lambda_{-t(w)} + \mathcal{C}^0_{0\nu}\nu_{t(w)} \\ \mathcal{C}^0_{1\Lambda}\Lambda_{-t(w)} + \mathcal{C}^0_{1\nu}\nu_{t(w)} \\ \mathcal{C}^0_{2\Lambda}\Lambda_{-t(w)} + \mathcal{C}^0_{2\nu}\nu_{t(w)} \\ \vdots \end{bmatrix}
\end{aligned}
\tag{9}
$$

where $\mathcal{C}^0_{i\nu} = [\mathcal{C}^0_{i\xi}, \mathcal{C}^0_{i\varepsilon}]$ and $\nu_{t(w)} = [\mathbb{E}_w \Xi'_{t(w)}, (\varepsilon^e_{t(w)})']'$. Now note that the top row of this rewritten system corresponds to a VAR model for $\mathbb{E}_w x_{t(w)}$. Furthermore, if $\mathcal{C}^0_{i\Lambda} = (\mathcal{C}^0_{0\Lambda})^i$ and $\mathcal{C}^0_{i\nu} = (\mathcal{C}^0_{0\nu})^{i-1}$ then row $i$ corresponds to the VAR forecast for $\mathbb{E}_w x_{t(w)+i-1}$ from the VAR model specified in the first row. This fact motivates our use of a VAR model to generate forecasts for the evaluation of monetary policy stance adequacy.

A key element for the use of a VAR model to generate the forecasts is that the statistical model performs similarly to the forecasts that underpin the policy decisions of the FOMC, i.e., the Summary of Economic Projections or the Greenbook forecasts, as well as the forecasts performing well in general. Furthermore, due to the objective of the present paper being real-time monitoring, we need a way to consistently generate forecasts for the target variables that incorporate new information as it becomes available. This naturally leads us to consider a forecasting model based on a nowcasting framework that incorporates high frequency information as it is released. However, monetary policy decisions are made considering a much longer horizon than typically considered in the nowcasting literature. In the present paper, we assume the horizon is 5 years as in Barnichon and Mesters (2023). As detailed below, model forecasts at such horizons typically tend towards the unconditional mean of the model variables. As this mean is calculated based on historical data, this implies that there is a form of model misspecification when it comes to forecasts far in the future as the model cannot easily capture changes in the long run mean of the variables. To overcome this issue, we introduce long run survey expectations into the long run forecasts using exponential tilting. This strikes a balance between using the forecasting model to capture how the inflow of newly available information affects the short end of the forecasts and the survey expectations that capture how the model variables will evolve in the long end of the forecast. Using the model to bridge the transition between the two gives us forecasts that are based on up-to-date information and expert knowledge about the long-run while consistently respecting the interdependence among the variables over the forecast horizon.

## 2.2 The Nowcasting and Forecasting BVAR model

While we have so far been silent on which variables enter the general linear model of the previous section and how they depend on their lagged values, we now assume that we can approximate the expected paths of the target variables $\mathbb{E}_w Y_{t(w)}$ using forecasts based on VAR models with a finite number of variables and lags. Let us begin by defining $x_{t(w)} = (y'_{t(w)}, z'_{t(w)}, p'_{t(w)})'$ as the $n \times 1$ vector of the time $t(w)$ values of the endogenous target variables, other endogenous variables, and the policy tools from the model in (2) and (4). In order to lighten the notation, let us write $t_q = t(w)$ as the quarterly time index.

We begin by presenting a standard quarterly Bayesian Vector Autoregressive model (QB-VAR) that will serve as a benchmark to which we will compare the nowcasting performance of the Cube Root Bayesian VAR (CR-BVAR) model of Cimadomo et al. (2022), which incorporates higher frequency information to improve the accuracy of the nowcasts.

### 2.2.1 Baseline Quarterly Bayesian VAR model

Let the $n \times 1$ vector $x_{t_q}$ of endogenous variables at a quarterly frequency follow a vector autoregression of order $l$

$$x_{t_q} = A_0 + A_1 x_{t_q-1} + \ldots + A_p x_{t_q-l} + \eta_{t_q} \tag{10}$$

where $\eta_{t_q}$ is a Normally distributed multivariate white noise process with covariance matrix $\Sigma_\eta$ and $A_i$ are matrices of model parameters. Given that all the variables in $x_{t_q}$ are observed, this model can be estimated using standard Bayesian methods in a straightforward manner (see, e.g., Karlsson, 2013).

We will assume a Normal-Inverse Wishart prior. Under that assumption we assume an inverse Wishart prior for the covariance matrix of the residuals, $\Sigma_\eta$, with a diagonal matrix $\Psi$ as the scale parameter and $d = n + 2$ degrees of freedom. We treat the diagonal of $\Psi$ as a $n \times 1$ vector of hyperparameters and denote this vector as $\psi$.

As for the coefficients, we assume a flat prior for the vector of constants $A_0$ and a combination of the Minnesota prior of Litterman (1979) and the sum-of-coefficients prior of Doan, Litterman and Sims (1984). The Minnesota prior postulates that conditional on the covariance matrix of the residuals, the prior distribution of the autoregressive coefficients is a Normal with the following means and variances

$$\mathbb{E}(A_1) = \mathrm{diag}(\mathbf{d}), \quad \mathbb{E}(A_2) = \ldots = \mathbb{E}(A_l) = \mathbf{0}_n \tag{11}$$

$$Cov[(A_s)_{ij}, (A_r)_{hm}|\Sigma_\eta] = \lambda^2 \frac{\Sigma_{\eta,ih}}{s^2 \Psi_{ii}} \quad \text{if } m = j \text{ and } r = s, \text{ zero otherwise} \tag{12}$$

where the elements of the vector $\mathbf{d}$ are either one, if the prior is centered on a random walk, or zero, if the prior is centered on a white noise. The sum-of-coefficients prior on the other hand postulates that the sum of the coefficients on the own lags of each variable equals one with the sum of the coefficients corresponding to lags of other variables equals zero. This prior is implemented using dummy observations with the intensity by which it is enforced is captured by the parameter $\mu$.

Thus, the priors depend on the hyperparameters $\lambda$, $\psi$, and $\mu$. These hyperparameters are treated as random variables, as in Giannone, Lenza and Primiceri (2015), and are drawn from their posterior distributions. We use the same diffuse priors described in Giannone, Lenza and Primiceri (2015) and the posterior distributions are recovered as part of the estimation algorithm. The last parameter to choose is the lag length $l$ which we set equal to 5.

### 2.2.2 Utilizing higher frequency information - Cube Root BVAR

When it comes to nowcasting, the main interest lies in utilizing higher frequency information to forecast the current time period, in this case the current quarter. A potential challenge that could arise is that the data can be of mixed frequency. In the present case we have data both at a monthly frequency and quarterly frequency. To handle the mixed frequency nature of the data we will treat the quarterly variables as monthly variables which are only sampled at a quarterly frequency. Following Giannone, Reichlin and Small (2008), the variables are transformed to correspond to a quarterly quantity when observed at the end of a quarter. Let $x_{t_m} = (x_{1,t_m}, \ldots, x_{n,t_m})'$ be the vector of potentially latent monthly variables corresponding to the variables that enter the quarterly model (10). Note that the vector $X_{t_m} = (x'_{t_m}, \ldots, x'_{t_m-3l+3})'$ corresponds to the quarterly model concept $X_{t_q}$ when observed in the last month of each quarter where $t_q = t_m/3$ for $t_m = 3, 6, 9, \ldots$

Consider a quarterly $VAR(p)$ model written in companion form:

$$X_{t_q} = \Phi X_{t_q-1} + v_{t_q} \tag{13}$$

where $X_{t_q} = (x'_{t_q}, \ldots, x'_{t_q-l+1})'$ where $l$ is the number of lags in the quarterly model and $v_{t_q} = (\eta'_{t_q}, 0_{1\times n(l-1)})'$, $v \sim N(0, \Omega)$ and

$$\Phi = \begin{bmatrix} A_1 & A_2 & \ldots & A_p \\ I_n & 0_n & \ldots & 0_n \\ 0_n & \ddots & \ldots & 0_n \\ 0_n & \ldots & I_n & 0_n \end{bmatrix} \quad \Omega = \begin{bmatrix} \Sigma_\eta & 0_n & \ldots & 0_n \\ 0_n & \ldots & \ddots & 0_n \\ 0_n & 0_n & \ldots & 0_n \end{bmatrix}. \tag{14}$$

Note that this model could also be written in terms of monthly quantities

$$X_{t_m} = \Phi X_{t_m-3} + v_{t_m} \tag{15}$$

when $t_m$ corresponds to the last month of a quarter and $X_{t_m} = (x'_{t_m}, x'_{t_m-3} \ldots, x'_{t_m-3l+1})'$.

We will assume that a monthly counterpart to the model in Equation (13) can be written as

$$X_{t_m} = \Phi_m X_{t_m-1} + v_{m,t_m} \tag{16}$$

where $v_{m,t_m} = (\eta'_{m,t_m}, 0_{1\times n(l-1)})'$, $v_m \sim N(0, \Omega_m)$ and

$$\Phi_m = \begin{bmatrix} \Phi_{m11} & \Phi_{m12} & \dots & \Phi_{m1p} \\ \Phi_{m21} & \ddots & & \\ \vdots & & & \\ \Phi_{mp1} & & & \Phi_{mpp} \end{bmatrix} \quad \Omega_m = \begin{bmatrix} \Sigma_{\eta_m} & 0_n & \dots & 0_n \\ 0_n & \dots & \ddots & 0_n \\ 0_n & 0_n & \dots & 0_n \end{bmatrix} \tag{17}$$

where the elements of $\Phi_m$ are assumed to be real and stable.

Note that the top $n$ rows of the model in (16) correspond to the restricted monthly VAR

$$x_{t_m} = \Phi_{m11} x_{t_m-1} + \Phi_{m12} x_{t_m-4} + \cdots + \Phi_{m1p} x_{t_m-3l+2} + \eta_{m,t_m} \tag{18}$$

where the restriction is that current monthly values are only a function of a single month within each lagged quarter. Restrictions on how the lagged monthly states are updated with the arrival of new information make up the remaining rows. Note that, as is the case for the quarterly variables, these monthly states can be latent. The restrictions imply that the lagged states on the left-hand side also depend on the future states on the right-hand side. This is the case since the assumptions mean that the states of the monthly model match the states of the quarterly model at the end of each quarter and therefore the arrival of new information means that all the latent states within a quarter must be updated.

Iterating the model above yields

$$X_{t_m} = \Phi_m^3 X_{t_m-3} + v_{m,t_m} + \Phi_m v_{m,t_m-1} + \Phi_m^2 v_{m,t_m-2} \tag{19}$$

which implies that the relationship between the quarterly and monthly models is captured by

$$\Phi_m = \Phi^{\frac{1}{3}} \tag{20}$$

$$v_{t_m} = v_{m,t_m} + \Phi_m v_{m,t_m-1} + \Phi_m^2 v_{m,t_m-2} \tag{21}$$

Finding the right mapping between the two models boils down to finding the cube root of $\Phi$. The problem, however, is that this entails the possibility of multiple solutions. Leaving the discussion of non-diagonalizable matrices to Giannone, Monti and Reichlin (2016), consider the case when the autoregressive matrix $\Phi$ is diagonalizable, i.e., we can write $\Phi = VDV^{-1}$ where $D$ is diagonal. In this case, we can find the cube root of $\Phi$ as $\Phi^{\frac{1}{3}} = VD^{\frac{1}{3}}V^{-1}$ where $D^{\frac{1}{3}}$ is a diagonal matrix of the cube roots of the elements of $D$. While the real elements of $D$ have a unique real cube root which, when combined with their associated real eigenvectors, give real values, complex conjugate eigenvalues have a total of three complex cube roots. These still result in real values when multiplied with their respective eigenvectors. More precisely, if $k$ is the number of complex conjugate couples of eigenvalues in $D$ there will be $3^k$ real-valued cube roots for $\Phi$. To select among these, we follow Giannone, Monti and Reichlin (2016): select the real cube root for real eigenvalues and select the cube root that corresponds to the least oscillatory behavior for the case of complex conjugate couples.

Therefore, the use of the CR-BVAR model involves three steps. The first step involves the estimation of a quarterly VAR($l$) model. Given these parameter estimates, $\Phi$ and $\Omega$, a monthly model is defined with the parameters $\Phi_m$ and $\Omega_m$ which are recovered from the quarterly counterparts. Finally, the distributions of the forecasts are computed conditional on the real-time data flow using the Kalman filtering techniques as described in Banbura, Giannone and Lenza (2015) and subsequently converted back to a quarterly frequency to produce forecasts for $x_{t_q}^{t_q,t_q+H} = x_{t(w)}^{t(w),t(w)+H}$, where $H$ is the forecast horizon.

## 2.3 Entropy tilting for long run

The method proposed for evaluating the policy decision of the central bank relies on having a forecast for the target variables, inflation and unemployment, over the entire horizon that the policy maker has under consideration. While the VAR model above should deliver reliable forecasts for the current and next quarters, the unrestricted long run forecasts will tend to the unconditional means of the variables.

As these unconditional means are estimated based on historical data, they do not necessarily reflect the most likely long-run values that the variables will tend towards. This is, for example, obvious in the case of structural changes that change the long-run values of the variables which is not necessarily captured in historical data. A possible remedy to this issue lies in long-run forecasts from surveys of professional forecasters. These long-run expectations will adjust to any underlying changes in the economy much quicker than the unconditional means. This is, in part, due to the expanded information set professional forecasters have access to, vis-a-vis a VAR model. These include, among others, central bank communication about current and future policy actions.

As in Robertson, Tallman and Whiteman (2005), we incorporate long run expectations using relative entropy. The approach takes a given predictive distribution and forms a new predictive distribution such that it satisfies a given set of moment conditions while minimizing the relative entropy between the two predictive distributions.

Denote the unrestricted predictive density by $p(x^{t_q,t_q+H}|X^{t_q})$ where $x$ is the $n$-dimensional random variable from the VAR model and $X^{t_q}$ denotes all available data at time $t(w)$. Assuming that this predictive density consists of $D$ draws $\{x_i, i = 1, \ldots, D\}$, then the corresponding weights are $\{w_i = 1/D, i = 1, \ldots, D\}$. Now assume that we want to impose moment conditions, captured in the matrix $\bar{g}$, on the predictive distribution such that $\sum_{i=1}^{D} w_i p(x_i^{t_q,t_q+H}) \neq \bar{g}$. In other words, the mean of the unrestricted predictive distribution does not equal the mean specified by the moment conditions. For the equality to hold, the weights must be modified. Denote these modified weights by $\{w_i^\star, i = 1, \ldots, D\}$. These new weights that satisfy the moment conditions are equivalent to finding a new predictive distribution that is as close to the original predictive distribution as possible in the information-criterion sense.

In particular, the relative entropy or Kullback-Leibler information criterion of $w^\star$ to $w$ is $K(w^\star : w) = \sum_{i=1}^{D} w_i^\star \log(\frac{w_i^\star}{w_i})$. The method solves for the new weights by minimizing $K(w^\star : w)$ subject to $w_i^\star \geq 0$, $\sum_{i=1}^{D} w_i^\star = 1$, and $\sum_{i=1}^{D} w_i^\star p(x_i^{t_q,t_q+H}) = \bar{g}$. The solution to the minimization problem when using the Lagrange method is

$$w_i^\star = \frac{w_i \exp(\gamma' p(x_i^{t_q,t_q+H}))}{\sum_{i=1}^{D} w_i \exp(\gamma' p(x_i^{t_q,t_q+H}))} \tag{22}$$

where $\gamma$ is the vector of Lagrange multipliers. Thus, the initial weights $w_i$ have been tilted exponentially to obtain the new weights $w_i^\star$. The vector of Lagrange multipliers can be obtained as

$$\gamma = \arg\min_{\tilde{\gamma}} \sum_{i=1}^{D} w_i \exp(\tilde{\gamma}'[p(x_i^{t_q,t_q+H}) - \bar{g}]) \tag{23}$$

Following this, other functions of interest can be computed using the newly computed weights as $\sum_{i=1}^{D} w_i^\star h(x_i^{t_q,t_q+H})$. As discussed in Cogley, Morozov and Sargent (2005), if the interest lies in the modified probabilistic density $g(x^{t_q,t_q+H})$, importance sampling techniques could be used to redraw $x_i^{t_q,t_q+H}$ from the original density $p(x^{t_q,t_q+H})$ using the new weights $w_i^\star$. This can, for example, be done using the multinomial resampling algorithm of Gordon, Salmond and Smith (1993) and we use the draws from the resulting modified density $g(x^{t_q,t_q+H})$ to approximate the expected path of the target variables, $\mathbb{E}_w Y_{t(w)}$, and the uncertainty around the expected path.

When using a VAR model, any conditioning or tilting at a point in the future will have an effect on the entire path of the forecast. For this reason, we additionally condition the mean of the first quarter, or nowcast, of the forecast distribution to equal that produced by the VAR model in the previous section. Furthermore, conditioning on multiple variables will result in forecasts that capture the cumulative effect of these conditions. The use of entropy as opposed to other conditioning methods is motivated by its ease of use, computational simplicity and flexibility. It allows for the potential combination of a mean condition and a variance condition.[3] If only a mean condition is specified there is no automatic shrinkage of the variance to zero around the mean condition and the variance is in fact the same as in the unconditional forecast. Furthermore, relative entropy does not rest on a Gaussianity assumption for neither the original nor the tilted densities.

A natural question that arises when conditioning the forecast on long-run projections from surveys is when the conditioning should occur. While the idea of the long-run would suggest the conditioning should occur in the distant future, the fact that many macroeconomic variables have little persistence and thus converge relatively quickly to their unconditional means would suggest that the conditioning should occur sooner. In fact, we should start influencing the trend estimate of the unconditional forecast towards the trend implied by the survey as soon as the model implied trend is expected to dominate the forecast. If the conditioning is imposed at too distant a horizon, its effect can fail to significantly shift the forecast at the horizon of interest and leave the forecast biased towards the model's implied steady state. The point at which the conditioning should start taking effect should also vary across variables according to their persistence.

We estimate this persistence as

$$\rho_t^i = \sum_{l=1}^{p} \hat{\phi}_{t,l}^i \tag{24}$$

where $\hat{\phi}_{t,l}^i$ is the estimated $l$-th autoregressive coefficient in a univariate autoregression of variable $i$ that uses data up to time $t$. The variables we use for the tilting are GDP growth, the unemployment rate, core CPI inflation, and core PCE inflation. The quarter at which the forecast reverts to the implied steady state is then given by

$$h_t^i = \frac{1}{1-\rho_t^i} \tag{25}$$

To account for the possibility that $h_t^i$ exceeds the practical limit of the forecast horizon, the horizon at which the long-run projections from the survey are combined with the

[3] The addition of a variance condition would be possible using the variance of survey responses. We do not explore this option in the present work.

unconditional forecast is then set as

$$h_t^{i\star} = \min\{\max\{H^{MIN}, h_t^i\}, H^{MAX}\} \tag{26}$$

where $H^{MIN} - 1$ specifies the minimum number of quarters before the survey takes over the VAR forecast and $H^{MAX}$ specifies the maximum number of quarters until the survey takes over the VAR forecast. This ensures that at least the first $H^{MIN} - 2$ quarters and at maximum the first $H^{MAX} - 2$ quarters after the nowcast quarter are given by the VAR forecast. Given that we use the VAR model to generate forecasts for the next 10 years we set $H^{MAX} = 35$ and following Tallman and Zaman (2020), we set $H^{MIN} = 5$.

The resulting horizon for which the survey expectations take over range from 6 to 15 quarters for GDP growth, 17 to 34 quarters for the unemployment rate, 9 to 33 quarters for the core CPI inflation rate, and 19 to 28 quarters for the core PCE inflation rate. These results follow a similar pattern as in Tallman and Zaman (2020) who find that GDP growth has the shortest horizon (5 quarters), unemployment has the longest horizon (10-27 quarters), and CPI inflation in between (5 to 17 quarters). Note that, as opposed to headline CPI inflation which they used, we use core CPI inflation and therefore we should expect more persistence. Tallman and Zaman (2020) do not report results for PCE inflation, neither headline nor core.

## 2.4 Causal effect estimates

In order to compute the OPP statistic, in addition to the forecasts for the target variables, we need estimates of the causal effects of the policy instruments on the target variables. In other words, we need to estimate the impulse response functions of unemployment and core PCE inflation to shocks to the Fed Funds rate and the slope of the yield curve.

Given that the OPP statistic is calculated using forecasts in year-on-year percentage changes, we require IRFs specified in the same form. While using the VAR model which generates the nowcasts and forecasts to also give us the IRFs would be an attractive approach, the VAR model presented above is specified in levels and thus not usable for this purpose.[4] Therefore, while the CR-BVAR model, along with the tilting, forms our approximation of the forecasts from the model in (2) and (4), we will need to explore other alternatives to approximate the causal effects of policy shocks on the target variables found in the general linear model. Li, Plagborg-Møller and Wolf (2022) explore a variety of estimators of structural impulse responses based on a comprehensive set of simulated data mimicking U.S. macroeconomic time series. They find that there is a clear bias-variance trade off involved with the selection of estimation methods.

Along the lines of the Brainard (1967) conservatism principle, we favor an estimator that minimizes the bias as we would prefer an unbiased estimate of the causal effects. While this would lead to a more accurate value of the OPP statistic, it entails a higher variance and we can reject optimality less frequently. This is preferable to an estimator with lower variance but greater bias, which could lead to more frequent rejections of optimality but a worse estimate of the OPP statistic. Based on these criteria and the results in Li, Plagborg-Møller and Wolf (2022), we opt to estimate the causal effects using penalized local projections.

We will follow, e.g., Barnichon and Mesters (2023), Eberly, Stock and Wright (2020), and Kuttner (2001) and assume that the Fed's reaction function remained unchanged over the period 1990 to 2020, and thus that the IRFs are time-invariant, and we will use instrumental variable methods where the instruments are monetary policy surprises as measured in a 30 minute window around the FOMC announcements. In order to identify the effects of a shock to the current Fed Funds rate, we will use the difference between the expected Fed Funds rate as implied by Fed Funds futures contracts and the actual Fed Funds rate. To identify the shocks to the expected path of the Fed Funds rate, we use surprises to the 10-year on-the-run Treasury yield, orthogonalized with respect to surprises to the current Fed Funds rate.

[4] We did explore VAR models specified in year on year changes but unfortunately these performed much more poorly when it came to nowcasting and forecasting than VAR models specified in levels and therefore a level specification was chosen. In addition, the fact that estimating the causal effects of slope shocks necessitates using only data over the period of time that the slope tool was used makes estimating a 20 variable VAR with 5 lags impractical.

To estimate the impulse response functions we use the Smooth Local Projections of Barnichon and Brownlees (2019). This is a form of a penalized regression modification to local projections which involves modeling the sequence of the impulse response coefficients as a linear combination of B-splines basis functions. The coefficients of the linear combination are then estimated using a shrinkage estimator, shrinking the impulse response toward a polynomial. As the estimation boils down to a standard ridge regression a choice must be made regarding the penalty parameter. Following the recommendation of Barnichon and Brownlees (2019) we use $k$-fold cross-validation (Racine, 1997).

In order to use as much information as possible, we estimate the IRFs to shocks to the Fed Funds rate over the period 1990 to 2018 while the IRFs to shock to the slope of the yield curve are estimated over the period 2006-2018.

As discussed in the next subsection, we will need to account for the uncertainty surrounding the estimates of the causal effects. More specifically we want to be able to sample from the distribution of the parameter estimates. A straightforward way to achieve this is to employ Bayesian methods. Note that for a given penalty parameter, a Gaussian prior for the regression coefficients, and a diffuse prior for the variance of the error term, the posterior for the regression coefficients is a Normal distribution that is centered at the ridge regression estimates. This provides a simple way to characterize the estimation uncertainty for the causal effects.

To be precise, we estimate the IRFs using a two stage least squares approach. In the first stage, we regress the policy tool on an external instrument and in the second stage we use the fitted values of the first stage regression in lieu of the original policy tool.

Note that in the present paper we have assumed that the central bank only has two poliy instruments available, the Fed Funds rate and the slope of the expected path of the policy rate. Further we have assumed that the central bank has two target variables, core PCE inflation and the unemployment rate. Therefore, in the present work the matrix of causal effects $\mathcal{R}^0$ consists of four blocks, the responses of the two target variables to the two policy tools.

$$\mathcal{R}^0 = \begin{pmatrix} \mathcal{R}^0_{\pi,FFR} & \mathcal{R}^0_{\pi,\Delta} \\ \mathcal{R}^0_{UGAP,FFR} & \mathcal{R}^0_{UGAP,\Delta} \end{pmatrix} \tag{27}$$

where $\mathcal{R}^0_{i,j} = (r_{ij,0}, r_{ij,1} \ldots)'$, $r_{ij,h}$ is the causal effect of policy tool $j$ on variable $i$ at horizon $h$, and, to lighten notation, we let $t = t_q$.

Additionally, note that equation (8) takes a form very reminiscent of local projections. Beginning with the standard local projection (ignoring constants and other controls or assuming they have already been projected out), we have that we can estimate the elements of these blocks as the sequences $r_{ij,h}, h = 0, \ldots, H$ where $H$ is the maximum horizon from the sequence of regressions

$$y_{i,t+h} = r_{ij,h} v_{j,t} + u_{ij,h,t+h} \tag{28}$$

for target variable $i$ and where $v_{j,t}$ is the fitted value from a first stage regression of policy tool $j$ on an external instrument and $u_{ij,h,t+h}$ is the combination of the corresponding element of $\Upsilon_{t(w)}$ and the other policy news shock. For the remainder of this section, for ease of notation, we will suppress the $i$, $j$, and $ij$ notation.

Barnichon and Brownlees (2019) propose to approximate the $r_h$ coefficient by a linear B-splines basis function expansion, that is

$$r_h = \sum_{k=1}^{K} b_k B_k(h) \tag{29}$$

where $B_k : \mathbb{R} \to \mathbb{R}$ for $k = 1, \ldots, K$ is a set of B-spline basis functions and $b_k$ for $k = 1, \ldots, K$ is a set of scalar parameters. We can thus approximate the local projection above as

$$y_{t+h} = \sum_{k=1}^{K} b_k B_k(h) v_t + u_{h,t+h} \tag{30}$$

Note that this model is still linear in the parameters. Let $\mathcal{Y}_t$ for $t = 1, \ldots, T$ be the vector $(y_{t+H}, \ldots, y_{min(T,t+H)})'$ and let $d_t$ denote the size of the vector. Let $\mathcal{V}_t$ be defined as a $d_t \times K$ matrix whose $(h,k)$th element is $B_k(h)v_t$. Denote by $\theta$ the B-splines parameters $b_1, \ldots, b_K$.

We can then present the approximate model above as

$$\mathcal{Y}_t = \mathcal{V}_t\theta + \mathcal{U}_t \tag{31}$$

where $\mathcal{U}_t$ is the $d_t \times 1$ prediction error vector. If we denote the vertically stacked versions of the matrices above by $\mathcal{Y}$ and $\mathcal{V}$, we can estimate the Smooth Local Projection parameters by the generalized ridge estimation

$$\hat{\theta} = \arg\min_{\theta} \left\{ \|\mathcal{Y} - \mathcal{V}\theta\|^2 + \kappa\theta'\mathbf{P}\theta \right\} \tag{32}$$

$$= \left(\mathcal{V}'\mathcal{V} + \kappa\mathbf{P}\right)^{-1} \mathcal{V}'\mathcal{Y} \tag{33}$$

where $\kappa$ is a positive shrinkage parameter and $\mathbf{P}$ is a positive semidefinite penalty matrix. Following Barnichon and Brownlees (2019), we set $\mathbf{P} = \mathbf{D}_\tau'\mathbf{D}_\tau$ where $\mathbf{D}_\tau$ is the matrix representation of the $r$th difference operator $\Delta^\tau$ which leads to the IRFs being shrunk toward a polynomial of order $\tau - 1$.

An issue with this approach in the context of the present paper is that the asymptotic distribution of the estimate is poorly understood. Nonetheless, as demonstrated in the next subsection, we will need to be able to sample from the distribution of the estimates in order to construct the OPP statistic and its confidence bounds. Here we will draw a parallel to Bayesian Ridge regression for which the full posterior is known and can therefore be sampled from. Assume a flat prior on $\sigma^2$, the variance of the error term $u_{h,t+h}$ and that the error term is normally distributed so that $u_{h,t+h} \sim N(0, \sigma^2)$ along with a Normal prior on $\theta$ conditional on $\sigma^2$ such that $\theta|\sigma^2 \sim N(0, \sigma^2\kappa^{-1}\mathbf{P}^{\star^{-1}})$ where $\mathbf{P}^\star = \mathbf{P} + \varsigma I$ where $\varsigma$ is the smallest possible scalar such that all eigenvalues of $\mathbf{P}^\star$ are different from zero and thus that the inverse exists. We then have that the posterior of $\theta$ is a normal distribution with mean equal to the (adjusted) ridge estimator $\hat{\theta}^{R^\star} = \left(\mathcal{V}'\mathcal{V} + \kappa\mathbf{P}^\star\right)^{-1} \mathcal{V}'\mathcal{Y}$ and covariance matrix equal to $\sigma^2 \left(\mathcal{V}'\mathcal{V} + \kappa\mathbf{P}^\star\right)^{-1}$. The adjustment from $\mathbf{P}$ to $\mathbf{P}^\star$ is extremely marginal in the present paper and does not affect the resulting estimate in any meaningful way.[5] The estimation results, along with 68% credible intervals are presented in Figure 1.

## 2.5 OPP statistic calculation

Recall that the OPP statistic is calculated as

$$\delta_w^{\star} = -(\mathcal{R}^{0\prime}\mathcal{W}\mathcal{R}^0)^{-1}\mathcal{R}^{0\prime}\mathcal{W}\mathbb{E}_w Y^0_{t(w)} \tag{34}$$

Note that when implementing the test, there are two sources of uncertainty: one related to the estimation uncertainty regarding the causal effects $\mathcal{R}^0$, and the other regarding the forecast $\mathbb{E}_w Y^0_{t(w)}$. Given that the forecasting model relies on Bayesian estimation, the uncertainty regarding the forecast is captured by the posterior distribution of the forecast after tilting towards the long run survey expectations. On the other hand, the estimation uncertainty regarding the causal effects is characterized by the posterior distribution of the regression coefficients.

Let $r = \text{vec}(\mathcal{R})$ and denote by $r^{(j)}$ a draw from the posterior distribution of the causal effects. Furthermore, denote by $\hat{Y}_{t(w)|w}$ the stacked vector of per target variable forecasts which is an approximation to the conditional expectations $\mathbb{E}_w Y^0_{t(w)}$. Denote by $\hat{Y}^{(j)}_{t(w)|w}$ a draw from the posterior distribution of the tilted forecasts. Finally, we need to select values for $\beta$ and $\lambda$. Here we set $\beta_t = 1 \; \forall t$ and $\lambda = (1, 0.6)$, where the value 0.6 is taken from Barnichon and Mesters (2023) as the value that makes it most difficult to reject that policy is optimally set.

We can now construct confidence intervals for the test statistic using simulation to approximate the distribution of $\delta_w^{\star} = -(\mathcal{R}^{0\prime}\mathcal{W}\mathcal{R}^0)^{-1}\mathcal{R}^{0\prime}\mathcal{W}\mathbb{E}_w Y^0_{t(w)}$ by computing

$$\delta_w^{(j)} = -(\mathcal{R}^{(j)\prime}\mathcal{W}\mathcal{R}^{(j)})^{-1}\mathcal{R}^{(j)\prime}\mathcal{W}\hat{Y}^{(j)}_{t(w)|w}, \quad j = 1, \ldots, B \tag{35}$$

[5]In the present paper, $\varsigma = 10^{-8}$.

where $r^{(j)} = \text{vec}(\mathcal{R})$ is a draw from the posterior distribution of the impulse response functions, $\hat{Y}^{(j)}_{t(w)|w}$ is a draw from the posterior distribution of the tilted forecasts, and $B$ is the number of draws. The empirical section below reports median and upper and lower bounds of the simulated distribution $\{\delta^{(j)}_w, j = 1, \ldots, B\}$ at each point in time. The decision rule followed is that we will reject the hypothesis that the policy is optimally set if zero lies outside the 50% confidence bounds calculated as the 25th and 75th quantiles of the simulated distribution of $\delta_w$. This choice is motivated by the fact that we are interested in an online monitoring framework that provides early warning of optimization failures. We would thus rather raise the alarm too often than too seldom and risk not detecting an optimization failure in time.

## 2.6 Summary of procedure

To give an overview of the steps involved in the online monitoring framework, we now provide a stepwise summary of the procedure. Given an estimate of the causal effects $\mathcal{R}^0$ as in Section 2.4, then for each week $w$ we make the following steps:

1. Update the dataset with any new data released in week $w$.

2. If new National Accounts have been released, reestimate the parameters of (13) and obtain new values for $\Phi_m$ and $\Omega_m$ for the model in (16).

3. Generate nowcasts and forecasts using the CR-BVAR model of Section 2.2.2.

4. Using the unconditional predictive density from the previous step, $p(x^{t_q,t_q+H}|X^{t_q})$, and following the procedure in Section 2.3, tilt the long end of the forecasts to match the most recently published survey long-run expectations to obtain the modified probabilistic density $g(x^{t_q,t_q+H})$ and use it as an approximation to the expected path of the target variables $\mathbb{E}_w Y^0_{t(w)}$.

5. Using the modified posterior distributions of the forecasts and the causal effects simulate the OPP statistic $\delta^{(j)}_w = -(\mathcal{R}^{(j)\prime}\mathcal{W}\mathcal{R}^{(j)})^{-1}\mathcal{R}^{(j)\prime}\mathcal{W}\hat{Y}^{(j)}_{t(w)|w}, \quad j = 1, \ldots, B$

6. Reject the stance of monetary policy being optimally set in week $w$ if zero lies outside of the 50% confidence interval of the simulated distribution of the OPP.

# 3 Data

The VAR model consists of 20 time series of monthly or quarterly frequency. The variables include key real macroeconomic variables, labor market indicators, financial market variables, real indicators, price data, credit indicators, and a measure of uncertainty. The macroeconomic variables are real GDP, real consumption, real investment, and a measure of real disposable income. The labor market indicators are real wage inflation (based on compensation per hour), employment (in thousands of persons), the unemployment rate, initial claims, and average weekly hours. The financial market variables are the Fed Fund rate and the spread between the annualized Moody's Seasoned Baa corporate bond yield and the 10-year Treasury note yield at constant maturity, the excess bond premium of Gilchrist and Zakrajsek (2012), and the difference between the 10-year Treasury note yield at constant maturity and the Fed Fund rate, capturing the slope of monetary policy. The real indicators are industrial production and house starts. The price data consists of core CPI and core PCE price indices and the GDP deflator while the credit indicator is business loans and the measure of uncertainty is the economic policy uncertainty index of Baker, Bloom and Davis (2016).[6] The data on GDP, investment, the GDP deflator, and compensation per hour are only available at a quarterly frequency while the rest of the variables are available at a monthly frequency or higher, in which case the data is aggregated up to a monthly frequency.

The dataset consists of 720 real-time weekly vintages of data, thus accurately reflecting the available data as of each Friday from the beginning of 2005 to the end of 2019. In all

[6]With the exception of initial claims and the difference between the 10-year Treasury note yield at constant maturity and the Fed Fund rate, the variables coincide with the variables used in Cimadomo et al. (2022) and as they note are variables "that are monitored closely by professionals and institutional forecasters and are important for their information content and the timeliness of their release". Initial claims are included due to their timely indication of unemployment developments and the slope of monetary policy is included as it is one of the instruments we are interested in evaluating.

vintages the variables are available from October 1986. The variables enter the VAR model in log-levels with the exception of those variables already defined in terms of rates, in which case the variables enter in levels.

The expectations data used for the tilting step are taken from the Survey of Professional Forecasters (SPF), a quarterly survey published around the middle of the second month in a given quarter. We collect long run expectations for real GDP growth, CPI inflation, PCE inflation, and the unemployment rate. We use the same definition of long run expectations as in Tallman and Zaman (2020). For CPI and PCE inflation we use the response to the questions about the 10-year PCE and CPI inflation rates, defined as the annual average inflation over the current and next nine years. Long run expectations for GDP growth as the 10-year real GDP growth rate, defined as the annual average growth over the current and next nine years. Finally, for the long run unemployment rate we use the response to the question on the natural rate of unemployment. While the SPF inquires about expectations for long run CPI and PCE inflation every quarter, they only address long run GDP growth expectations and the natural rate of unemployment in the surveys conducted in the first quarter and the third quarter of each year respectively. For all expectations we use the median of the survey responses as our point estimate, as is the norm in the forecasting literature (see, e.g., Tallman and Zaman, 2020). The only variable that does not cover the entirety of our evaluation period is the 10-year PCE inflation rate which was first addressed during the first quarter of 2007. Given that the correlation between the two inflation expectations series is 0.87 we extend the long run PCE inflation expectations series back to the beginning of 2005 using changes in the CPI inflation expectations.

# 4 Forecasting Analysis

As stated previously, the time period under analysis spans from the first week of 2005 to the last week of 2019. We begin by comparing the ability of the quarterly QBVAR model and the CR-BVAR model to nowcast the current quarter. We do this by performing a weekly comparison of the point nowcasts that are generated by each model for a total of 13 weeks per quarter. Figure 2 plots the path of the RMSE for the CR-BVAR and QBVAR models along with the RMSE of the Greenbook and SPF nowcasts. These results are tabulated in Table 1 which reports the root mean squared errors (RMSE) for the two models and their ratio for the two target variables of interest: core PCE inflation and unemployment. Additionally, the RMSE for the Greenbook and SPF nowcasts for each variable is presented. For inflation, the RMSE is lower for the CR-BVAR model across all weeks of the quarter, with the exception of week 5, where the models perform roughly equally well, indicating that the inclusion of higher frequency information leads to improvements in nowcasting ability. This is further supported by performing a one-sided Diebold and Mariano (1995) (DM) test of whether the CR-BVAR outperforms the QBVAR. For the first two weeks of a quarter we can reject equal nowcasting ability at the 10% level. From the ninth week we can reject the null hypothesis at the 5% level and from the 11th to 13th we can reject at the 1% level. Comparing these results to the RMSE of the Greenbook nowcast and the SPF nowcast we see that, while the CR-BVAR model performs similarly to the SPF for the first four weeks of a quarter, the RMSEs diverge from the fifth week onwards with the CR-BVAR outperforming the SPF. At the same time, while the Greenbook nowcast outperforms the CR-BVAR nowcast for the first four weeks, the CR-BVAR model closes most of the gap during the fifth week.

Looking at the panel for the unemployment rate the results are even more stark. Across all weeks of a quarter, the RMSE for the CR-BVAR model is consistently lower than for the QBVAR model. Performing a one-sided Diebold-Mariano test allows us to reject the null that the models perform equally well at the 1% level across all the weeks of a quarter against the alternative of the CR-BVAR outperforming the QBVAR. Again, this indicates that incorporating higher frequency information improves nowcasting ability. Comparing the CR-BVAR nowcasts to that of the Greenbook and SPF, we see that the CR-BVAR nowcast outperforms both across all the weeks of a quarter although the Greenbook does catch up to the CR-BVAR nowcast in the last two weeks of a quarter.

A crucial note to keep in mind is that the SPF forecast is conducted once a quarter and the Greenbook nowcast is performed before each meeting of the FOMC while the CR-BVAR model gives us a nowcast each week. This means that the CR-BVAR nowcast can incorporate new information as it is made publicly available. Additionally, while the Greenbook nowcast is a staff forecast and not the forecast of the FOMC, it contains the forecasts presented for the FOMC and it is therefore reasonable to assume that these are the forecasts that underpin the FOMC discussion at any given time. The fact that the RMSE of the CR-BVAR nowcasts is relatively close to the RMSE of the Greenbook supports the claim that we can use the CR-BVAR nowcasts as a good approximation to the Fed's assessment of current economic conditions at the time the FOMC takes its decisions. A further benefit of the CR-BVAR is that, while we can generate forecasts each week using only publicly available information, the Greenbook is only made public with a 5 year lag, rendering it useless for a real-time monitoring purpose. Similarly, the SPF is only conducted and published once a quarter, again severely limiting its real-time use.

Moving beyond the evaluation of the model performance in the nowcasting quarter, Table 2 presents the RMSE at 1, 4, 8, 12, 16, and 20 quarters, along with cumulative RMSE at those horizons for the raw CR-BVAR forecasts and the tilted CR-BVAR forecasts along with their ratios for core PCE inflation and the unemployment rate. Starting with the point forecasts for the inflation rate, we see that the tilted forecast outperforms the raw forecast at 4, 8, 12 and 16 quarters with a one-sided DM test rejecting equal forecasting performance at the 10% level at 8 quarters and at the 5% level at 12 and 16 quarters. A two-sided test (not reported) does not reject equal forecasting performance at the 4 and 20 quarter horizons while it does reject at 1 quarter.[7] Looking at the cumulative RMSE we see that from 8 quarters onwards the tilted forecast outperforms the raw forecast by 1 to 15%.

Similarly stark results regarding the unemployment rate are evident in the tilted forecast improving upon the raw forecast across all horizons. A one-sided DM test rejects equal

[7]This could point one in the direction of in addition to tilting the nowcasting quarter for inflation to also tilt the first forecasting quarter. In the interest of treating both target variables in the same fashion and the fact that the tilted forecast for unemployment outperforms the raw forecast at the 1 quarter horizon, this is not explored in the present text.

forecasting performance in favor of the alternative of the tilted forecast being superior at the 1% level at the 1 and 4 quarter horizons, at the 5% level at 8 quarters, and at the 10% level at the 12, 16, and 20 quarter horizons. This is also evident when looking at the cumulative RMSE, which is in all cases lower for the tilted forecast with the improvement being constant for the 1, 4, and 8 quarter horizons, but then decreasing sharply for the 12, 16, and 20 quarter horizons.

A final consideration is how closely the SPF long run expectations match those of the FOMC. Figure 3 plots the long run expectations found in the SPF along with the median and midpoint of central tendency of the Summary of Economic Projections (SEP), which gathers the expectations of the FOMC. The median of the SEP is available from 2015 while the midpoint is available from 2009. Looking at the results for inflation, we see that from 2013 the two are almost perfectly aligned while there is a slight disagreement before that time with the largest difference reaching about half a percentage point. This could potentially be due to the fact that the SEP does not report expectations on long run core PCE inflation but only asks about headline PCE inflation while the SPF asks for both core and headline PCE inflation. In fact, comparing the headline and core PCE inflation expectations in the SPF we see that headline expectations are up to 0.4 percentage points lower than core inflation expectations for the period when the SPF and SEP expectations do not align perfectly.

Moving on to the figure for the unemployment rate, we see that again these expectations measures are close and move in tandem, especially so the median of the SEP and the SPF surveys. Taken together, we view this as support for our use of the SPF responses to anchor the long end of the forecasts as a reasonable approximation of the FOMC information set while using publicly available non-Fed generated data.

Summing up the results for the nowcast and the forecast evaluations, we find that the use of higher frequency information improves the nowcasting accuracy over a standard quarterly BVAR model and that including the external information contained in the SPF survey on long-run expectations improves the forecasting performance over the horizon relevant to monetary policy decisions. While we see improvements for both the inflation and unemployment rates, the results are stronger for the unemployment rate. Note that the horizon at which the long run expectations take over is at its shortest 17 quarters for unemployment and 19 quarters for core inflation. Therefore, these results are more driven by the effect the tilting has on the entire forecast path rather than the effect of the point value of the long run expectations themselves. These results motivate our use of the CR-BVAR with long-run tilting to generate forecasts for the target variables to be used to calculate the OPP.

# 5 OPP results

Figure 4 presents the results for the OPP statistic, calculated at the end of each week over the evaluation period beginning at the start of 2005 and ending at the end of 2019, along with 50% confidence bounds for both the Fed Funds rate and the slope policy. Starting with the top panel, which presents the results for Fed Funds rate, we see that we cannot reject that the level of the Fed Funds rate was optimally set during the interest rate hike phase from the beginning of 2005 to mid-2006. During this time the OPP statistic fluctuates around zero with a slight indication during mid-2005 that the interest rate hike was too rapid although this is not statistically significant. Around the end of 2006 and beginning of 2007 the OPP would suggest that a slight decrease in the Fed Funds rate would be appropriate but again, this is not statistically significant and reverts to zero by mid-2007. However, from that point onwards, the OPP grows increasingly negative until the Fed Funds rate reaches the zero lower bound (ZLB) at the end of 2008. We can reject that the Fed Funds rate was optimally set as early as the beginning of February 2008, the same week the Fed lowered its interest rate by 0.5 percentage points. Furthermore, with the exception of the weeks of February 29, March 14, May 18, and August 1, we can reject optimality in every week leading up to the Fed hitting the ZLB at the end of 2008. This indicates that according to the OPP the Fed should have lowered its interest rate both sooner and more aggressively than it did in actuality.

The Fed began raising its interest rate at the end of 2015. However, there is some indication that the interest rate hike phase began prematurely as the OPP turned negative by about 25 basis points at the same time as the Fed raised its rate by 25 points. While the OPP remains negative until around the first half of 2017 we cannot reject that the Fed Funds rate was optimally set in the period after the zero lower bound.

The bottom panel of Figure 4 presents the results for the slope policy. We see that around the time the Fed Funds rate is reaching the zero lower bound at the end of 2008 we can reject the hypothesis that the slope policy was set optimally. According to the OPP, the Fed should have employed its slope policy to bring the slope almost a percentage point lower than it actually was at the onset of the ZLB. As the long term interest rate started rising through to mid-2009, while the Funds rate was stuck at the ZLB, the OPP indicates that the Fed should have conducted its policy such that the long term interest rate, and thus the slope, should have been up to 2 percentage points lower than it actually was. In fact, we can reject slope policy being optimally set until the end of May 2013, with the exception of mid-August and October 2010. Additionally, we can reject the slope policy being optimally set in November and December of 2013. From then on, we cannot reject the slope policy being optimally set.

These results are generally in line with the results in Barnichon and Mesters (2023) until February 2008 at which point we can reject the Fed Funds rate being optimally set while they cannot reject optimality until April 2008. As in the present case, they do not reject optimality in the post-ZLB period. For the slope policy, they also reject optimality from 2009-2012 but as opposed to the present paper, they can reject optimality in 2013 whereas we cannot. The fact that the results are qualitatively so similar is not to be overlooked. While Barnichon and Mesters (2023) rely on FOMC forecasts published in the Summary of Economic Projections (SEP) to construct the conditional expectation needed to compute the OPP, we only rely on a VAR model and the Survey of Professional Forecasters. While the SEP is only published four times a year, we can generate forecasts each week using newly released data combined with survey expectations. However, this highlights a fundamental difference between the two papers; while the goal of Barnichon and Mesters (2023) is to test the optimality of FOMC decisions, and therefore they only calculate the OPP statistic at points in time where a FOMC meeting occurs, the present paper tests the optimality of policy at the end of each week given recently published data and thus providing a timely indicator of whether the stance of monetary policy is adequate in light of contemporary macroeconomic developments. This highlights the complementary nature of the two approaches.

# 6 Lead up to the zero lower bound

In order to better understand the benefit of the high frequency nature of the present approach, Figure 5 focuses on the developments from mid-2007, at which point the OPP statistic was at zero, until the end of 2008 when the Fed Funds rate reached the zero lower bound. The top panel of the Figure shows the OPP statistic, the 50% bounds and the actual Fed Funds rate changes of the FOMC. The middle and bottom panels show, for inflation and unemployment respectively, the nowcasts and the long run expectations in deviations from targets, along with the mean deviation of the forecasts from the target calculated over the horizon under consideration.

From August 2007, we see that the OPP statistic starts to drift away from zero and continues to do so throughout the rest of 2007. During this time we can see that while both the nowcast and long run expectations on the unemployment rate are slightly below the NAIRU, the mean deviation over the horizon is small and slightly positive in the last quarter of the year. At the same time, the nowcast for inflation is below target from late August and while the long run expectations are slightly above target from around the same time, the mean deviation over the horizon keeps getting more negative, reaching a trough at the beginning of November at which point the nowcast starts to increase and goes above target in mid-December, although the mean deviation remains negative. Combined, these developments contribute to the OPP statistic drifting below zero in the latter half of 2007.

At the beginning of January of 2008 we see that the nowcast for inflation is right at the Fed's target while the mean deviation from target over the horizon is negative despite long run expectations remaining above target. At the same time, the nowcast for the deviation of the unemployment rate from the NAIRU switches from negative to positive pushing the mean deviation over the horizon up by .15 percentage points per quarter, while the long run expectations remain unchanged and negative by the same number. Through the rest of January we see that the nowcast for the unemployment rate remains more or less unchanged while the mean deviation over the horizon increases slightly. This leads to the continued decrease in the OPP statistic despite the nowcast for inflation increasing by almost .1 percentage points and the mean deviation of inflation over the horizon shrinking and the Fed lowering the target rate by 75 basis points.

At the beginning of February we see that, despite the Fed lowering its target rate again, the nowcast for the deviation of the unemployment rate increases and along with it the mean deviation over the horizon leading to the first instance of rejection of policy optimality according to the OPP. The following week the nowcast for inflation drops and with it the mean deviation of inflation over the horizon, which leads to an even stronger rejection of policy optimality. In the subsequent week the long run expectations of inflation are revised upwards, pushing the OPP statistic towards zero. However, the optimality of policy can still be rejected, albeit by a small margin. The last week of February sees the nowcast for inflation increasing although the mean deviation over the horizon grows slightly more negative. At the same time, the mean deviation of unemployment decreases slightly while the nowcast remains unchanged. The combination of the two lifts the OPP statistic closer to zero and we cannot reject the optimality of policy in that week.

In the first week of March we see that the nowcast for inflation continues to rise and the mean deviation of inflation to shrink towards zero. However, despite the nowcast for unemployment being lowered the mean deviation over the horizon increases leading the OPP to grow more negative and we can reject optimality of policy. The following week we see that the mean deviation of inflation over the horizon shrinks to zero and we cannot reject policy being optimally set, although only barely. By the third week of March we see that, while the nowcasts for both unemployment and inflation are practically unchanged, the mean deviation of unemployment grows more positive while for inflation it grows more negative. This leads to the OPP to grow more negative and us being able to reject the optimality of the stance of policy. This remains the case in the subsequent week where the nowcast for inflation drops by almost 15 basis points and the mean deviation over the horizon to be lowered by almost 10 basis points.

For the first two weeks of April we can reject the optimality of the policy stance. The nowcast in April, and thus the second quarter of 2008, is substantially higher than for the previous quarter and although the nowcast for inflation is slightly higher than in the last week of March the mean deviation of inflation and unemployment remain more or less unchanged. In the third week of April the mean deviation of inflation shrinks slightly towards zero, leading to a failure to reject optimality but this is reversed in the subsequent week and we can reject the optimality once more.

From the first week of May we see that, while the nowcast for inflation is hovering above target, the mean deviation over the horizon is growing increasingly negative, reaching a trough at the beginning of July. Over the same period the nowcast for the unemployment rate is trending slightly upwards with the mean deviation doing the same. Taken together, this leads the OPP statistic to remain steadily below zero and we can reject the optimality of the stance of policy. In fact, with the exception of the first week of August, we can always reject the optimality of the policy stance up to and including the end of 2008 when the Fed Funds rate reaches the zero lower bound. The nowcast for the unemployment rate keeps trending upwards along with the mean deviation of the unemployment rate over the horizon and despite the nowcast for inflation increasing and remaining well above target as well as the mean deviation of inflation from target over the horizon becoming positive from the beginning of August until mid-December the OPP statistic keeps growing more negative and we can reject optimality of the policy stance with growing confidence.

## 6.1 Comparison with the Greenbook

To demonstrate the value of the proposed procedure and the use of high frequency information we turn to a comparison of the forecasts generated by our proposed procedure with the forecasts presented in the Fed's Greenbook which are prepared for the FOMC meetings.

The first Greenbook of 2008 is from January 23. In that forecast they predict that the unemployment rate will be above the NAIRU in 2008 and across the forecast horizon. Furthermore, they forecast core PCE inflation to be slightly above target in 2008 and then slightly below target for the rest of the forecast horizon. For both variables, the forecasts generated using the method proposed in the present paper are in accordance with the January Greenbook. Additionally, the mean deviation of inflation over the forecast horizon is -0.1 percentage points in the Greenbook and -0.13 percentage points using the nowcasting model. For the mean deviation of the unemployment rate, however, it is 0.16 percentage points in the Greenbook but 0.38 percentage points using the nowcasting model.

The next Greenbook is from March 18th which begins by stating that the labor market was turning out weaker than expected, just as the nowcasting model had predicted. The Greenbook forecast for the unemployment rate was revised upwards over the entire horizon with the biggest revision for 2008. With the revision the mean deviation of the rate of unemployment from the NAIRU goes up to 0.44 percentage points, a value reached by the nowcasting model already in early February and increased to 0.5 percentage points by the time the March Greenbook was presented to the FOMC. On the other hand, the forecast for inflation was revised upwards for the year 2008 but slightly lowered at the long end of the horizon leading to the mean deviation over the horizon to grow slightly more negative. Comparing these developments to the nowcasting model we see that the nowcasting model had already begun increasing the nowcast by mid-February. The mean deviation according to the nowcasting model had shrunk towards zero over that period and stands at about -0.05 percentage points compared to the Greenbook's -0.12 percentage points.

The following Greenbook is dated April 23rd. While there is a reference to a continued weak labor market, the forecast is more or less unchanged with a slight downward revision at the tail end of the horizon. The mean deviation over the horizon is now 0.4 percentage points as opposed to 0.56 for the nowcasting model which had increased steadily between the two Greenbooks. The inflation forecast is revised slightly upwards for 2009 but otherwise unchanged, bringing the mean deviation over the horizon to -0.1 percentage points, which pretty closely matches the nowcasting model which reached -0.13 percentage points at the end of March and stood -0.11 by the time the Greenbook was made.

A final note is that in the subsequent Greenbook, dated June 18, the mean deviation of the rate of unemployment from target over the horizon had reached 0.52, catching up with what the nowcasting model predicted months earlier and had stabilized around. The inflation forecast was, however, revised upwards over the horizon leading to a mean deviation of zero over the horizon. It therefore appears that the nowcasting model is able to preempt changes in the Greenbook forecasts and adjust sooner, leading to earlier detection of optimization failure in the stance of economic policy of the FOMC. This preemption is especially clear when it comes to forecasts of the unemployment rate, in no doubt due to the superior nowcasting performance of the methodology proposed in the present paper.

# 7 The flow of information and changes in the OPP

An aspect of the policy problem we have not addressed is its sequential nature, i.e., at each week $w$ we calculate the OPP statistic with the current information set. To make the discussion concrete, we calculate the OPP statistic at time $w-1$ and again at time $w$. At both time periods, the first order conditions that provide the foundation of the OPP dictate that

$$\mathcal{R}^{0\prime}\mathcal{W}\mathbb{E}_w Y^0_{t(w)} = 0 \quad \text{and} \quad \mathcal{R}^{0\prime}\mathcal{W}\mathbb{E}_{w-1} Y^0_{t(w-1)} = 0$$

where $\mathbb{E}_w$ denotes the expectation operator given the information set available in week $w$ and $Y^0_{t(w)}$ is the path of the target variables starting from the time period $t(w)$ which denotes the quarter that week $w$ belongs to.

We can decompose the difference between the two gradients as

$$\mathcal{R}^{0\prime}\mathcal{W}\mathbb{E}_w Y^0_{t(w)} - \mathcal{R}^{0\prime}\mathcal{W}\mathbb{E}_{w-1} Y^0_{t(w-1)} = \mathcal{R}^{0\prime}\mathcal{W}\underbrace{\left(\mathbb{E}_w Y^0_{t(w)} - \mathbb{E}_{w-1} Y^0_{t(w)}\right)}_{\text{Information update}} + \mathcal{R}^{0\prime}\mathcal{W}\underbrace{\mathbb{E}_{w-1}\left(Y^0_{t(w)} - Y^0_{t(w-1)}\right)}_{\text{Preference shift}}$$

where the part dubbed 'Information update' captures the change in the expected path of the target variables due to changes in the information set available, while the part dubbed 'Preference shift' captures changes in the objectives of the policy maker. Note that this implies that within a quarter, the only changes to the OPP arise from the inflow of new data through the information update since for any two weeks belonging to the same quarter, the preference shift term is zero. In the present paper interest lies in the effect of the information update.

Finally recall that the OPP statistic is a re-scaling of the gradient and thus we have that

$$\delta^\star_w - \delta^\star_{w-1} = \mathcal{D}\underbrace{\left(\mathbb{E}_w Y^0_{t(w)} - \mathbb{E}_{w-1} Y^0_{t(w)}\right)}_{\text{Information update}} + \mathcal{D}\underbrace{\mathbb{E}_{w-1}\left(Y^0_{t(w)} - Y^0_{t(w-1)}\right)}_{\text{Preference shift}} \tag{36}$$

where $\mathcal{D} = -(\mathcal{R}^{0\prime}\mathcal{W}\mathcal{R})^{-1}\mathcal{R}^{0\prime}\mathcal{W}$.

Figure 6 shows this decomposition of changes in the OPP statistic into information update and preference shift from July 2007 to December 2008. As discussed above, we can see that the preference shift only plays a role in the first week of a quarter, when the quarters over which the OPP statistic is calculated shifts. The second panel of the figure shows changes in the inflation nowcast and decomposes it into changes stemming from the revision of previously released data and changes caused by new data becoming available. An interesting observation is that on average, revision of previously published data does not play a large role in changing the nowcast for inflation. Comparing changes in the inflation nowcast to changes in the OPP we actually find that the correlation is negative as opposed to the expected positive correlation. The correlation between changes in the inflation nowcast and changes in the mean deviation of inflation over the forecast horizon is, however, positive and around 0.32. The changes in the mean deviation are positively correlated with changes in the OPP statistic, as expected, although the correlation is very close to zero. The reason for this is that over the period under examination the Fed faced a trade-off when it comes to the stabilization of inflation and unemployment since for almost the entire period the deviations of the nowcasts for inflation and the unemployment rate from their targets had the same sign and thus in terms of the nowcasts the two target variables sent opposing signals as to what the policy rate should be. This trade-off is less prevalent in the mean deviations, however, which is why the negative correlation for the inflation rate disappears. But since the mean deviation for the unemployment rate is numerically larger than the mean deviation for the inflation rate, changes in the OPP are driven more by changes in the mean deviation of the unemployment rate which has the expected negative correlation with changes in the OPP with a correlation coefficient of -0.4. Furthermore, changes in the nowcast for the unemployment rate have the expected positive correlation with changes in the mean deviation of the unemployment rate over the horizon with a coefficient of 0.32 and, again, the expected negative correlation with changes in the OPP directly with a coefficient of -0.37. This further cements the observation that over the period under consideration, the OPP is driven more by the unemployment rate than by the inflation rate. A last note is that, while there are only four changes in long-run expectations during the period under consideration, in all cases the OPP responds in the expected direction. Mid-August 2007, when the long run expectation of inflation increases above target and at the same time the long run expectation of the unemployment rate decreases below the NAIRU, there is a positive change in the OPP as standard economic theory would predict. In mid-February 2008, the OPP increases again when the long run expectation of inflation increases further above target, and when the long run expectation of the unemployment rate increases above the NAIRU, the OPP shifts downwards. Both instances again conform to standard economic theory.

Another decomposition of the changes in the OPP, also presented in Figure 6, is to recompute the OPP each week using revised historical data only. That is, in a given week, we only use observations that were available in the previous week but with the new values for the observations if the data has been revised. The difference between this revised OPP and the OPP statistic calculated using newly released data, denoted by $\Delta\delta^{rev}_{t(w)}$, should capture the effect that the new observations have on the OPP net of the effect of historical revisions. The correlation of this measure of changes in the OPP with the Information Update in Equation (36) is 0.7.

## 7.1 What drives changes in the nowcasts

Figure 7 presents the contribution of the different variables to changes in the nowcasts for the inflation rate and the unemployment rate grouped by Financial variables, Labor market variables, Macroeconomic variables, Price variables, Real Indicators, Credit variables, and Uncertainty variables as well as the contribution of the revision of previously published data for July 2007 to the end of 2008.[8]

The contribution of the revision of historical data to the nowcast is calculated as the difference between the nowcasts generated using the data available in the previous week and the nowcast generated using the revised values of data available in the previous week given data available in the present week. The calculation of the contribution of newly released data is slightly more involved. First we calculate the difference between the realized value, that is released in the present week, and the forecast for that value after accounting for revisions of the previously released data. We then compute the contribution of the newly released observation to changes in the nowcast as this difference, or news shock, multiplied by a weight given by the Kalman Gain.

The first thing to note is that if we look at the shares of total contribution to changes, then

[8]The grouping is the same as in the Data Section: The macroeconomic variables are real GDP, real consumption, real investment, and a measure of real disposable income. The labor market indicators are real wage inflation (based on compensation per hour), employment, the unemployment rate, initial claims, and average weekly hours. The financial market variables are the Fed Fund rate and the spread between the annualized Moody's Seasoned Baa corporate bond yield and the 10-year Treasury note yield at constant maturity, the excess bond premium of Gilchrist and Zakrajsek (2012), and the difference between the 10-year Treasury note yield at constant maturity and the Fed Fund rate, capturing the slope of monetary policy. The real indicators are industrial production and house starts. The price data consists of core CPI and core PCE price indices and the GDP deflator while the credit indicator is business loans and the measure of uncertainty is the economic policy uncertainty index of Baker, Bloom and Davis (2016).

the revision of previously published data accounts for 11% of total contributions to changes in the nowcasts for the inflation rate and 6% for the unemployment rate. For the core PCE inflation, the biggest contributor to changes in the nowcast is, unsurprisingly, the release of new Price variable data which accounts for 36% of total contributions to changes in the nowcast. New Financial variable data come next and account for 16% of total contributions and new releases of Real Indicator data account for a further 14%, with the remaining variable groups accounting for less than 10% each, with Credit variables accounting for the smallest share of a little under 5%.

For the unemployment rate nowcast we see that, again unsurprisingly, the new release Labor market variables account for 56% of total contributions to changes in the unemployment rate nowcast. The second largest contributor is new releases of Financial variable data accounting for a little over 10% of total contributions to changes, closely followed by releases of Macroeconomic variable data at a little under 9%. The remaining groups account for 6% or less each, with the release of credit variables again having the smallest share of 3%.

To shed some light on how, through their effect on the nowcast, these variable groups affect the mean deviation of the target variables from their targets over the horizon and the OPP statistic, Table 3 presents the results from regressing the mean deviations of the target variables on the contributions to changes in their respective nowcasts and the regression of $\Delta\delta^{rev}_{t(w)}$ on the contributions to changes to both the target variables. All the data has been standardized to facilitate the comparison and spans the period from July 2007 to the end of 2008.

Starting with the first column we have the regression of the mean deviation of core PCE inflation over the horizon on the contribution to changes in the nowcast of core PCE inflation from the revision of historical data and the release of new observations. The first thing to note is that, although revisions of historical data account for 11% of changes in the nowcast for core PCE inflation, changes in the nowcast do not lead to changes in the mean deviation of core PCE inflation over the horizon. Furthermore, of the statistically significant coefficients, increases in the nowcast of core PCE inflation due to the release of new observations of Financial variables, Price variables, Credit variables and Uncertainty variables all lead to increases in the mean deviation over the horizon with, unsurprisingly, the largest effect of changes being due to new Price data observations becoming available. The only statistically significant coefficient with a counterintuitive sign is for the contribution to changes in the nowcast for core PCE inflation stemming from newly available observations on Macroeconomic variables. Increases in the nowcast due to new observations of Macroeconomic variables appear to be associated with a decrease in the mean deviation over the horizon, implying that while the new observations might cause an increase in the near term, they are associated with lower inflation after the near term. It should be borne in mind, however, that the release of Macroeconomic variables accounts for only about 5% of total contributions to change in the nowcast of core PCE inflation.

Turning to the second column of Table 3 we have the results from regressing the mean deviation of unemployment from NAIRU over the horizon onto a constant and the contribution to changes in the nowcast of the unemployment rate from the revision of historical data and the release of new observations. Starting with the change in the nowcast for the unemployment rate due to the revision of historical data, we see that, as opposed to for the core PCE inflation, that the effect on the mean deviation of the unemployment rate is statistically significant and positive, as expected, albeit very small. Furthermore and unsurprisingly, the contribution of newly released Labor market variable data to changes in the nowcast has the largest coefficient but, however, it is not statistically significant. Of the statistically significant coefficients, contributions to increases in the nowcast due to the release of Real Indicator variables, Credit variables, and Uncertainty variables all have the expected sign and are associated with increases in the mean deviation of the unemployment rate, while the coefficients are relatively small. The only coefficient with an unexpected sign is the contribution to increases in the nowcast due to the release of Price variables, which is associated with a decrease in the mean deviation. However, the contribution to changes in the nowcast due to Price variables only accounts for less than 6% of total contributions to changes.

Finally, the last column presents the regression of the change in the OPP net of data revisions, $\Delta\delta^{rev}_{t(w)}$, on a constant and the contributions to changes in the nowcasts of core PCE inflation and the unemployment rate from the publication of new data. The first thing to note is that for the period in question the only statistically significant effect from changes in the nowcast for inflation comes from changes due to new observations of the Uncertainty variable being released. Interestingly, the sign of the coefficient is negative, implying that if the nowcast for core PCE inflation increases due to the uncertainty variable, the OPP decreases. The same story emerges for increases in the nowcast for the unemployment rate that are caused by the publication of new observations of the uncertainty variable which are associated with an increase in the OPP statistic. The remaining statistically significant coefficients are all on changes in the unemployment rate nowcast and have the expected negative sign. The largest of these is on changes in the nowcast of unemployment rate due to new observations on Labor Market variables being published, followed by changes due to the release of Financial variables at about a third of the effect of Labor Market variables and lastly changes due to the release of Credit variables with a relatively very small coefficient.

Table 3 demonstrates that changes in the mean deviations over the horizon of core PCE inflation and the unemployment rate from their targets can be associated with the publication of new observations of multiple groups of variables in addition to the revision of historical data in the case of the unemployment rate. However, changes in the OPP statistic net of changes due to the revision of previously published observations are associated with the release of a much more selective group of variables. Indeed, the only association with changes in the nowcast of core PCE inflation comes through changes driven by the release of Uncertainty variable observations, which also affects the OPP statistic through changes in the nowcast of the unemployment rate. Besides the Uncertainty variable, changes in the OPP statistic net of revisions are driven by changes in the nowcast of the unemployment rate that stem from the release of new observations of Financial variables, Labor Market variables, and, to a much lesser extent, Credit variables.

# 8 Conclusions

Early indication of deviations from optimality of monetary policy can be of great use for policy makers and market participants alike. We have presented a framework that combines a nowcasting model with entropy tilting to generate timely forecasts that incorporate new data as it is released to provide up to date estimates of the current state of the economy while anchoring the long end of the forecast at survey expectations. We show that this framework performs well in terms of forecasting accuracy, both at the nowcasting horizon and over the forecasting horizon. Combining these forecasts with estimates of the causal effects of monetary policy tools on the target variables inflation and the unemployment gap, we present a weekly version of the Optimal Policy Perturbation statistic which allows for an online evaluation of the adequacy of the current stance of monetary policy given the most up to date data possible.

In a retrospective analysis of the Federal Reserve's monetary policy decisions we find that we can reject the optimality of the policy stance as early as the beginning of February 2008, anticipating the optimization failure in April 2008 found in Barnichon and Mesters (2023). The reason for this early detection stems from the nowcasting model anticipating revisions to the Fed's Greenbook forecasts.

An analysis of the main drivers of changes in the nowcasts in the lead up to the Great Recession and the Fed Funds Rates reaching the zero lower bound reveals that new observations of Price variables, Financial variables and Real Indicator variables accounts for about 65% of all contributions to changes in the inflation nowcast, while new observations of Labor Market variables and Financial variables account for about 65% of all contributions to changes in the unemployment rate nowcast. When it comes to changes in the mean deviation over the forecast horizon of the target variables from their targets, we find association between the contribution to changes in the nowcast from the release of Financial variable, Price variable, Credit variable, Macroeconomic variable, and Uncertainty variable observations and changes in the mean deviation of the inflation rate. For changes in the mean deviation of the unemployment rate we find association with the contributions to change in the nowcast from the release of Real Indicator variable, Credit variable, Price variable, and Uncertainty variable observations. Finally, changes in the OPP statistic net of changes due to the revision of previously published observations are associated with the release of a much more selective group of variables. The only effect of changes in the nowcast of core PCE inflation is through the release of Uncertainty variable observations. For the unemployment rate, however, changes in the nowcast due to the publication of Uncertainty variables, Financial variables, Labor Market variables and Credit variables all have a statistically significant effect on changes in the OPP statistic net of revisions. This shows that failures in setting the stance of monetary policy optimally in the lead up to the Great Recession are primarily driven by not fully taking into account changes to the outlook on the unemployment rate.

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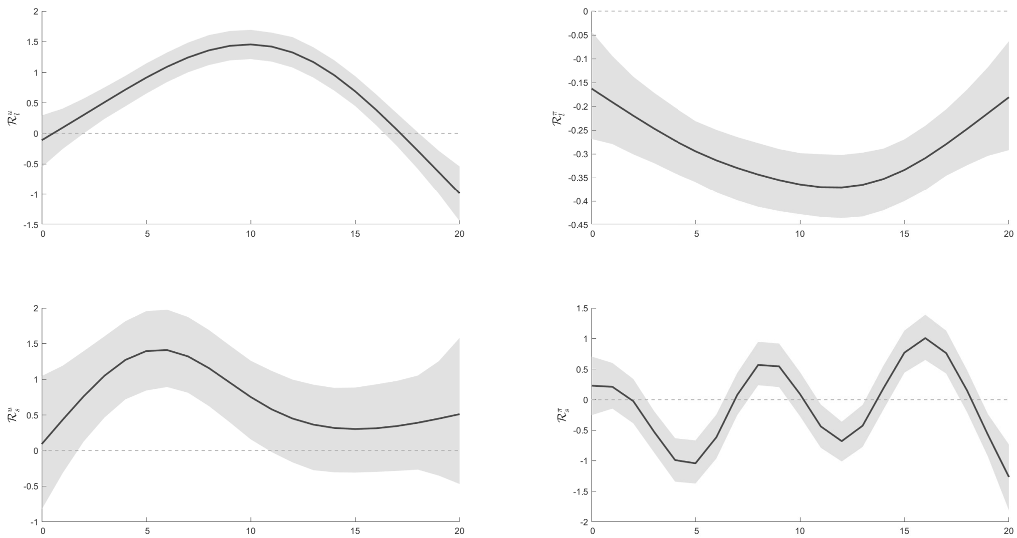
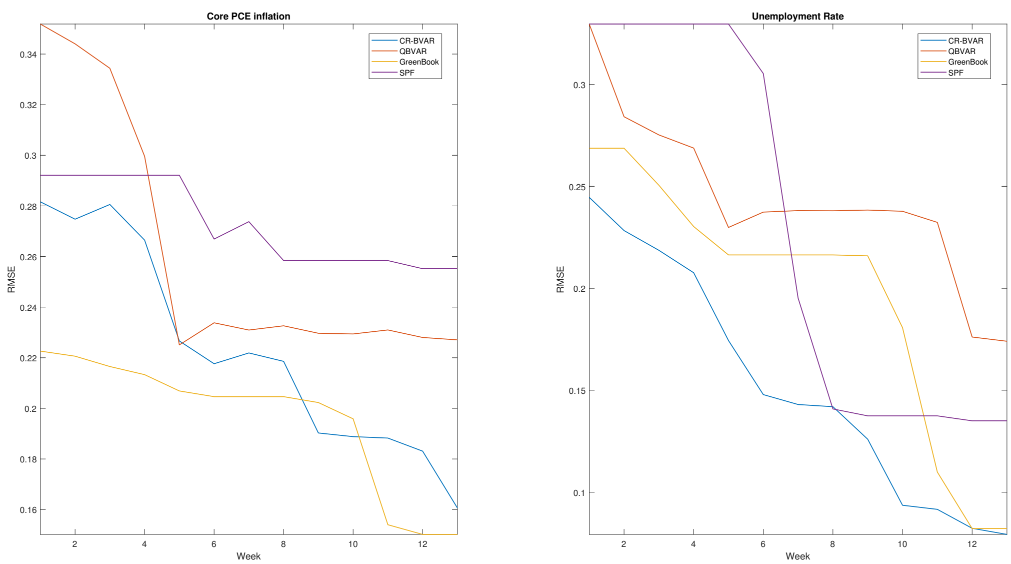
Figure 1: Causal Effect Estimates



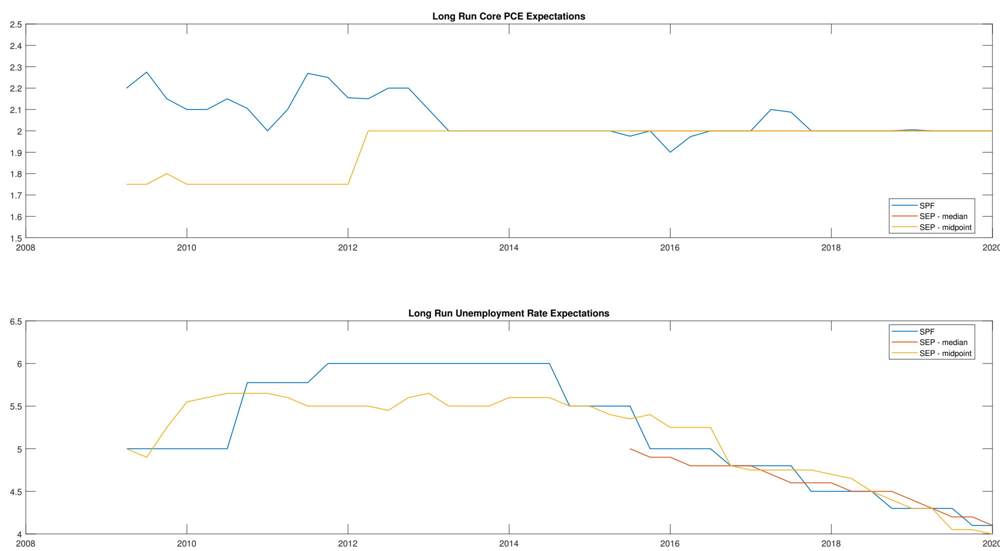
*Notes:* Left panel: Impulse responses of core PCE inflation and unemployment rate to a unit Fed Funds rate shock. Right panel: Impulse responses of core PCE inflation and unemployment rate to a unit slope policy shock. The shaded bands denote the 68 percent credible intervals.

Figure 2: Evolution of Nowcasting RMSE Over Weeks of Quarter



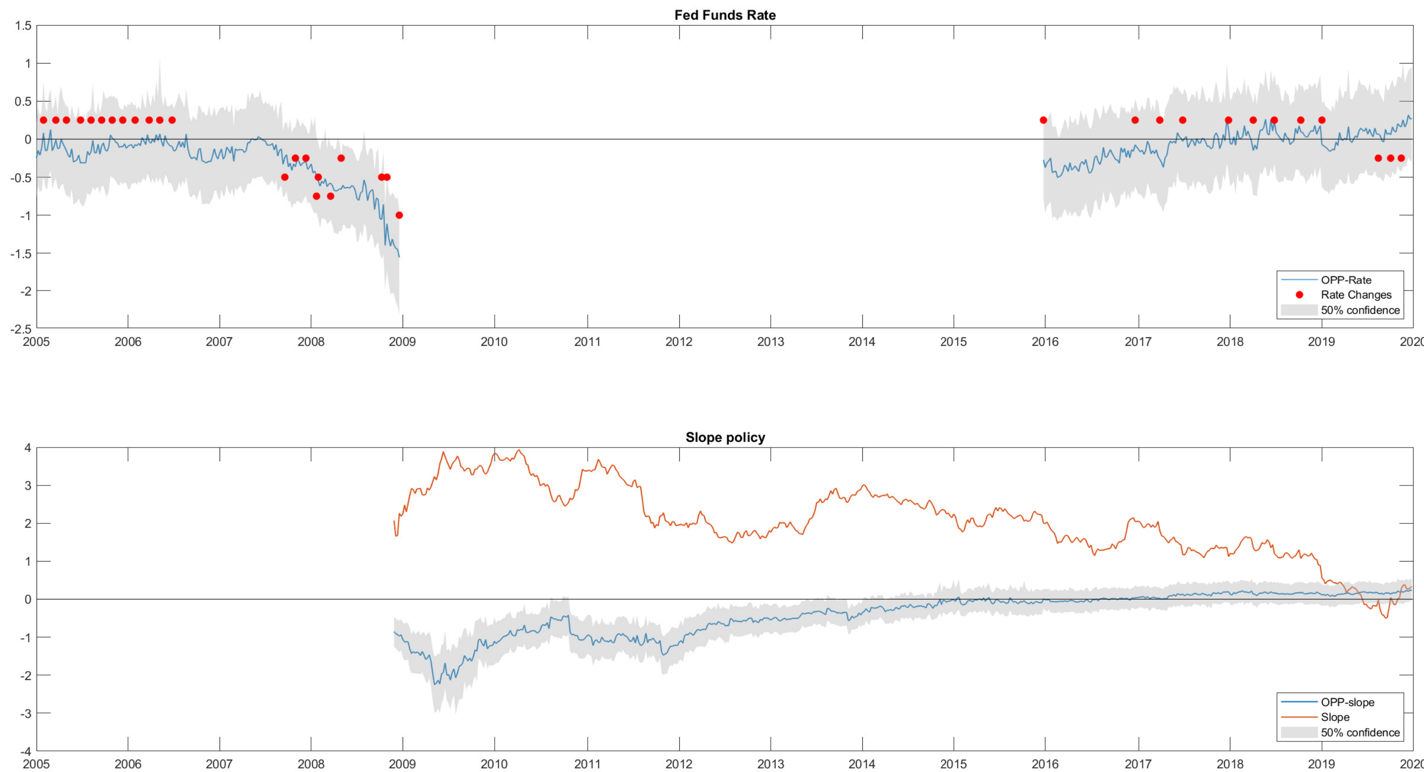

*Notes:* Left panel: Root Mean Squared Error (RMSE) of core PCE inflation nowcasts by week of quarter. Right panel: RMSE of unemployment rate nowcast by week of quarter. CR-BVAR refers to the cube-root Bayesian VAR model, QBVAR refers to the quarterly Bayesian VAR model, Greenbook refers to the Federal Reserve's Greenbook forecast, and SPF refers to the Survey of Professional Forecasters.

Figure 3: Comparison of Long Run Expectations



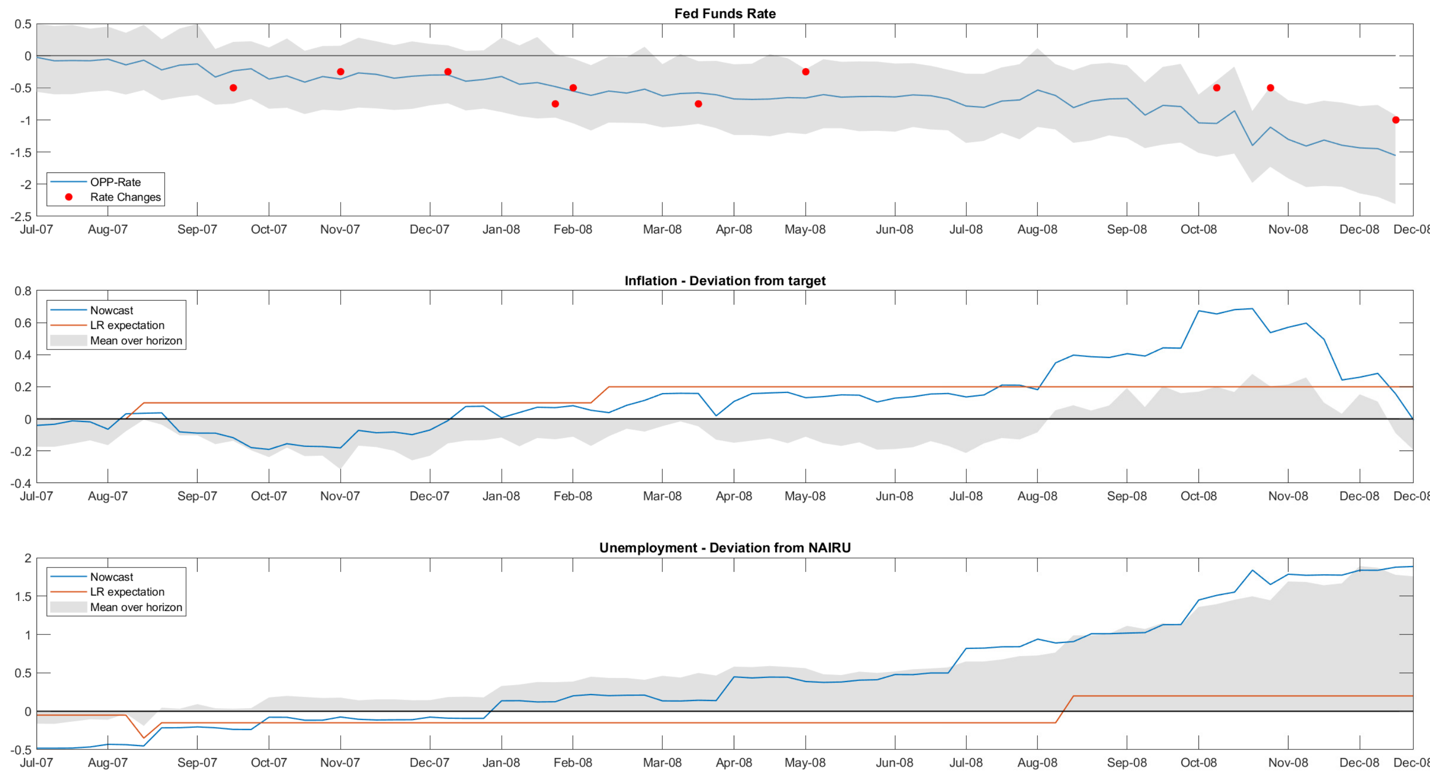

*Notes:* Top panel: Long run core PCE inflation expectations given by the Survey of Professional Forecasters (SPF), the median and midpoint of central tendency of the Summary of Economic Projections (SEP). Bottom panel: Long run unemployment rate expectations given by the Survey of Professional Forecasters (SPF), the median and midpoint of central tendency of the Summary of Economic Projections (SEP).

Figure 4: OPP Results



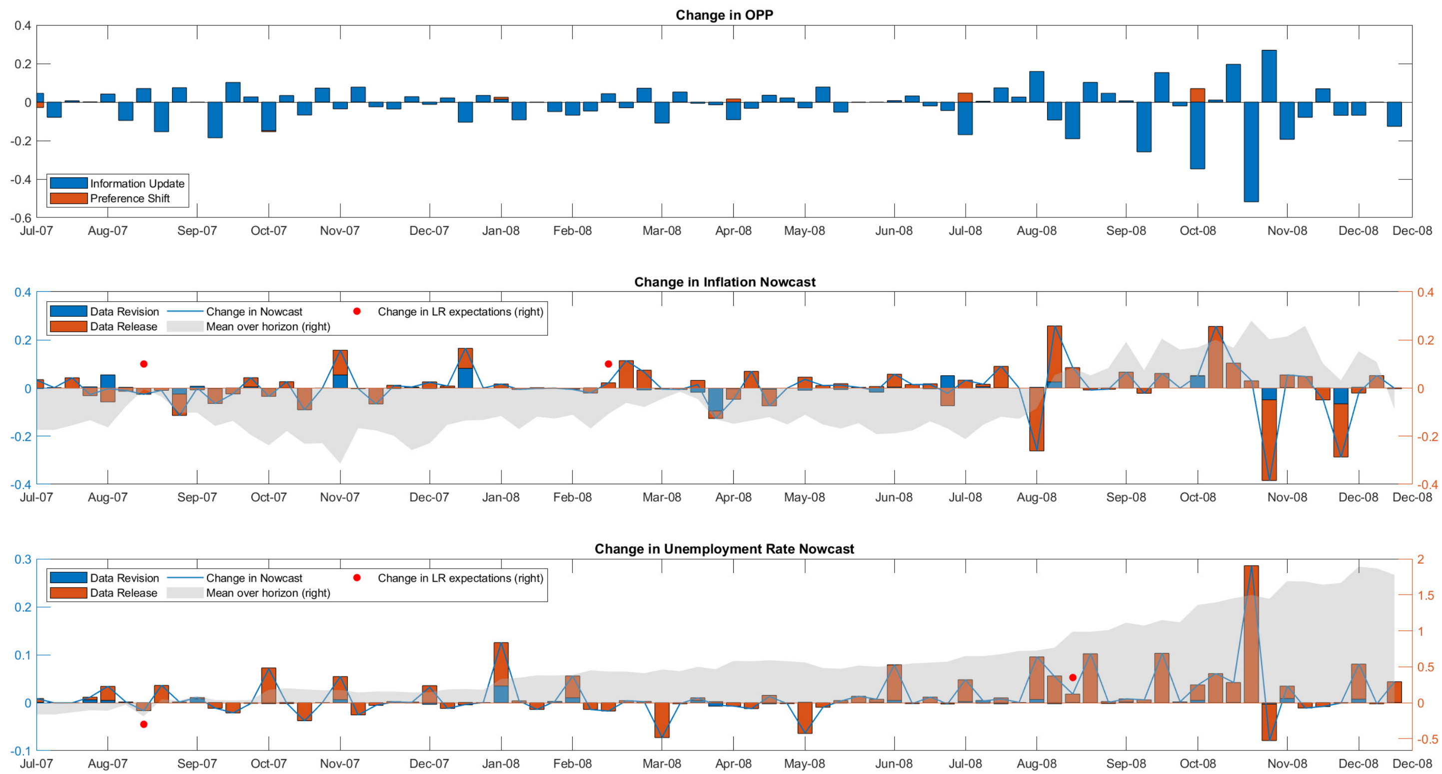

*Notes:* Top panel: OPP statistic for the Fed Funds rate and realized changes to the Fed Funds target rate. Bottom panel: OPP statistic for the slope policy and the slope of the yield curve defined as the difference between the 10-year bond yield and the Fed Funds rate. Shaded areas represent impulse response and model uncertainty at 50 percent confidence.

Figure 5: Analysis of Lead Up to Great Recession



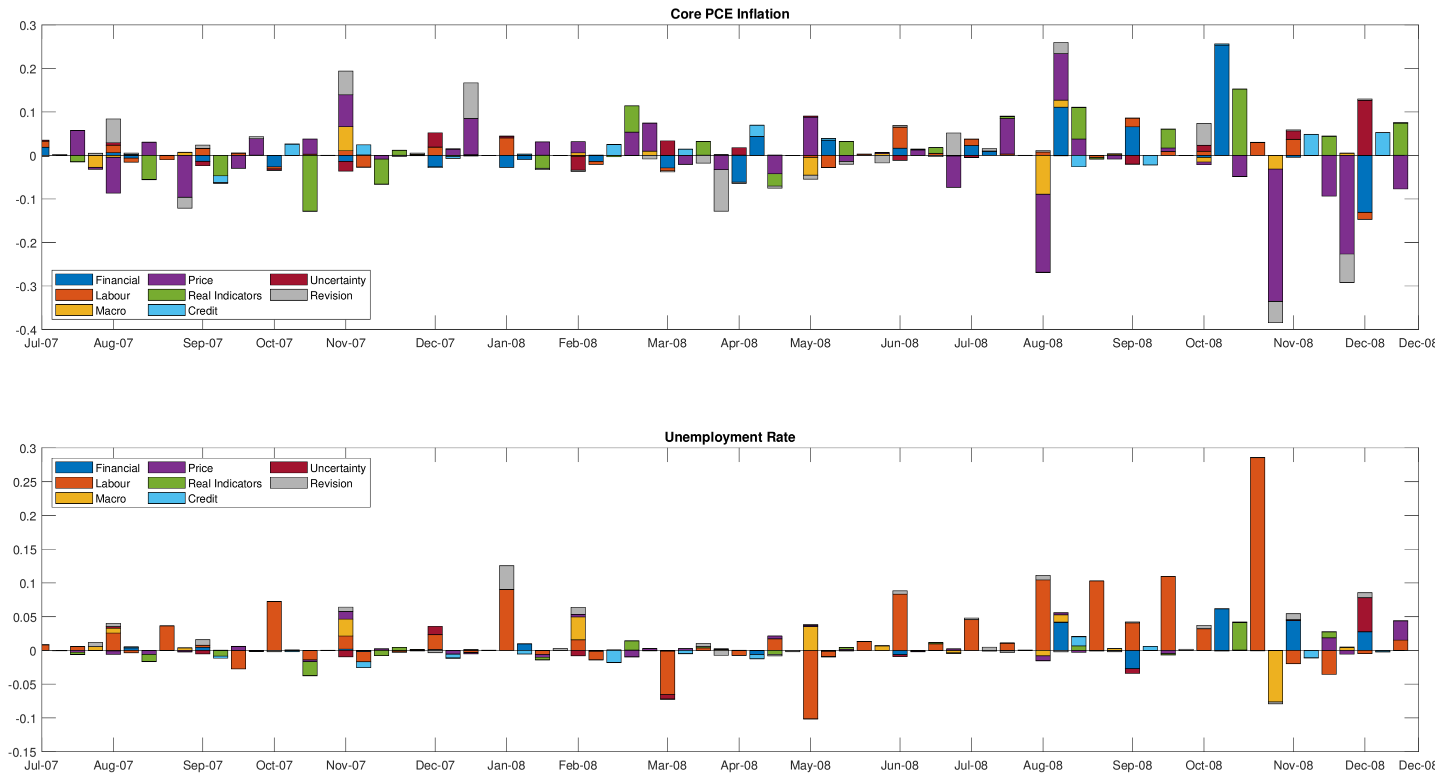

*Notes:* Top panel: OPP statistic for the Fed Funds rate and realized changes to the Fed Funds target rate in the lead up to the zero lower bound. Shaded areas represent impulse response and model uncertainty at 50 percent confidence. Middle panel: Core PCE inflation nowcast and long run expectations in deviations from the 2% inflation target and the mean deviation from target of the core PCE inflation forecast over the 5 year horizon. Bottom panel: Unemployment rate nowcast and long run expectations in deviations from NAIRU and the mean deviation from target of the unemployment rate forecast over the 5 year horizon.

Figure 6: OPP Information Update and Changes in Nowcast




*Notes:* Top panel: Changes in the OPP statistic decomposed into changes caused by changes in the information set and changes caused by preference shifts. Middle panel: Left axis: Changes in core PCE inflation nowcast and its decomposition into changes caused by revision of historical data and changes caused by the release of new data. Right axis: Changes in long run expectations and the mean deviation of the forecast from target over the forecast horizon. Bottom panel: Left axis: Changes in unemployment rate nowcast and its decomposition into changes caused by revision of historical data and changes caused by the release of new data. Right axis: Changes in long run expectations and the mean deviation of the forecast from target over the forecast horizon.

Figure 7: Contribution to Changes in Nowcasts




*Notes:* Left panel: Contribution to changes in core PCE inflation nowcast caused by revision of historical data and the release of new data by variable type. Right panel: Contribution to changes in unemployment rate nowcast caused by revision of historical data and the release of new data by variable type

Table 1: Nowcasting Performance

| | Week of Quarter | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
| Core PCE inflation | | | | | | | | | | | | | |
| QBVAR | 0.35 | 0.34 | 0.33 | 0.30 | 0.23 | 0.23 | 0.23 | 0.23 | 0.23 | 0.23 | 0.23 | 0.23 | 0.23 |
| CR-BVAR | 0.28 | 0.27 | 0.28 | 0.27 | 0.23 | 0.22 | 0.22 | 0.22 | 0.19 | 0.19 | 0.19 | 0.18 | 0.16 |
| Ratio | 0.80* | 0.80* | 0.84 | 0.89 | 1.01 | 0.93 | 0.96 | 0.94 | 0.83** | 0.82** | 0.82*** | 0.8*** | 0.71*** |
| Greenbook | 0.22 | 0.22 | 0.22 | 0.21 | 0.21 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.15 | 0.15 | 0.15 |
| SPF | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.27 | 0.27 | 0.26 | 0.26 | 0.26 | 0.26 | 0.26 | 0.26 |
| Unemployment Rate | | | | | | | | | | | | | |
| QBVAR | 0.33 | 0.28 | 0.28 | 0.27 | 0.23 | 0.24 | 0.24 | 0.24 | 0.24 | 0.24 | 0.23 | 0.18 | 0.17 |
| CR-BVAR | 0.24 | 0.23 | 0.22 | 0.21 | 0.17 | 0.15 | 0.14 | 0.14 | 0.13 | 0.09 | 0.09 | 0.08 | 0.08 |
| Ratio | 0.74*** | 0.80*** | 0.79*** | 0.77*** | 0.76*** | 0.62*** | 0.60*** | 0.60*** | 0.53*** | 0.39*** | 0.39*** | 0.47*** | 0.46*** |
| Greenbook | 0.27 | 0.27 | 0.25 | 0.23 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.18 | 0.11 | 0.08 | 0.08 |
| SPF | 0.33 | 0.33 | 0.33 | 0.33 | 0.33 | 0.31 | 0.20 | 0.14 | 0.14 | 0.14 | 0.14 | 0.14 | 0.14 |

*Notes:* The table presents the RMSE by week of quarter. QBVAR refers to the quarterly Bayesian VAR model which serves as the benchmark. CR-BVAR refers to the cube-root Bayesian VAR model which utilizes higher frequency data. The rows labeled Ratio present the relative RMSE. The table reports statistical significance based on the Diebold-Mariano test using one-sided standard normal critical values for the null-hypothesis that the CR-BVAR outperforms the QBVAR.

* Indicates significance at the 10% level

** Indicates significance at the 5% level

*** Indicates significance at the 1% level

Table 2: Forecasting Performance

| | Horizon in quarters | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 4 | 8 | 12 | 16 | 20 |
| **Core PCE inflation** | | | | | | |
| Raw | 0.30 | 0.52 | 0.55 | 0.65 | 0.58 | 0.53 |
| Tilted | 0.31 | 0.51 | 0.49 | 0.48 | 0.45 | 0.58 |
| Ratio | 1.03 | 0.99 | 0.89* | 0.73** | 0.77** | 1.09 |
| Cum. raw | 0.21 | 0.35 | 0.44 | 0.49 | 0.53 | 0.51 |
| Cum. tilted | 0.21 | 0.35 | 0.43 | 0.44 | 0.45 | 0.46 |
| Ratio | 1.02 | 1 | 0.99 | 0.91 | 0.85 | 0.89 |
| **Unemployment Rate** | | | | | | |
| Raw | 0.39 | 1.12 | 1.96 | 2.64 | 3.18 | 3.46 |
| Tilted | 0.35 | 1.06 | 1.85 | 2.39 | 2.76 | 2.7 |
| Ratio | 0.88*** | 0.95*** | 0.95** | 0.91* | 0.87* | 0.78* |
| Cum. raw | 0.21 | 0.52 | 0.99 | 1.49 | 1.98 | 2.39 |
| Cum. tilted | 0.20 | 0.49 | 0.92 | 1.33 | 1.71 | 1.98 |
| Ratio | 0.93 | 0.93 | 0.93 | 0.89 | 0.86 | 0.83 |

*Notes:* The table presents the RMSE by forecast horizon in quarters. QBVAR refers to the quarterly Bayesian VAR model which serves as the benchmark. CR-BVAR refers to the cube-root Bayesian VAR model which utilizes higher frequency data. The rows labeled Ratio present the relative RMSE. The table reports statistical significance based on the Diebold-Mariano test using one-sided standard normal critical values for the null-hypothesis that the tilted forecasts outperform the raw forecasts.
* Indicates significance at the 10% level
** Indicates significance at the 5% level
*** Indicates significance at the 1% level

Table 3: Contributions to Changes in Nowcasts and the OPP

| | Mean Deviation of Inflation | Mean Deviation of Unemployment Rate | $\Delta\delta^{rev}_{t(w)}$ |
|---|---|---|---|
| $const$ | 0.0000 | 0.0000 | 0.0000 |
| $PCE^{FIN}$ | 0.1088** | | 0.0337 |
| $PCE^{LAB}$ | 0.0198 | | 0.0089 |
| $PCE^{MAC}$ | −0.0656*** | | −0.0188 |
| $PCE^{PRI}$ | 0.4385*** | | −0.0323 |
| $PCE^{REI}$ | −0.0102 | | 0.0592 |
| $PCE^{CRE}$ | 0.0340*** | | 0.0009 |
| $PCE^{UNC}$ | 0.0801*** | | −0.0877* |
| $PCE^{REV}$ | 0.0000 | | |
| $UR^{FIN}$ | | 0.0276 | −0.0294* |
| $UR^{LAB}$ | | 0.0765 | −0.1088** |
| $UR^{MAC}$ | | 0.0065 | 0.0041 |
| $UR^{PRI}$ | | −0.0110** | −0.0017 |
| $UR^{REI}$ | | 0.0118* | −0.0087 |
| $UR^{CRE}$ | | 0.0101** | −0.0063* |
| $UR^{UNC}$ | | 0.0171*** | 0.0310** |
| $UR^{REV}$ | | 0.0002*** | |
| $R^2$ | 0.3036 | 0.3443 | 0.2414 |

*Notes:* Coefficient estimates from regressing the mean deviation of inflation from target over the horizon, the mean deviation of the unemployment rate from target over the horizon, and the difference between the OPP statistic calculated using all available data and the OPP statistic calculated only using revised historical data, $\Delta\delta^{rev}_{t(w)}$, on a constant and the contributions to changes in the nowcasts for core PCE inflation and the unemployment rate. $FIN$ denotes financial variables, $LAB$ labor market variables, $MAC$ macroeconomic variables, $PRI$ price variables, $REI$ real indicators, $CRE$ credit variables, $UNC$ uncertainty variables, and $REV$ the contribution of revision of historical data. All variables are standardized and standard errors are calculated using Newey and West (1987). The data used is July 2007 through end of year 2008.

* Indicates significance at the 10% level

** Indicates significance at the 5% level

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