Central Bank Communication that Works: Lessons from Lab Experiments[☆]

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Abstract

The causal effects of central bank communication on economic expectations and their underlying mechanisms are tested in controlled laboratory experiments. We find that central bank communication has a stabilizing effect on individual and aggregate outcomes, and the size of the effect varies with the type of communication. Announcing past interest rate changes has the largest effect, reducing volatility of individual price and expenditure forecasts by one-quarter and four-fifths, respectively, and cutting a quarter of macroeconomic volatility. Forward-looking announcements have less effect on individual forecasts, especially if they do not clarify the timing of future policy changes. There is little evidence that central bank communication transmits via its influence on forecasters' ability to predict future nominal interest rates. Rather, communication is effective via simple and relatable backward-looking announcements that exert strong influence on less-accurate forecasters.

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1. Introduction

Central bank communication has become a salient feature of monetary policy frameworks in the last few decades. Extremely low nominal interest rates and the need for continuing monetary stimuli since the Great Financial Crisis have led central banks to increase the scale and scope of their communication programs. Limited economic data, incomplete information about central banks' interest rate policies, ever-evolving communication strategies and the diversity of markets and market participants has made it extremely challenging to empirically assess the effectiveness of central bank communication.[1] To circumvent these challenges, we implement controlled laboratory experiments that systematically vary central bank communication. In our experiments, identification is based on experimental data generated under controls that are not available in economic data. Direct observation of the timing and magnitude of the shocks allows us to construct conditional responses. Heterogeneity across forecasters provides evidence on how expectations affect individual and aggregate outcomes. Knowledge of the central bank's policy rule and occasional monetary policy inaction helps to identify the exogenous components of interest rate changes. Finally, variation in the type of central bank announcements allows us to distinguish the mechanisms behind communication effects.

Our experimental framework is a learning-to-forecast (LTF) experiment based on an extended version of the Woodford (2013) model of heterogeneous expectations and monetary policy. In the model, households and firms make dynamic expenditure and price decisions based on their subjective expectations about future economic conditions and their own future decisions. In the LTF setup, participants ("subjects") provide incentivized period-by-period forecasts that are used as stand-ins for households' and firms' expectations. Experimental outcomes are computed sequentially based on these forecasts and the

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[1]Blinder et al. (2008), Coenen et al. (2017), and Moessner, Jansen, and de Haan (2017) survey the literature on central bank communication.

model's equilibrium equations. LTF experiments are an appealing experimental framework to study expectations without complications associated with suboptimal behavior (Bao, Duffy, and Hommes, 2013). They have been used to study questions related to forecasting heuristics, asset pricing, and monetary policy (Marimon and Sunder, 1994; Adam, 2007; Hommes et al., 2008; Assenza et al., 2019; Pfajfar and Žakelj, 2016).

To study central bank communication, we extend this setup along two dimensions. First, the automated central bank in our experiment occasionally keeps its interest rate unchanged. Zero interest rate changes are common in the data: they accompany a share of fixed-date monetary policy announcements of major central banks.[2] Central banks can disburse information with and without interest rate changes, which underscores the role of central bank communication as an *independent* tool of monetary policy. Moreover, in the absence of interest rate changes, e.g., when they are constrained by the zero lower bound, the public's attention is drawn to central bank announcements, potentially amplifying their influence. For simplicity, we assume that the timing of inaction is random and exogenous, which gives us an additional source of exogenous variation for identifying the effects of central bank communication.

Second, we add monetary policy communication in the form of occasional announcements by a monetary authority. We explore three different types of central bank communication that major central banks have pursued to bolster the impact of monetary policy. In the COM-BACK treatment, the central bank announces the direction of the central bank's *past* interest rate action. This information helps participants better understand how monetary policy responds to the recent state of the economy. In the COM-FWD treatment, the central bank announces its expected rate change in the upcoming period based on current and expected economic fundamentals. This treatment helps investigate how short-term state-contingent forward guidance can influence expectation formation. Finally, in the COM-COMMIT treatment, during monetary policy inaction, the central bank announces the number of periods before the next rate change. This treatment captures the effects of time-dependent forward guidance and reduced policy uncertainty. The effects of communication are identified by econometric analysis of the differences between the control experiment (no communication) and each of the treatments.

Overall, the dynamics in our experiments demonstrate clear links between information constraints faced by forecasters and monetary policy. In the control experiment, the responses of forecast errors to demand and monetary policy shocks are large and persistent, suggesting that participants do not fully utilize information that is relevant for their forecasts. Consequently, aggregate outcomes exhibit volatility and persistence that are substantially greater than predicted under full-information rational expectations (FIRE). On rare occasions, extreme fluctuations in output and inflation are observed. Such evidence is typical for lab experiments and surveys of households or firms, and it has served as the basis for ruling out FIRE (Nagel, 1995; Coibion and Gorodnichenko, 2012a). Nonetheless, in response to unexpected interest rate changes, forecasts respond in the same direction as FIRE forecasts, indicating that subjects qualitatively understand the impact of interest rate changes on the variables they forecast. Altogether, laboratory outcomes reflect information constraints and behavioral tendencies that are directly relevant for studying central bank communication.

We find that central bank communication has a stabilizing influence on individual forecasts. In all COM treatments, forecast responses are more muted after a demand shock and the associated forecast errors are smaller. Quantitatively, COM-BACK treatment has the largest effect, reducing individual price and expenditure forecast responses by about one-quarter and four-fifths, respectively. The associated forecast errors decrease by one-tenth for prices and almost by a half for expenditures. Interest rate forecasts are also significantly muted. Treatment effects are statistically significant for expenditure and interest rate forecasts, and only weakly significant for price forecasts. The effects of FWD and COMMIT communication are smaller than BACK effects by about a half and are less significant.

While communication mutes interest rate forecasts, our evidence does not link the effects of communication to forecasters' ability to predict future nominal interest rates. If central bank communication caused participants to revise their interest rate forecasts after a demand shock, the participants would revise their price and expenditure forecasts in the opposite direction because they understand the countercyclical influence of interest rate changes on the economy. By contrast, in the experiments communication stabilizes all forecasts. This suggests that central bank communication does not operate via the traditional expectations channel by directly influencing interest rate expectations. We present evidence that participants may encounter sizeable information costs of translating central bank's interest rate announcements onto price and expenditure forecasts. For example, interest rate disagreement rises

[2]Based on the data from BIS on central bank policy rates, the fraction of quarters with zero quarter-to-quarter interest rate changes is 0.59 in the United States, 0.58 in the United Kingdom, 0.44 in Canada, 0.80 in Japan (all for the period 1993Q1–2017Q4), and 0.57 in Euro Area (1999Q1–2017Q4).

after a demand shock, but it is not passed through to an increase in forecast dispersion in prices and expenditures.

The stabilization benefits of COM-BACK materialize even though it provides no content about the future course of the economy. Rather, BACK communication is effective because it is simple and relatable. When we dissect responses by subjects' forecasting ability, communication affects less-accurate forecasters the most. For the bottom half of forecasters, expenditure forecasts after a demand shock are reduced completely in COM-BACK treatment and by almost two thirds in COM-FWD and COM-COMMIT treatments. Central bank communication can also reduce forecast volatility by making interest rate policy more salient and by providing an anchoring point for expectations. Experiment participants behave as if communication accompanying a contractionary policy surprise is signaling that that the economy is on the rise. Central bank "information shocks" may influence the beliefs about the future path of economic variables and confound measurement of "pure" monetary policy surprises (Melosi, 2016; Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020). Secondly, realized individual expenditures and prices tend to move less than subjective forecasts, thus providing a natural anchoring point. This is especially important for forecasters who are confused, unaware or less informed about monetary policy, and who tend to put a significant weight on past experience in their forecasting decisions (Coibion et al., 2020).

Stabilization of expectations by central bank communication translates into more stable aggregate responses. Quantitatively, the largest stabilization occurs in COM-BACK and COM-COMMIT treatments where the interest rate response after two periods following the demand shock is one-quarter that of the control experiment. The effects of communication on inflation and output are somewhat weaker because they are partially offset by a milder adjustment of interest rates, as prescribed by a Taylor-type policy rule. In a counterfactual exercise, we re-estimate inflation and output responses by holding the response of interest rates the same as in the control treatment with no communication. When we control for the interest rate response, inflation and output treatment effects for COM-BACK and COM-COMMIT more than double and become statistically significant. Treatment effects are the smallest and statistically insignificant in COM-FWD treatment.

Our key takeaway is that central bank communication based on simple and relatable information can be more effective than complex messaging. Central banks are exploring ways to make their communication more accessible to a wider public by using simple language, visualization, and social media. Coibion et al. (2020) argue that such new communication strategies are promising for lifting the "veil of inattention" of households and firms to monetary policy announcements in low-inflation economies. Bholat et al. (2019) find that visualized and relatable information in the summary of the Bank of England's Inflation Report improve public comprehension and trust. We provide evidence that the benefits of communication emerge mainly from its influence on less-informed participants who form more anchored expectations.

The complexity of the messaging is a factor for both FWD and COMMIT communication in our experiments, as neither type of guidance yields improvement in interest rate forecasts. Existing evidence on the effectiveness of forward-guidance policies is mixed at best. Campbell et al. (2017) explain that when central banks' communication fails to distinguish the assessment of economic outlook from the projection of future interest rate responses, forward-guidance stabilization is limited. Jain and Sutherland (2018) find that while interest rate projections and forward guidance reduce disagreement about upcoming rate decisions, they have little impact on macroeconomic forecasts. Ehrmann et al. (2019) show that even time-contingent forward guidance can increase interest rate responsiveness to macroeconomic news. Central bank communication provides salient focal points for our experimental participants' expectations by explicitly referencing the past (BACK) or future (COMMIT) interest rates. Hence, for time-dependent forward guidance, anchoring of expectations offsets its complexity for experiment participants. By contrast, qualitative guidance (FWD) is less effective for managing the expectations of less-accurate participants, likely because it provides no explicit focal points.

While the literature mostly studies the impact of central bank announcements on financial markets and professional forecasters, a growing literature studies empirical evidence for households and non-financial firms. These studies explore a variety of methods to identify the effects of central bank communication using randomized treatments in surveys and field experiments (Haldane and McMahon, 2018, Coibion, Gorodnichenko, and Weber, 2019), textual analysis (Bholat, Hans, Santos, and Schonhardt-Bailey, 2015), and high-frequency identification (Lamla and Vinogradov, 2019). Learning-to-forecast experiments complement these approaches by basing identification on experimental data generated under controls that are not available in economic data.

Related experiments have explored communication in conjunction with conventional policy options, such as inflation targets under single and dual mandates (Cornand and M'baye, 2018) and time-varying inflation targets at the zero lower bound (Arifovic and Petersen, 2017). Others studied how macroeconomic forecasts can be managed through various types of central bank projections (Mokhtarzadeh and Petersen, 2017; Rholes and Petersen, 2020) and macroeconomic literacy training (Mirdamadi and Petersen, 2018). We add to this literature by incorporating different types of central bank communication directly into the design and testing their respective effects on individual and aggregate outcomes.

In what follows, Section 2 lays out the elements of our experimental framework: model, procedures, treatments, and interface. Section 3 explains the econometric analysis of experimental outcomes and presents the dynamics in the control experiment. Section 4 provides the estimated treatment effects of central bank communication. Section 5 contains broad discussion of the paper's findings and offers conclusions.

2. Experimental Framework

Our framework is a learning-to-forecast (LTF) experiment based on an extended version of Woodford (2013) model of heterogeneous expectations and monetary policy. The New Keynesian model with heterogeneous expectations was first introduced in the lab by Mauersberger (2017). In the LTF setup, participants provide incentivized period-by-period forecasts that are used as stand-ins for households' and firms' expectations. Experimental outcomes are computed sequentially based on these forecasts and the model's equilibrium equations.[3] The next section provides a brief overview of the model.

2.1. Model

Aggregate demand and supply equations. The demand side is derived from the optimization problem of a large number of infinitely-lived ex-ante identical households who maximize expected discounted utility by choosing sequences of consumption and hours worked while forming subjective expectations about the future stream of income and the rate of return on savings. Households trade a risk-free nominal one-period government debt. They choose hours worked which are demanded by firms at the wage set by labor unions on households' behalf. The consumption expenditure problem is fairly standard, except expectations are subjective and specific to the household. Under the assumption that taxes and public debt have no direct influence on households' expectations, log-linear approximation of consumption expenditures for household k can be characterized by the evolution of individual state variables $\{\overline{v}_{kt}\}$, given by the following recursive equation:[4]

$$\overline{v}_{kt} = (1-\beta)\sum_{k}\overline{v}_{kt} - \beta\sigma(i_t - \pi_t) + \beta E_{kt}\overline{v}_{kt+1}, \tag{1}$$

where all variables are log deviations from a deterministic steady state, i_t is nominal interest rate, π_t is inflation rate, and $E_{kt}(\cdot)$ denotes household k's *subjective* expected value in period t. The expectational variable $\overline{v}_{kt}$ summarizes joint evolution of household k's expected flow of total expenditures over time based on their future forecasts.[5] In our experiments, for simplicity, we refer to $\overline{v}_{kt}$ as "expenditures."

This specification of the household's problem makes two important deviations from standard models with full-information rational expectations, demonstrated convincingly in Preston (2005). First, the expectational variable $\overline{v}_{kt}$ reflects expectations many periods into the future. Second, individual expectations cannot be directly aggregated into expectations of a "representative agent." [6]

Aggregate demand is given by

$$y_t - r_t^n + \sigma\pi_t = \sum_{k}\overline{v}_{kt}, \tag{2}$$

where y_t is the log deviation of aggregate output from the steady state, and r_t^n is an exogenous "demand shock", associated, for example, with a shock to government purchases or to the marginal utility of

[3]Our motivation for focusing solely on expectation formation stems from the general view that central bank communication is thought to influence the economy primarily through its effect on expectations. Alternative frameworks to elicit expectations include individual choice and production economy experiments (Bao, Duffy, and Hommes, 2013; Noussair, Pfajfar, and Zsiros, 2015; Petersen, 2015).

[4]Some of the assumptions required for Ricardian expectations or log-linear approximation may not always hold in the experiment. For example, expectation errors are not always small and fluctuations may be explosive. We primarily focus on non-explosive experimental outcomes, leaving these issues for future research. See Woodford (2013) for a detailed discussion of the assumptions in the model.

[5]Individual consumption c_{kt} is a function of the subjective future expected value of $\overline{v}_{kt}$, individual debt holdings, b_{kt}, aggregate output less tax revenue, $y_t - \tau_t$, deviations of the real interest rate from the rate of time preference, $\beta i_t - \pi_{t+1}$, income from government debt, $s_b(\beta i_t - \pi_t)$, and preference shocks to consumption, $\bar{c}_t$: $c_{kt} = (1-\beta)\,b_{kt} + (1-\beta)\,(y_T - \tau_t) - \beta\,(\sigma - (1-\beta)\,s_b)\,i_t - (1-\beta)\,s_b\pi_t + \beta\bar{c}_t + \beta E_{kt}\overline{v}_{kt+1}$.

[6]Preston (2005) explains how these deviations can lead to important implications for the stability of learning dynamics.

consumption. We assume that r_t^n follows an AR(1) process, $r_{t+1}^n = \rho_r r_t^n + \epsilon_{t+1}$, with i.i.d. innovations $\epsilon_t \sim N\left(0, \sigma_r^2\right)$.

Aggregate supply is based on optimization by a large number of monopolistically competitive firms. With probability α the firm's price will remain unchanged from the previous period. With probability $1-\alpha$ the firm j can set its price to a level p_{jt}^*, which satisfies

$$p_{jt}^* = (1-\alpha)\sum_j p_{jt}^* + (1-\alpha\beta)\zeta y_t + \alpha\beta E_{jt} p_{jt+1}^*, \tag{3}$$

where ζ is the degree of real rigidity, y_t is the output gap,[7] and where inflation is

$$\pi_t = (1-\alpha)\sum_j p_{jt}^*. \tag{4}$$

Interest rate policy. The interest rate policy is determined by a Taylor rule with a possibility of *inaction*. Monetary policy inaction is determined by the realization of the i.i.d. Poisson random variable $\mathcal{I}_t$ taking on values of 1 with arrival rate ρ_i, and 0 otherwise. When the random variable is 1, the interest rate in t is equal to $i_t^* \equiv \phi_\pi \pi_t + \phi_y y_t$, and otherwise it is equal to the interest rate in $t-1$:

$$i_t = \begin{cases} i_t^* & w.p.\ \rho_i \\ i_{t-1} & w.p.\ 1-\rho_i. \end{cases} \tag{5}$$

To explain the specification of the interest policy rule (5), we re-write it identically in the form of the Taylor rule with interest-rate smoothing:

$$i_t = (1-\rho_i)\, i_{t-1} + \rho_i i_t^* + \Delta_t \tag{6}$$

where $\Delta_t \equiv (\mathcal{I}_t - \rho_i)\,(i_t^* - i_{t-1})$ is the interest rate innovation. In the standard Taylor rule typically employed in the literature, innovation Δ_t is an i.i.d. random variable that represents the monetary policy shock. In our framework, innovation Δ_t is endogenous. It reflects the infrequent occurrence of interest rate changes, given by zero-mean i.i.d. random variable $\mathcal{I}_t - \rho_i$, and the endogenous gap between the shadow interest rate and previous interest rate, $i_t^* - i_{t-1}$. For example, if the monetary authority acts after an expansionary demand shock, $\mathcal{I}_t = 1$ and $i_t^* > i_{t-1}$, resulting in a contractionary monetary policy innovation, $\Delta_t > 0$. Likewise, if the monetary authority does not act while the economy is in recession, $\mathcal{I}_t = 0$ and $i_t^* < i_{t-1}$, which also implies a contractionary innovation, $\Delta_t > 0$.

In general, the interest rate gap $i_t^* - i_{t-1}$ persists over time, which implies that the endogenous interest rate innovation Δ_t is serially correlated. The exogenous component of Δ_t can be interpreted as the monetary policy shock—estimated directly from Δ_t in the next section. The persistent component of Δ_t reflects a combination of infrequent changes in interest rates and persistence of equilibrium shadow rate i_t^*, which in turn is due to serially correlated demand shocks, sticky prices, and monetary policy inaction itself.

Our assumption of interest rate inaction captures the intrinsic inertia of interest rate decisions by the monetary authority. Through the lens of the stylized policy reaction function (6) this inertia manifests in the form of the interest rate smoothing term $(1-\rho_i)\, i_{t-1}$ and persistence of innovations Δ_t. Coibion and Gorodnichenko (2012b) explain that a stylized Taylor rule specification (6) fails to discriminate between competing explanations of policy inertia in the United States. They propose a variety of empirical approaches to flesh out those explanations, concluding in favor of intrinsic interest-rate smoothing by the Fed. In our framework, we do not face this issue because we can estimate the monetary policy shock directly as the exogenous component of interest rate innovation Δ_t, and therefore, we do not need to estimate the entire interest rate rule.[8]

Inaction is also crucial for identifying the effects of central bank communication in the experiments. First, it allows us to differentiate communication treatments based on information about the timing of

[7] In this simple setup, we are abstracting from model features that drive a wedge between output gap and aggregate output deviations from its steady state (e.g., exogenous variations in firm's desired price markup). In the text, we use "output", "output deviation" and "output gap" interchangeably.

[8] Random timing of inaction excludes an option for monetary policy in the model to accelerate or delay interest rate changes to stabilize the economy. Such an assumption, therefore, better reflects situations when interest rates are pegged or constrained by the zero-lower bound on monetary policy (Arifovic and Petersen, 2017, Hommes, Massaro, and Salle, 2019). Exogenous timing of interest rate changes also allows us to keep the history of inaction identical in experimental treatments.

interest rate changes, not only their magnitude. This is useful, for example, for differentiating between state and time-dependent forward guidance. Second, experimental subjects may find it easier to unpack implications of monetary policy that bifurcates between action and inaction than when monetary policy acts every period. Likewise, central bank's communication may be especially useful for subjects at the time when interest rates do not move. For example, if in the midst of a recession the interest rate is fixed but the central bank communicates its forthcoming decrease, forecasters may scale back their expectations of the fall in prices and expenditures. Finally, inaction captures the role of central bank communication as an independent tool of monetary policy. For example, since early 2000s, scheduled central bank policy announcements are routinely accompanied by a press release even though roughly half of the time there is no interest rate change. In addition, central banks regularly communicate their views between announcements via public speeches and testimonies.

Expectations. The model is closed by specification of processes for subjective expectations $\{E_{kt}\overline{v}_{kt+1}\}$ and $\{E_{jt}p^{*}_{jt+1}\}$. When expectations are full-information rational, the model is a standard New Keynesian DSGE model akin to Clarida, Galí, and Gertler (1999). In a general case of independently specified expectations, Woodford (2013) demonstrates that a concept of "temporary equilibrium" can be applied where subjective expectations are consistent with equilibrium dynamics.

2.2. Experimental Implementation

In the learning-to-forecast experiment, expectations are supplied period-by-period by experiment participants, who provide a forecast for one household's expenditure and one firm's price. The sequential unraveling of information in the learning-to-forecast experiment imposes timing restrictions on experimental decisions and outcomes. When making their forecast decisions in period t, subjects do not observe endogenous variables for that period because those variables depend on period-t forecasts (see, for example, equation 1 for $\overline{v}_{kt}$). Intuitively, each period is divided in two sub-periods: before forecasting decision ("morning") and after ("evening"), see Figure A.1 in the Supplementary Material.

In the morning of period t, subject k observes the realization of the demand shock ϵ_t, central bank communication, if any, COM_t, realizations of monetary policy inaction in the evening of period $t-1$, $\mathcal{I}_{t-1}$, individual price and expenditure variables in period $t-1$, denoted by X_{kt-1}, inflation and output in period $t-1$, denoted by X_{t-1}, and nominal interest rate i_{t-1}. Subject k then submits her subjective forecasts for price and expenditure in period $t+1$, $E_{kt}(X_{kt+1})$, and for interest rate in period $t+1$, $E_{kt}(i_{t+1})$. After all forecasts are submitted, i.e., in the evening of period t, monetary policy inaction in period t is realized, $\mathcal{I}_t$, and individual prices and expenditures, aggregate output, inflation, and interest rate in period t are determined, according to equations (1)–(5).

We choose parameter values that allow the model to replicate salient features of inflation and output-gap fluctuations in Canada between 1993Q1 and 2017Q4. Our calibration exercise uses a version of the model with adaptive expectations (see Section A.2 in the Supplementary Material), although assuming rational expectations does not substantially alter the model's fit to the data. Standard deviation and serial correlation of the demand shock process, σ_r and ρ_r, the degree of real rigidities, ζ, and Taylor rule inflation parameter, ϕ_π, are calibrated to match the following four moments in the Canadian data: standard deviation and serial correlation of inflation deviations (0.54 per cent and 0.4, respectively), the ratio of standard deviations of the output gap and inflation, 2.1, and the ratio of standard deviations of the nominal interest rate and inflation, 1.

This gives us $\sigma_r = 0.012$, $\rho_r = 0.45$, $\zeta = 0.8$, and $\phi_\pi = 1.4$. The fraction of quarters with non-zero quarterly change in nominal interest rate is 0.56, which pins down the frequency of monetary policy action ρ_i. The remaining parameters are assigned values commonly used in the literature: the discount factor, β, is $0.96^{1/4}$; intertemporal elasticity of substitution, σ, is one; quarterly probability of price adjustment, $1-\alpha$, is 0.49 (or 0.20 at monthly frequency), and the Taylor-rule coefficient on the output gap is 0.07.

2.3. Procedures

The experiment was conducted at the University of British Columbia's Experimental Economics Laboratory in Vancouver, British Columbia. The subject pool consists of undergraduate participants who have, as a general population, been shown to be well-incentivized by monetary rewards and whose forecasting behavior is consistent on many dimensions with professional forecasters, households, and firms (Cornand and Hubert, 2020). The experiment has a *between-subject* design, standard in the experimental macroeconomics literature (Bao, Duffy, and Hommes, 2013). Each treatment consisted of eight independent sessions. Each session comprised seven subjects participating in 30 minutes of instruction and 90 minutes of simulation. Subjects with no experience in learning-to-forecast experiments were invited through Online Recruitment System for Economic Experiments (Greiner, 2015). No subject participated in more than one session, and subjects in the same session faced the same treatment condition.[9]

Each session is organized as a 70 period learning-to-forecast experiment. The participants' only task is to form expectations about future economic variables, and their decisions are automated according to a data-generating process presented above. At the beginning of the experiment, subjects were provided with detailed verbal and paper instructions, and explained their roles and payoffs (Section B in the Supplementary Material). Instructions contain qualitative and quantitative information about households' and firms' decisions, and the central bank's reaction function. In particular, participants are informed that the central bank responds to deviations of inflation and output gap from target, and that the central bank reacts more than one-for-one with inflation. Subjects serve as professional forecasters for their designated households and firms (one household and one firm per participant), and are also asked to forecast period-by-period the nominal interest rate. Each period, before making their new forecasts, participants observe on their screen time series plots of the complete history of past forecasts and realizations of the nominal interest, their own prices and expenditures, as well as realizations of aggregate spending, aggregate price changes, and the concurrent demand shock. Outcomes are computed period-by-period using the model in Section 2.1 and forecasts submitted by participants. For aggregate expectations we use median, rather than mean, forecasts to reduce influence of individual entries on aggregate outcomes.

Participants are remunerated based on their forecast accuracy. Subject i's accuracy score S_{kt} in period t is determined by the following function of their own absolute forecast errors:

$$S_{kt} = 0.33(2^{-0.01|p_{kt}-E_{kt-1}p_{kt}|} + 2^{-0.01|\overline{v}_{kt}-E_{kt-1}\overline{v}_{kt}|} + 2^{-0.01|i_t-E_{kt-1}i_t|}),$$

where $E_{kt-1}X_{kt}$ is subject k's forecast in period $t-1$ for variable X_{kt}. At the end of the experiment, each participant's total score $\sum_t S_{kt}$ is translated into cash remuneration at an exchange rate of 1 point = CDN 0.75. A subject could earn a maximum of 69 points, or \$51.75, if they make accurate forecasts. Such scoring rules incentivize participants to make accurate forecasts: for every additional error of 100 basis points for each of their three forecasts, the subjects' score in that period would decrease by half.

Each experimental session consisted of four practice periods before participating in 70 sequential periods of the paid experiment. Both the practice periods and the experiment were initialized at the steady state. Periods lasted for 75 seconds for the first nine periods and 60 seconds thereafter. An additional five-second warning was given if a subject had not submitted her forecast on time before continuing onto the next period. In all, 99.2% of forecasts were submitted on time. Earnings, including a \$10 fee for showing up on time, ranged from \$15 to \$43 and averaged \$32 for 2 hours.

Our experimental framework offers appealing features for studying the effects of communication on expectations. Shocks are Gaussian, and the number of time observations per forecaster is greater than in surveys of forecasters. These features help reduce econometric challenges associated with the use of forecaster-level data, such as measurement errors, sample bias, or extreme shocks (Pesaran and Weale, 2006). Furthermore, both the data-generating process and participants' accuracy scores are symmetric around zero, which diminishes the scope for alternative interpretations of individual expectations formation, such as heterogeneity in loss aversion (Capistrán and Timmermann, 2009) and forecast smoothing (Croushore, 1997). And since participants' forecasts are private and aggregate variables are based on the medians, the incentives for strategic behavior are limited (Ottaviani and Sørensen, 2006).

2.4. Treatments

In the control experiment, there is no central bank communication. The remaining three treatments introduce different types of central bank communication in the form of occasional announcements to all subjects. During the instruction phase subjects are informed about the conditions under which the announcements are made.

In COM-BACK treatment, subjects receive central bank announcements about the previous period interest rate changes. The announcement states "The interest rate increased last period" or "The interest rate decreased last period," and there is no announcement if the interest rate has not changed, or if the change is smaller than 25 basis points in magnitude (16% of all non-zero changes). Since participants observe the complete history of interest rates, including the most recent change in the interest rate,

[9] In a *between-subject* design subjects participate in only one session of a *single* treatment, in contrast to a *within-subject* design where subjects participate in all treatments. Between-subject designs are standard in experimental economics, especially when participants interact in a repeated-group setting. There are two key advantages of using a between-subject design. First, sessions are considerably shorter in length as they only involve one treatment. Second, it provides the flexibility to test multiple treatments without exposing each subject to more than one treatment, thus avoiding identification issues associated with the order of treatments. See Charness, Gneezy, and Kuhn (2012) for a review of the merits of between- and within-subject experimental designs.

backward-looking announcements do not provide new information to participants. Therefore, COM-BACK treatment can be useful for testing whether participants use historical information effectively and whether focusing their attention on recent interest rate action is impactful.

In COM-FWD treatment, all subjects receive announcements about the central bank's expected policy decision in the evening. The announcement states "The interest rate will likely increase this period" or "The interest rate will likely decrease this period," and there is no announcement if the interest rate is expected to stay within 25 basis point from zero. Subjects are informed the announcement is based on the central bank's period-$(t-1)$ forecast of the period t interest rate given by[10]

$$E_{t-1}^{CB} i_t = 0.007 + 0.317 i_{t-1} + 0.084 r_{t-1}^n.$$

If $E_{t-1}^{CB} i_t$ exceeded (fell short of) i_{t-1} by more than 25 basis points, the central bank would announce that the interest rate was likely to increase (decrease) this period. In contrast to COM-BACK treatment, the announcement in COM-FWD treatment is informative about how interest rates will respond to economic developments later in period t and thereafter. This treatment, therefore, explores how short-term qualitative forward guidance can influence expectation formation.

In the COM-COMMIT treatment, subjects are informed that, occasionally, the nominal interest rate will stay unchanged, and during those periods, the central bank will announce the number of periods before the next change. At the end of these periods of inaction, the central bank announces that the interest rate will change in the current period. For example, an announcement in Period 10 that "The interest rate will remain unchanged for 3 periods" means that the interest rate will stay constant at its Period 9 level until Period 12. In Period 11, subjects receive a message "The interest rate will stay unchanged for 2 periods." In Period 12, the announcement states "The interest rate will change in the next period." Finally, in Period 13, the message says "The interest rate will change this period." This treatment removes uncertainty about the timing of future path of interest rates, and thereby it captures the effects of time-dependent forward guidance.

Each session within a treatment was based on randomly selected 70-period sequences of demand shocks r_t^n and monetary policy action shocks $\mathcal{I}_t$. Identical shock sequences were employed in all treatments to facilitate comparisons across treatment. Section B in the Supplementary Material provides details of experimental interface.

3. Unconditional and Conditional Responses in Control Treatment

This section begins with a summary of unconditional moments for experimental outcomes. We then explain how conditional responses are estimated and report these responses in the control treatment.

3.1. Summary of experiments

Across experimental sessions, there is rich variation in individual forecasts, both across subjects and over time for each subject. These behaviors lead to a wide range of inflation and output dynamics, providing useful data for studying the effects of monetary policy and its communication. For the most part, inflation, output, and interest rates exhibit stable cyclical behavior.[11]

Table 1 provides descriptive statistics for experimental outcomes. Panel A provides standard deviations of forecasts and forecast errors for individual price (p_{kt}^*), individual expenditure ($\overline{v}_{kt}$) and interest rate (i_t), expressed relative to standard deviations of respective forecast variables. Forecast errors are computed as $X_{kt} - E_{kt-1} X_{kt}$, with negative values indicating that participant k over-forecasts a positive-valued variable, and vice versa. In the FIRE model, forecasts are much less volatile than forecasted variables, with relative standard deviations of 0.21, 0.62, and 0.49 for price, expenditure, and interest rate, respectively. Subjects' forecasts and forecast errors are more volatile and persistent relative to full-information rational forecasts and forecast errors, suggesting substantial information constraints or limited information processing capacity facing subjects. By design, both demand and monetary action shocks are common for all subjects, and therefore, if heterogeneity in information processing is not very large, individual and aggregate variables should exhibit similar volatility. In the experiments, individual

[10]The central bank's forecast is the predicted value of the OLS regression for i_t on i_{t-1} and r_{t-1}^n using model simulations under adaptive expectations.

[11]Section C.1 in the Supplementary Material provides time series for all four treatments. Occasionally, there are episodes with explosive aggregate outcomes defined as periods for which the absolute value of inflation or interest rate exceeds 10 times the standard deviation of the demand shock (1344 bps), or the absolute value of output gap exceeds 20 standard deviations of the shock (2688 bps). For econometric analysis of stable dynamics, we exclude explosive episodes and two periods before and after each episode to dismiss transition to and from explosive episodes. Section C.2 in the Supplementary Material analyzes explosive dynamics.

prices and especially expenditures are more volatile than their aggregates, by a factor between 1.09 and 1.13 for price and between 2.54 and 4.32 for expenditures.[12]

Panel B provides standard deviations for inflation, output and interest rate, and the fractions of their variance explained by demand shocks and monetary policy surprises. Like individual variables, aggregate variables are more volatile in the experiment than in the FIRE model.

Unconditional statistics in Table 1 (columns 3–5) suggest that central bank communication is associated with differences in the volatilities of individual and aggregate variables across treatment experiments. Nonetheless, drawing inference about the effects of communication based only on unconditional moments is complicated due to: 1) aggregation of each subject's responses to different shocks, 2) aggregation of responses across subjects, and 3) countercyclical responses of interest rates. Our experimental design allows us to address these issues. Since the shocks are observed, we identify and estimate experimental outcomes *conditional* on demand shocks and monetary policy surprises. We then test whether these conditional moments are affected by central bank communication.

3.2. Monetary policy shocks

A monetary policy shock is defined as the exogenous component of the innovation to interest rate Δ_t in the Taylor rule (6) that characterizes interest rate policy in the framework with inaction. As shown in Section 2.1, innovation Δ_t is the product of monetary policy inaction, $\mathcal{I}_t - \rho_i$, and the gap between the desired interest rate and existing interest rate, $i_t^* - i_{t-1}$. Since the interest rate gap persists over time, the interest rate innovation Δ_t is serially correlated. We therefore estimate the following auto-regressive specification for Δ_t:

$$\Delta_t \quad = \quad c + \sum_{l=0}^{L} a_l \epsilon_{t-l} + \sum_{m=1}^{M} b_m \Delta_{t-m} + \iota_t \,. \tag{7}$$

For estimation, we apply OLS regression with $L = 9$ and $M = 5$ to each experimental session and each simulation of the FIRE model. The corresponding residual term ι_t is the measure of the monetary policy shock in our framework.

Estimation of monetary policy shocks using an agnostic empirical model (7) is appropriate in our experimental framework. By construction, the realized paths of demand and inaction shocks are identical in all treatments ; however, the endogenous component of interest rate innovation, $i_t^* - i_{t-1}$, depends on the response of subjects' expectations and, therefore, may differ across communication treatments. This implies that, in general, central bank communication affects *measured* components of central bank reaction function, such as interest-rate smoothing, and relative contributions of shocks to the economy, including monetary policy shocks. In our framework, the monetary policy shock can be estimated directly from (7), and therefore, we do not need to estimate the central bank reaction function.

Although central bank communication is designed to reduce uncertainty associated with interest rate policy, it does not fully remove it. In particular, COM-COMMIT treatment removes uncertainty about the timing of future interest rates, but still leaves uncertainty about the direction and size of those changes. Furthermore, forecasters may not fully incorporate information from central bank announcements about the timing of future interest rate changes, either because they do not pay attention (Mackowiak and Wiederholt, 2012) or because they cannot completely distill the transmission of pre-announced interest rate changes to economic variables (Mokhtarzadeh and Petersen, 2017). Evidence for both behaviors is presented in Section 4. Because of such mechanisms, forecasters' perspectives on the effect of monetary policy on the economy may vary over time, even when the nominal interest rate is known to stay unchanged. The resulting variation in the Taylor-rule innovation Δ_t in COM-COMMIT can be characterized by specification (7) and used to estimate the sequence of monetary policy shocks.

3.3. Estimation of conditional responses to shocks

The advantage of the experimental framework is that the exogenous processes for demand shock r_t^n and monetary policy action $\mathcal{I}_t$ are observed by the experimenter. This allows us to identify exogenous monetary policy shocks ι_t and estimate the dynamics of the endogenous variables as functions of the sequences of ϵ_t and ι_t. We use Jordà (2005) local projections method for estimating impulse responses to ϵ_t and ι_t. Let $X_{k,t}$ denote individual k's forecast in period t. For the control experiment (no

[12]Excessive volatility of individual forecasts is well-documented in LTF literature, especially in heterogeneous expectations environments (Pfajfar and Žakelj, 2016; Mauersberger, 2017).

communication), we estimate the following empirical specification for the change in $X_{k,t}$ over h periods:

$$X_{k,t+h} - X_{k,t-1} \quad = \quad c^h + \sum_{l=0}^{L} \beta_l^h \epsilon_{t-l} + \sum_{m=0}^{M} \gamma_m^h \iota_{t-m} + \sum_{n=1}^{N} \delta_n^h X_{k,t-n} + D_s + S_i + error_{kst}^h \tag{8}$$

Specification (8) conditions on the history of shocks ϵ_{t-l}, where $l = 0, ..., L$, and ι_{t-m}, $m = 0, ..., M$, lags of endogenous variable $X_{k,t-n}$, $n = 1, ..., N$, session dummies D_s and subject fixed effects S_k. In all estimations, we use $L = M = N = 5$.[13] Equation (8) is estimated independently for each variable X_{kt} by OLS regression. Since shocks are aggregate and persistent we use Driscoll and Kraay (1998) standard errors for estimated coefficients. To exclude outliers, observations for explosive episodes and all observations for subjects ranked 7 are excluded; forecasts are then winsorized at 2nd and 98th percentile.

Estimated coefficients β_0^h provide responses of $X_{k,t}$ to a demand impulse at horizon $h = 0, 1, ...$; similarly, γ_0^h provide responses to a monetary shock impulse. Since participants enter their forecasts before the realization of the monetary policy impulse, we restrict $\gamma_0^0 = 0$ in the estimation. This constraint does not apply in the estimation for individual prices or expenditures, or for aggregate variables, because these variables are realized on impact of the monetary policy impulse. For estimating the responses of aggregate variables, we estimate specification (8) using pooled OLS and Driscoll-Kraay standard errors.

To estimate the effects of communication of type $T \in \{$COM-BACK, COM-FWD, COM-COMMIT$\}$, we estimate the expanded version of specification (8) on data pooled from sessions in the control and treatment T. Let Γ_T denote communication dummy Γ_T, taking on zero values for observations from the control experiment and unit values for observations in treatment T. The expanded specification is

$$\begin{aligned} X_{k,t+h} - X_{k,t-1} \quad &= \quad c^h + \sum_{l=0}^{L} \left(\beta_l^h + \widetilde{\beta}_l^h \Gamma_T\right) \epsilon_{t-l} + \sum_{m=0}^{M} \left(\gamma_m^h + \widetilde{\gamma}_m^h \Gamma_T\right) \iota_{t-m} \\ &\quad + \sum_{n=1}^{N} \left(\delta_n^h + \widetilde{\delta}_n^h \Gamma_T\right) X_{k,t-n} + D_s + S_k + error_{kst}^h. \end{aligned} \tag{9}$$

Coefficients $\beta_0^h + \widetilde{\beta}_0^h \Gamma_T$ provide impulse responses to a demand shock at horizon h for treatment T, and $\widetilde{\beta}_0^h$ are corresponding treatment effects. Likewise, coefficients $\gamma_0^h + \widetilde{\gamma}_0^h \Gamma_T$ yield responses to a monetary impulse, and $\widetilde{\gamma}_0^h$ are the treatment effects.

3.4. Control experiment

Participants are exposed to demand and monetary policy shocks throughout the experiment. To better gauge the information problems facing participants, we compare responses in the control experiment with those in the FIRE model. Figure 1 shows responses to a +1% demand impulse. Under rational expectations, the demand shock stimulates both concurrent and future output and inflation, causing nominal interest rates to rise. The increase in nominal interest rates raises real interest rates, motivating a delay of the current spending till later periods. A rational agent will make unavoidable forecast errors on impact of the demand shock, but zero forecast errors thereafter.

Outcomes in the control experiment are determined by subjects' ability to (i) recognize the size and duration of fluctuations of relevant observables, (ii) discern the sources of those fluctuations, and (iii) incorporate changes in interest rates into their forecasts. The literature has emphasized that due to information constraints forecasters only partially respond to shocks (Mankiw and Reis, 2010). That is the case in our experiment. Following the demand shock, individual price forecasts respond by a total of +1.31% after the first two periods (+0.39% on impact and +0.92% in the subsequent period), and expenditure forecasts by +1.22%. Forecast responses dissipate to zero after four periods. Compared to the FIRE model, forecasts are significantly more volatile, and exhibit a hump-shaped pattern for prices and interest rates that is typical for expectations formed under substantial costs of acquiring, absorbing and processing information (Reis, 2006).

Figure 2 shows responses to a +1 percentage point (ppt) interest rate impulse. In the FIRE model, a contractionary monetary policy surprise lowers expenditures and prices. Because the surprise occurs in the "evening" of the shock period, i.e., after forecasts have been submitted, forecast errors respond in the first two periods and are zero thereafter.

[13] We explored specifications with the number of lags chosen to maximize Akaike information criterion. Those specifications do not yield significantly different results. To keep estimation methodology the same between control and treatments, we therefore apply exactly the same specification for different experiments.

As with demand shocks, forecast responses to a monetary shock in the experiments are significantly more volatile than in the model with rational expectations. One period after the monetary shock, individual price and expenditure forecasts fall by $+0.49\%$. The sluggishness of forecast decreases leads to negative initial responses of forecast errors, i.e., participants under-anticipate changes in the target variables. For either shock, price and expenditure forecasts persist longer than corresponding forecast variables, which leads forecast errors to switch sign from negative to positive. This highlights partial forecast adjustment not only at a point in time but also over time. Notably, after monetary surprises, forecasts respond in the same direction as FIRE forecasts indicating that subjects qualitatively understand the impact of interest rate changes on the variables they forecast.

Partial adjustment of forecast responses at the time of the shocks and over time implies in our LTF setting that individual and aggregate outcomes are both more volatile and more persistent relative to full-information rational expectations case. In particular, the response of aggregate inflation to a monetary shock is hump-shaped (Figure 2), which is a feature that is hard to match in New Keynesian models without information rigidities where agents react immediately to the shock (Mankiw and Reis, 2002).

Two observations warrant additional explanation. First, expenditure forecasts in response to a demand shock decrease in the FIRE model but increase in the experiment. Unlike rational agents, experiment participants anticipate an increase in household spending during the expansion, effectively behaving as myopic hand-to-mouth households. Such myopic behavior could be attributed to information costs (Reis, 2006) or to insufficient understanding of the stabilizing effects of monetary policy (Carvalho and Nechio, 2014). Another interpretation is that forecasters may over-react to realizations of past individual expenditures, a feature of "diagnostic" expectations discussed in Bordalo et al. (2018). Second, in the experiments we observe that the initial output response to either shock is short-lived, switching its sign soon after the shock, whereas in the model it gradually subsides to zero. High interest rates persist to counteract lasting responses of inflation. Because in our calibrated framework output is more sensitive to interest rate persistence than inflation, output contracts before the inflation response subsides.

Experimental results reflect systematic differences across individual forecasters. To analyze heterogeneity in forecasting behavior, we split subjects in two groups by their forecasting ability. The "Top3" group includes subjects whose forecasting accuracy is ranked between 1 and 3 over the course of the entire experiment, and the "Bottom3" includes subjects ranked between 4 and 6. Estimations of the forecasting equations are repeated for each group separately. Not surprisingly, we find that forecasters with overall higher forecasting ability form much more accurate price and expenditure forecasts than the Bottom3 group in response to a demand shock (Section C.3 in the Supplementary Material). This difference in forecasting performance is not related to the ability to forecast interest rates as evidenced by similar forecasts errors for two groups. Instead, it reflects more stable forecasts for Top3 forecasters. Excessive sensitivity of the Bottom3 forecasts to demand shocks may indicate their relative insensitivity to the countercyclical response of interest rates. D'Acunto et al. (2019) use Finnish administrative data on cognitive abilities of men and find that low-IQ men are twice less sensitive to changes in interest rates when making borrowing decisions than high-IQ men.

Finally, we measure the degree to which demand and monetary policy shocks drive fluctuations in aggregate variables. To this end, the forecast error variance decompositions (FEVD) of inflation, output and interest rate are estimated at different horizons based on the method proposed by Gorodnichenko and Lee (2019) for the local projections framework. In the FIRE model, demand (monetary) shocks drive at least 80% (less than 20%) of the time series variation for output in inflation. Monetary shocks are more important for driving interest rate dynamics, accounting for more than half of the variance. Such breakdown is broadly consistent with short-run dynamics in applied dynamic stochastic general equilibrium models. For example, Smets and Wouters (2007) document that a slew of "demand" shocks in their model account for at least half of the forecast error variance of output within one year. They also document that monetary shocks account for only a small fraction of inflation and output variance, but a larger fraction of interest rate variance.

In the experiments, monetary policy surprises are more important for inflation and output than in the FIRE model, accounting now for close to 40% of their variance (see Section C.4 in the Supplementary Material). At the same time, demand shocks drive less than a third of the short-run variance in the experiments, markedly less than in the model. These differences in FEVDs reflect smaller sensitivity of individual forecasts to both shocks. As seen in the Euler equation (1), nominal interest rate and expectations of future expenditures affect current spending with roughly the same weight. Sluggish responses of expectations to a demand impulse will dampen the response of expenditures and prices; a monetary impulse, however, will have a direct contemporaneous influence on spending and, via the Phillips Curve (3), on prices.

4. Effects of Communication on Conditional Responses

This section presents the estimated treatment effects of central bank communication on responses of individual forecasts, their dispersion, and aggregate variables to demand and monetary policy shocks.

4.1. Individual forecasts

Figure 3 compares IRFs in treatment and control experiments after a demand shock. The difference between treatment and control IRFs represents treatment effects. The figure provides p-values (red diamond markers) for the null hypothesis of zero treatment effects at horizon h, i.e., for $\widetilde{\beta}_0^h = 0$.

Overall, central bank communication has a stabilizing influence on individual forecasts. In all COM treatments, forecast responses are more muted after a demand shock, and the associated forecast errors are smaller. Quantitatively, BACK communication has the largest effect, reducing price and expenditure forecast responses by 0.32 and 1.00 ppt after two periods, i.e., by about one-quarter and four-fifths, respectively, and interest rate forecasts by 0.22 ppt or one-third. The associated forecast errors decrease by one-tenth for price and almost by a half for expenditures. Treatment effects are statistically significant for expenditure and interest rate forecasts, and only weakly significant for price forecasts. The effects of FWD and COMMIT communication are smaller than BACK effects by about a half and are less significant.

What are the mechanisms that facilitate effective central bank communication? We find that stabilization of price and expenditure forecasts is not driven by subjects' ability to forecast interest rates. We established in Section 3.4 that participants understand qualitatively the countercyclical effect of interest rates on their forecasts. So, if central bank communication caused participants to revise their interest rate forecasts, then participants would revise their price and expenditure forecasts in the opposite direction. By contrast, in the experiments communication stabilizes all forecasts, as shown in Figure 3. Hence, our evidence suggests that central bank communication does not operate via the traditional expectations channel by directly influencing interest rate expectations.

Rather, communication works indirectly, by making interest rate policy more salient and by providing an anchoring point for expectations. First, some of the reduction in forecast volatility is due to subjects' own interpretation of communication around interest rates. In Figure 4, we document that following a contractionary monetary impulse, communication leads subjects to forecast a 0.20 ppt higher nominal interest rate in BACK treatment, and a 0.11 ppt higher in FWD treatment. These expectations do not reflect the change in volatility of actual interest rate, which, in fact, is lower in these treatments than in the control experiment (Table 1). Despite expecting tighter policy response, they expect *a smaller* fall in prices and no change in expenditures. Hence, participants behave as if communication accompanying a policy surprise is signaling that that the economy is on the rise. Central bank "information shocks" may influence the beliefs about the future path of economic variables and confound measurement of "pure" monetary policy surprises (Melosi, 2016; Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020) .

Second, realized individual expenditures and prices tend to be smaller than subjective forecasts, thus providing a natural anchoring point. Anchoring can also explain why communication stabilizes individual expenditure forecasts by more than it stabilizes price forecasts. Countercyclical interest rate response provides a direct and immediate stabilizing influence on individual expenditures after a demand shock, providing an additional anchor for the response of expenditure forecasts. The anchoring effect of BACK communication is especially important for forecasters who are confused, unaware or less informed about monetary policy, or who tend to put a significant weight on past experience in their forecasting decisions (Coibion et al., 2020).

Indeed, when dissecting responses by subjects' forecasting ability, we find that the communication effects in the experiments are almost entirely due to the effects on less informed subjects. Their expenditure forecasts are reduced completely in COM-BACK treatment and by almost two thirds in COM-FWD and COM-COMMIT treatments (see Section C.3 in the Supplementary Material). Price forecasts after a demand shock are reduced by almost a half in all treatments, although the effects are not statistically significant. And only in the COM-BACK treatment are interest rate forecasts of the bottom-half of forecasters stabilized more than for top-half forecasters. These results suggest that communication is more effective when it is accessible to a wider public. Such communication is disbursed via simple and easy-to-process information and appeals to participants' recent experience as in COM-BACK, rather than via more complex information presented in COM-FWD and COM-COMMIT.

This finding is consistent with Bholat et al. (2019) who report that visual summaries of the Bank of England's Inflation Report significantly improve comprehension over traditional executive summaries and help align public's economic outlook with that of the Bank of England. Moreover, public comprehension and trust can be improved by relating the summary of economic outlook and monetary policy to people's everyday experiences. Literature on financial literacy has documented that accounting training programs or retirement seminars benefit mostly those in the low end of wealth or education. Drexler, Fischer, and Schoar (2014) show that teaching simple accounting heuristics rather than standard accounting procedures results in significantly greater revenues and fewer accounting errors, specifically among those with poor financial literacy skills.

The effectiveness of forward-looking communication, FWD and COMMIT, is determined to a large degree by participants' perception of the likelihood that the central bank will adhere to its policy pronouncements. We refer to this perception as "anchoring" of expectations (Gürkaynak et al., 2007; Carvalho et al., 2020). Imperfect anchoring may limit the impact of central bank policies, such as "lower for longer" interest rates at the zero-lower bound, the unwinding of quantitative easing or the pace of normalization of nominal interest rates. We denote COM-FWD participants as anchoring on the central bank's announcement if they move their interest rate forecast in the same direction as the central bank's projected rate change, respectively. We denote a COM-COMMIT participant as anchoring on the central bank's commitment if she forecasts the observed interest rate to stay unchanged during periods of inaction.[14] Even in COM-BACK treatment, participants may anchor on announcements of past interest rate changes despite their irrelevance in the determination of future interest rates. Anchoring can either manifest itself as the participant forecasting the previous period's interest rate level or forecasting in the direction of the previous interest rate change.

We conduct a series of random effects probit regressions to evaluate the potential drivers of anchoring during periods of communication, see Section C.5 in the Supplementary Material. Overall, expectations are considerably unanchored with 27% of COM-FWD and 58% of COM-COMMIT participants adjusting their interest rate forecasts in a direction inconsistent with the central bank's announced path. This behaviour is entirely driven by inattention in the COM-COMMIT treatment where participants are fully informed about the interest rate path. Inattention can indicate subjects' limited ability to piece together the last observed interest rate and current central bank announcement, and a choice to pay attention elsewhere (Mackowiak and Wiederholt, 2012). In the COM-FWD treatment, at least some of the unanchoring is likely due to a lack of credibility in the central bank's own forecast of future interest rates. Anchoring declines over time in COM-FWD, but it improves with experience in COM-BACK and COM-COMMIT. Longer periods of recent monetary policy inaction significantly reduce participants' willingness to anchor on the central bank's communication in COM-FWD and COM-COMMIT.

Expectations of the Bottom3 group are anchored as much as for the Top3 participants in COM-BACK treatment, and they are more anchored in COM-COMMIT treatment. By contrast, Bottom3 forecasts are less anchored in COM-FWD treatment. Hence, we see evidence of central bank communication providing focal points for participants' expectations, explicitly referencing the past (BACK) or future (COMMIT) interest rates. By contrast, qualitative guidance (FWD) is less effective for managing the expectations of the Bottom3, who would benefit most from communication, likely because it provides no explicit focal points.

4.2. Forecast dispersion

To further distill the mechanisms underlying forecast responses, we document the response of forecast dispersion measured by the standard deviation of forecasts across participants. Mankiw and Reis (2010) and Coibion and Gorodnichenko (2012a) demonstrate that a significant increase of forecast dispersion after a positive or negative shock is consistent with sticky-information theories where information is updated infrequently at a fixed cost (Mankiw and Reis, 2002, 2006), whereas noisy-information theories (Woodford, 2001; Sims, 2003) predict no response.[15]

In the experiments, forecast dispersion responds differently to the two shocks, and its path depends on whether there is central bank communication. After a (positive or negative) demand shock in the control experiment, forecast dispersion generally does not statistically deviate from no response, whereas it increases after a monetary shock (Figures 5–6). Thus, for the demand shocks we cannot reject the null of no response, in accordance with noisy information theories. However, the increase in forecast dispersion after monetary shocks is in line with sticky-information theories or those noisy information theories in which participants differ in their ability to filter the signal from the noise (Coibion and Gorodnichenko, 2012a). The latter class of models is corroborated by evidence that participants differ in their average forecasting ability documented in Section 3.4.

[14] Because of the possibility of participants rounding their forecasts in COM-FWD, we denote anchoring as a forecast within 10 bps from the central bank's intended rate.

[15] Dispersion of individual price or expenditure forecasts captures "disagreement" among forecasters about the future course of the economy and also reflects different individual price or expenditure histories. We therefore use the term "forecast dispersion" when referring to price or expenditure forecasts, instead of "forecast disagreement" often used in the survey literature (Mankiw, Reis, and Wolfers, 2004).

Perhaps surprisingly, central bank communication increases disagreement about nominal interest rate response to a demand impulse, although only in the period of the shock (Figure 5). The treatment effect on interest rate forecast dispersion is the largest in BACK treatment, +0.23 ppt (p-value 0.02), and it is +0.16 ppt (p-value 0.05) in COMMIT and +0.15 ppt (p-value 0.14) in FWD. Forecast dispersion for prices and expenditures remain statistically unresponsive to the demand shock. By contrast, central bank communication decreases forecast dispersion for prices after a (positive or negative) monetary shock (Figure 6). Again, the largest treatment effect is for BACK: –0.40 ppt (p-value 0.12), and it is –0.35 ppt (p-value 0.09) for COMMIT and –0.25 ppt (p-value 0.12) for FWD treatments. The effects on forecast dispersion of expenditures and interest rates are less significant; notably, only in FWD treatment they both increase after the shock.

We draw several takeaways from these experimental results. Central bank communication has a stabilizing effect on price forecast dispersion after a monetary shock, suggesting that communication may relate useful information for price forecasts. On the flip side, however, information provided by central bank may be costly for participants to absorb, evidenced, for example, by the positive effect of communication on disagreement about future interest rates after a demand shock. Secondly, treatment effects on interest rate disagreement are not in sync with treatment effects on forecast dispersion of prices or expenditures. The increase in interest rate disagreement after a demand shock is not passed through to an increase in forecast dispersion in prices and expenditures; and the decrease in price forecast dispersion after a monetary shock is not associated with lower interest rate disagreement. These results suggest that central bank information about interest rates entails costs of translating this information onto price and expenditures forecasts. Survey evidence (Jain and Sutherland, 2018) and experimental evidence (Mokhtarzadeh and Petersen, 2017) find that unconditional dispersion of inflation forecasts can increase if central bank communicates interest rate projections. Finally, the effects of central bank communication are short-lived, pointing to sticky-information theories playing a role. We do not have strong evidence that the nature of information frictions varies with the type of central bank communication.

4.3. Aggregate outcomes

Panel B in Table 2 provides treatment effects for inflation, output gap and interest rate responses for periods 0 and 1 after the demand shock, and Figure 7 compares aggregate IRFs in treatment and control experiments. To gauge the significance of treatment effects, both the table and the figure provide p-values for the hypothesis of zero treatment effects for each period.

In all communication treatments aggregate responses to demand shocks are more stable, although treatment effects are weak for inflation and output responses The largest stabilization occurs in the COM-COMMIT treatment where interest rate and inflation responses at the time of the shock are stabilized by 0.13 ppt and 0.09 ppt respectively and significantly. COM-BACK delivers a similar reduction in interest rate but the effects on prices and expenditures are less significant. Communication effects are the smallest and statistically insignificant in the COM-FWD treatment. Treatment effects are insignificant for monetary surprises, except in COM-COMMIT where inflation and output respond more strongly. This indicates that participants can better discern monetary policy surprises when they are accompanied by COMMIT communication. This result is consistent with evidence in Section 4.1 suggesting a smaller information effect of COMMIT communication due to its emphasis on inaction of interest rates.

The stabilizing effects of communication on inflation and output would have been larger had interest rates not adjusted countercyclically, as prescribed by the Taylor rule. To assess the magnitude of communication effects without countercyclical response of monetary policy, we conduct a counterfactual exercise where we "switch off" interest rate response to central bank communication. We construct a counterfactual interest rate in period t as the sum of the observed interest rate i_t and an additional variation δi_t that depends on demand innovations in periods t and $t-1$: $\delta i_t = a_0\epsilon_t + a_1\epsilon_{t-1}$. Parameters a_0 and a_1 are selected so that the impulse response of counterfactual interest rate in periods 0 and 1 after the demand shock equals the response of the observed interest rate in the control experiment. Effectively, we compensate the responses of the realized interest rate in COM treatments so that they exactly match the responses in the control experiment in periods 0 and 1. Since interest rates no longer react to communication, counterfactual inflation and output are stabilized more than we document in the experiments. How much more depends on inflation and output's elasticities with respect to exogenous interest rate variations. We approximate these elasticities using inflation and output responses to the monetary shock in the control experiment.[16]

[16]Let $\left(\frac{\partial \pi}{\partial i}\right)_h$ denote the elasticity of inflation with respect to exogenous variations in interest rate at horizon h. We approximate this elasticity by the elasticity of inflation response at horizon h to a monetary surprise in the control experi-

Table 2 (Panel C) shows that treatment effects are substantially larger when we account for countercyclical adjustment of interest rates. For example, in COM-BACK the treatment effects on the inflation and output double in period 0 and triple in period 1, and are statistically significant. Quantitatively, BACK communication cuts volatility of inflation and output responses by about a quarter. In COM-COMMIT treatment the effects are slightly weaker and significant only in period 0. Counterfactual treatment effects in COM-FWD remain insignificant.

5. Discussion and Conclusions

The overarching result in our experiments is that simpler, more accessible central bank communication tends to be more effective in influencing participants' forecasts. In our experiment, the best stabilization is achieved by central bank communication that relates to participants' recent experience. Stabilization benefits materialize even though the central bank's messages lack content about the future course of the economy. Indeed, improvements in forecasting performance across communication treatments are not accompanied by proportional improvements in interest rate forecasts. Rather, simplified and relatable announcements have especially strong impact on less-informed decision-makers.

The effects of communication do not so much operate via their direct influence on forecasters' ability to predict future nominal interest rates; rather, they work via indirect mechanisms that promote public understanding of the central bank's goals and actions in the current economic context. Coibion, Gorodnichenko, and Kumar (2018) argue that central banks can "pierce this veil of inattention" by focusing their communication on helping less-informed firms or households distill recent economic conditions and understand central banks' actions. The upshot in our paper is that the increase in accessibility of central bank information to the general public is a promising direction for improving the effectiveness of central bank communication. Future research should explicitly incorporate behavioral aspects into macroeconomic models and analysis of monetary policy (Ball, Mankiw, and Reis, 2005) and expand the use of empirical methods—such as field and lab experiments, and online surveys—to augment our understanding of the channels that render central banks' communication effective (Haldane and McMahon, 2018).

Our findings support a cautious narrative for implications of forward-looking types of communication. We do not find much support for explicit communication of the path of nominal interest rates. Neither qualitative nor quantitative forward guidance yields substantial improvement in interest rate forecasts after a monetary surprise, which could be associated with the lack of clarity of the messaging or the lack of anchoring on the central bank's pronouncements. The dynamic of forecast dispersion in our experiments also suggests that interest-rate information provided by the central bank may be costly for participants to absorb and then translate onto their price and expenditure decisions. The lack of clarity in existing qualitative communications has been emphasized by Kahn (2007), who concludes that there is little to be gained from announcing an explicit numerical policy path.

In the experiments, quantitative time-contingent forward guidance is somewhat more effective at stabilizing forecast dispersion and aggregate responses than qualitative state-contingent forward guidance. The importance of credibility for the effectiveness of central bank communication has been highlighted in the context of unconventional monetary policies (Charbonneau and Rennison, 2015) and "open mouth" operations (Guthrie and Wright, 2000). Arifovic and Petersen (2017) find that communication of history-dependent quantitative inflation targets at the ZLB can lead to greater loss of credibility and more instability if the central bank is unsuccessful at coordinating expectations in its intended direction. With low financial and especially macroeconomic literacy, a central bank may be easily misunderstood by the public (Haldane and McMahon, 2018). When communication is associated with a noise that is common among the public, it may draw private beliefs away from fundamentals (Amato, Morris, and Shin, 2002). Communication can also amplify private noise and lead to confusion when there are differences in interpretation of the same message across individuals (Coenen et al., 2017). Empirical evidence on time-contingent forward guidance is also mixed. Filardo and Hofmann (2014) provide evidence that calendar-based forward guidance in the United States has been effective, although the effectiveness declined over time. Ehrmann et al. (2019) provide cross-country evidence that time-contingent forward guidance can increase interest rate responsiveness to macroeconomic news. Future work should seek

ment: $\left(\frac{\partial \pi}{\partial i}\right)_h \approx \frac{\widehat{\beta}_0^h(\pi)}{\widehat{\beta}_0^h(i)}$, where $\widehat{\beta}_0^h(\pi)$ and $\widehat{\beta}_0^h(i)$ are estimated inflation and interest rate responses to a monetary impulse in the control experiment. Counterfactual inflation in period t is the sum of the observed inflation in period t, π_t, and an additional variation $\delta\pi_t$ defined as $\delta\pi_t = \left(\frac{\partial \pi}{\partial i}\right)_0 \delta i_t + \left(\frac{\partial \pi}{\partial i}\right)_1 \delta i_{t-1}$. The counterfactual inflation time series are used to estimate impulse responses by local projections. We repeat these steps to estimate counterfactual effects for output.

more empirical evidence on the effects of forward guidance and continue investigating the mechanisms that may limit its effectiveness.

Our experimental framework includes novel elements that lead to evidence linking information rigidities to the effects of central bank communication, such as monetary policy inaction, heterogeneity of individual forecast decisions, the additional elicitation of interest rate forecasts, and variation in the type of central bank announcements . Further evidence on the nature and degree of information rigidities and expectations formation can advance our understanding of effective communication strategies. For example, future experimental work can supplement our design with information on forecast revisions currently explored in survey data (Coibion and Gorodnichenko, 2015; Bordalo et al., 2018).

We also abstracted from the question of how the central bank's messaging can be delivered to a wider audience, since experiment participants had immediate and continuous access to all relevant information. Household and firm survey data show that the general public is ignorant about central bank objectives and insensitive to their communications (Coibion et al., 2020; D'Acunto et al., 2019). Coibion, Gorodnichenko, and Kumar (2018) provide evidence from a survey of New Zealand firms that the main source of inaccurate inflation expectations by uninformed firms is their inattention to recent economic conditions. How much people are willing to act on their expectations is still a very much open question that individual choice, market, and production economy experiments can shed light on (Davis and Korenok, 2011; Armantier et al., 2015; Petersen, 2015). Quasi-experiments and online experiments focusing on decisions of a large number of non-financial and non-professional forecasters will surely yield fruitful evidence on behavioral aspects of information rigidities and on better means of getting central banks' messages across (Coibion, Gorodnichenko, and Weber, 2019; Arifovic et al., 2018; Hommes, Kopányi-Peuker, and Sonnemans, 2019).

Adam, Klaus. 2007. "Experimental evidence on the persistence of output and inflation." *The Economic Journal* 117 (520):603–636.

Amato, Jeffery D., Stephen Morris, and Hyun Song Shin. 2002. "Communication and Monetary Policy." *Oxford Review of Economic Policy* 18 (4):495–503.

Arifovic, Jasmina, Cars Hommes, Anita Kopányi-Peuker, and Isabelle Salle. 2018. "Are sunspots effective in a big crowd? Evidence from a large-scale bank run experiment." Tech. rep., Working paper.

Arifovic, Jasmina and Luba Petersen. 2017. "Stabilizing expectations at the zero lower bound: Experimental evidence." *Journal of Economic Dynamics and Control* 82:21–43.

Armantier, Olivier, Wändi Bruine de Bruin, Giorgio Topa, Wilbert Van Der Klaauw, and Basit Zafar. 2015. "Inflation expectations and behavior: Do survey respondents act on their beliefs?" *International Economic Review* 56 (2):505–536.

Assenza, Tiziana, Peter Heemeijer, CH Hommes, and Domenico Massaro. 2019. "Managing self-organization of expectations through monetary policy: a macro experiment." *Journal of Monetary Economics* .

Ball, Laurence, Gregory N. Mankiw, and Ricardo Reis. 2005. "Monetary policy for inattentive economies." *Journal of Monetary Economics* 52 (4):703–725.

Bao, Te, John Duffy, and Cars Hommes. 2013. "Learning, forecasting and optimizing: An experimental study." *European Economic Review* 61:186–204.

Bholat, David, Nida Broughton, Janna Ter Meer, and Eryk Walczak. 2019. "Enhancing central bank communications using simple and relatable information." *Journal of Monetary Economics* 108:1–15.

Bholat, David, Stephen Hans, Pedro Santos, and Cheryl Schonhardt-Bailey. 2015. *Text mining for central banks*. No. 33 in Handbooks. Centre for Central Banking Studies, Bank of England.

Blinder, Alan S., Michael Ehrmann, Marcel Fratzscher, Jakob De Haan, and David-Jan Jansen. 2008. "Central Bank Communication and Monetary Policy: A Survey of Theory and Evidence." *Journal of Economic Literature* 46 (4):910–945.

Bordalo, Pedro, Nicola Gennaioli, Yueran Ma, and Andrei Shleifer. 2018. "Over-reaction in Macroeconomic Expectations." NBER Working Papers 24932, National Bureau of Economic Research, Inc.

Campbell, Jeffrey R., Jonas D. M. Fisher, Alejandro Justiniano, and Leonardo Melosi. 2017. "Forward Guidance and Macroeconomic Outcomes since the Financial Crisis." *NBER Macroeconomics Annual* 31 (1):283–357.

Capistrán, Carlos and Allan Timmermann. 2009. "Disagreement and Biases in Inflation Expectations." *Journal of Money, Credit and Banking* 41 (2-3):365–396.

Carvalho, Carlos, Stefano Eusepi, Emanuel Moench, and Bruce Preston. 2020. "Anchored inflation expectations." CAMA Working Papers 2020-25, Centre for Applied Macroeconomic Analysis, Crawford School of Public Policy, The Australian National University.

Carvalho, Carlos and Fernanda Nechio. 2014. "Do people understand monetary policy?" *Journal of Monetary Economics* 66 (C):108–123.

Charbonneau, Karyne B. and Lori Rennison. 2015. "Forward Guidance at the Effective Lower Bound: International Experience." Discussion Papers 15-15, Bank of Canada.

Charness, Gary, Uri Gneezy, and Michael A Kuhn. 2012. "Experimental methods: Between-subject and within-subject design." *Journal of Economic Behavior & Organization* 81 (1):1–8.

Clarida, Richard, Jordi Galí, and Mark Gertler. 1999. "The Science of Monetary Policy: A New Keynesian Perspective." *Journal of Economic Literature* 37 (4):1661–1707.

Coenen, Günter, Michael Ehrmann, Gaetano Gaballo, Peter Hoffmann, Anton Nakov, Stefano Nardelli, Eric Persson, and Georg Strasser. 2017. "Communication of monetary policy in unconventional times." CFS Working Paper Series 578, Center for Financial Studies (CFS).

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

———. 2012b. "Why Are Target Interest Rate Changes So Persistent?" *American Economic Journal: Macroeconomics* 4 (4):126–62.
———. 2015. "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts." *American Economic Review* 105 (8):2644–78.
Coibion, Olivier, Yuriy Gorodnichenko, and Saten Kumar. 2018. "How do firms form their expectations? New survey evidence." *American Economic Review* 108 (9):2671–2713.
Coibion, Olivier, Yuriy Gorodnichenko, Saten Kumar, and Mathieu Pedemonte. 2020. "Inflation expectations as a policy tool?" *Journal of International Economics* :103297.
Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber. 2019. "Monetary Policy Communications and their Effects on Household Inflation Expectations." NBER Working Papers 25482, National Bureau of Economic Research, Inc.
Cornand, Camille and Paul Hubert. 2020. "On the external validity of experimental inflation forecasts: A comparison with five categories of field expectations." *Journal of Economic Dynamics and Control* 110:103746.
Cornand, Camille and Cheick Kader M'baye. 2018. "Does inflation targeting matter? An experimental investigation." *Macroeconomic Dynamics* 22 (2):362–401.
Croushore, Dean D. 1997. "The Livingston survey: Still useful after all these years." *Business Review-Federal Reserve Bank of Philadelphia* 2:1–12.
D'Acunto, Francesco, Daniel Hoang, Maritta Paloviita, and Michael Weber. 2019. "Human frictions in the transmission of economic policy." Working Paper Series in Economics 128, Karlsruhe Institute of Technology (KIT), Department of Economics and Business Engineering.
Davis, Douglas and Oleg Korenok. 2011. "Nominal shocks in monopolistically competitive markets: An experiment." *Journal of Monetary Economics* 58 (6-8):578–589.
Drexler, Alejandro, Greg Fischer, and Antoinette Schoar. 2014. "Keeping it simple: Financial literacy and rules of thumb." *American Economic Journal: Applied Economics* 6 (2):1–31.
Driscoll, John C. and Aart C. Kraay. 1998. "Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data." *The Review of Economics and Statistics* 80 (4):549–560.
Ehrmann, Michael, Gaetano Gaballo, Peter Hoffmann, and Georg Strasser. 2019. "Can more public information raise uncertainty? The international evidence on forward guidance." *Journal of Monetary Economics* 108:93–112.
Filardo, Andrew J. and Boris Hofmann. 2014. "Forward guidance at the zero lower bound." Bis quarterly review, Bank for International Settlements.
Gorodnichenko, Yuriy and Byoungchan Lee. 2019. "A Note on Variance Decomposition with Local Projections." *Forthcoming, Journal of Business and Economic Statistics* .
Greiner, Ben. 2015. "Subject pool recruitment procedures: organizing experiments with ORSEE." *Journal of the Economic Science Association* 1 (1):114–125.
Gürkaynak, Refet S., Andrew T. Levin, Andrew N. Marder, and Eric T. Swanson. 2007. "Inflation Targeting and the Anchoring of Inflation Expectations in the Western Hemisphere." In *Monetary Policy under Inflation Targeting*, *Central Banking, Analysis, and Economic Policies Book Series*, vol. 11, edited by Frederic S. Miskin, Klaus Schmidt-Hebbel, Norman Loayza (Series Editor), and Klaus Schmidt-Hebbel (Se, chap. 11. Central Bank of Chile, 415–465.
Guthrie, Graeme and Julian Wright. 2000. "Open mouth operations." *Journal of Monetary Economics* 46 (2):489–516.
Haldane, Andrew and Michael McMahon. 2018. "Central Bank Communications and the General Public." *AEA Papers and Proceedings* 108:578–583.
Hommes, Cars, Anita Kopányi-Peuker, and Joep Sonnemans. 2019. "Bubbles, crashes and information contagion in large-group asset market experiments." Tinbergen Institute Discussion Papers 19-016/II, Tinbergen Institute.
Hommes, Cars, Domenico Massaro, and Isabelle Salle. 2019. "Monetary and Fiscal Policy Design at the Zero Lower Bound: Evidence from the Lab." *Economic Inquiry* 57 (2):1120–1140.
Hommes, Cars, Joep Sonnemans, Jan Tuinstra, and Henk Van de Velden. 2008. "Expectations and bubbles in asset pricing experiments." *Journal of Economic Behavior & Organization* 67 (1):116–133.
Jain, Monica and Christopher Sutherland. 2018. "How Do Central Bank Projections and Forward Guidance Influence Private-Sector Forecasts?" Staff working papers, Bank of Canada.
Jarociński, Marek and Peter Karadi. 2020. "Deconstructing Monetary Policy Surprises–The Role of Information Shocks." *American Economic Journal: Macroeconomics* 12 (2):1–43.
Jordà, Òscar. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review* 95 (1):161–182.
Kahn, George A. 2007. "Communicating a policy path: the next frontier in central bank transparency?" *Economic Review* (Q I):25–51.
Lamla, Michael J and Dmitri V Vinogradov. 2019. "Central bank announcements: Big news for little people?" *Journal of Monetary Economics* 108:21–38.
Mackowiak, Bartosz and Mirko Wiederholt. 2012. "Information Processing and Limited Liability." *American Economic Review* 102 (3):30–34.
Mankiw, Gregory N. and Ricardo Reis. 2002. "Sticky Information Versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve." *Quarterly Journal of Economics* 117 (4):1295–1328.
———. 2006. "Pervasive Stickiness." *American Economic Review* 96 (2):164–169.
Mankiw, N. Gregory and Ricardo Reis. 2010. "Imperfect Information and Aggregate Supply." In *Handbook of Monetary Economics*, *Handbook of Monetary Economics*, vol. 3, edited by Benjamin M. Friedman and Michael Woodford, chap. 5. Elsevier, 183–229.
Mankiw, N. Gregory, Ricardo Reis, and Justin Wolfers. 2004. "Disagreement about Inflation Expectations." In *NBER Macroeconomics Annual 2003, Volume 18*, NBER Chapters. National Bureau of Economic Research, Inc, 209–270.
Marimon, Ramon and Shyam Sunder. 1994. "Expectations and learning under alternative monetary regimes: an experimental approach." *Economic Theory* 4 (1):131–162.
Mauersberger, Felix. 2017. "Monetary Policy Rules in a Non-Rational World: A Macroeconomic Experiment." Discussion Paper Series 1617 01, Columbia University, Department of Economics.
Melosi, Leonardo. 2016. "Signalling Effects of Monetary Policy." *The Review of Economic Studies* 84 (2):853–884.
Mirdamadi, Michael and Luba Petersen. 2018. "Macroeconomic Literacy and Expectations." Working paper, Simon Fraser University, Department of Economics.
Moessner, Richhild, David-Jan Jansen, and Jakob de Haan. 2017. "Communication About Future Policy Rates in Theory and Practice: A Survey." *Journal of Economic Surveys* 31 (3):678–711.

Mokhtarzadeh, Fatemeh and Luba Petersen. 2017. “Coordinating expectations through central bank projections.” Working paper, Simon Fraser University, Department of Economics.

Nagel, Rosemarie. 1995. “Unraveling in guessing games: An experimental study.” *The American Economic Review* 85 (5):1313–1326.

Nakamura, Emi and Jón Steinsson. 2018. “High-Frequency Identification of Monetary Non-Neutrality: The Information Effect.” *The Quarterly Journal of Economics* 133 (3):1283–1330.

Noussair, Charles N, Damjan Pfajfar, and Janos Zsiros. 2015. “Pricing decisions in an experimental dynamic stochastic general equilibrium economy.” *Journal of Economic Behavior & Organization* 109:188–202.

Ottaviani, Marco and Peter Norman Sørensen. 2006. “The strategy of professional forecasting.” *Journal of Financial Economics* 81 (2):441–466.

Pesaran, M. Hashem and Martin Weale. 2006. *Survey Expectations*, *Handbook of Economic Forecasting*, vol. 1, chap. 14. Elsevier, 715–776.

Petersen, Luba. 2015. “Do expectations and decisions respond to monetary policy?” *Journal of Economic Studies* 42 (6):972–1004.

Pfajfar, Damjan and Blaž Žakelj. 2016. “Inflation expectations and monetary policy design: Evidence from the laboratory.” *Macroeconomic Dynamics* :1–41.

Preston, Bruce. 2005. “Learning about Monetary Policy Rules when Long-Horizon Expectations Matter.” *International Journal of Central Banking* 1 (2):81–126.

Reis, Ricardo. 2006. “Inattentive consumers.” *Journal of Monetary Economics* 53 (8):1761–1800.

Rholes, Ryan and Luba Petersen. 2020. “Should Central Banks Communicate Uncertainty in their Projections?” Working paper dp20-01, Simon Fraser University, Department of Economics.

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

Smets, Frank and Rafael Wouters. 2007. “Shocks and frictions in US business cycles: A Bayesian DSGE approach.” *American Economic Review* 97 (3):586–606.

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

———. 2013. “Macroeconomic Analysis Without the Rational Expectations Hypothesis.” *Annual Review of Economics* 5 (1):303–346.

Table 1: Summary of second moments

	FIRE model	Control experiment	Treatment experiments		
			COM-BACK	COM-FWD	COM-COMMIT
	(1)	(2)	(3)	(4)	(5)
Panel A: Volatilities of subject-level variables					
Price					
std(forecast) / std(price)	0.210	1.004	0.964	1.005	1.022
std(f.e.) / std(price)	1.209	1.001	1.054	1.039	1.741
std(price) / std(agg price)	1.000	1.105	1.093	1.125	1.114
Expenditures					
std(forecast) / std(exp-s)	0.622	0.803	0.854	0.824	0.885
std(f.e.) / std(exp-s)	0.783	0.845	0.741	0.747	1.009
std(exp-s) / std(agg exp-s)	1.000	3.735	2.539	4.323	2.544
Interest rate					
std(forecast) / std(int rate)	0.493	0.970	0.877	0.898	0.979
std(f.e.) / std(int rate)	0.870	1.244	1.293	1.320	1.310
Number of observations		2983	2903	2943	2974
Panel B: Standard deviations of aggregate variables					
Inflation, %	0.33	1.96	1.86	1.69	2.11
Output, %	0.72	2.23	2.58	2.13	2.78
Interest rate, ppt	0.37	2.74	2.55	2.39	2.87
Number of observations		498	487	490	490

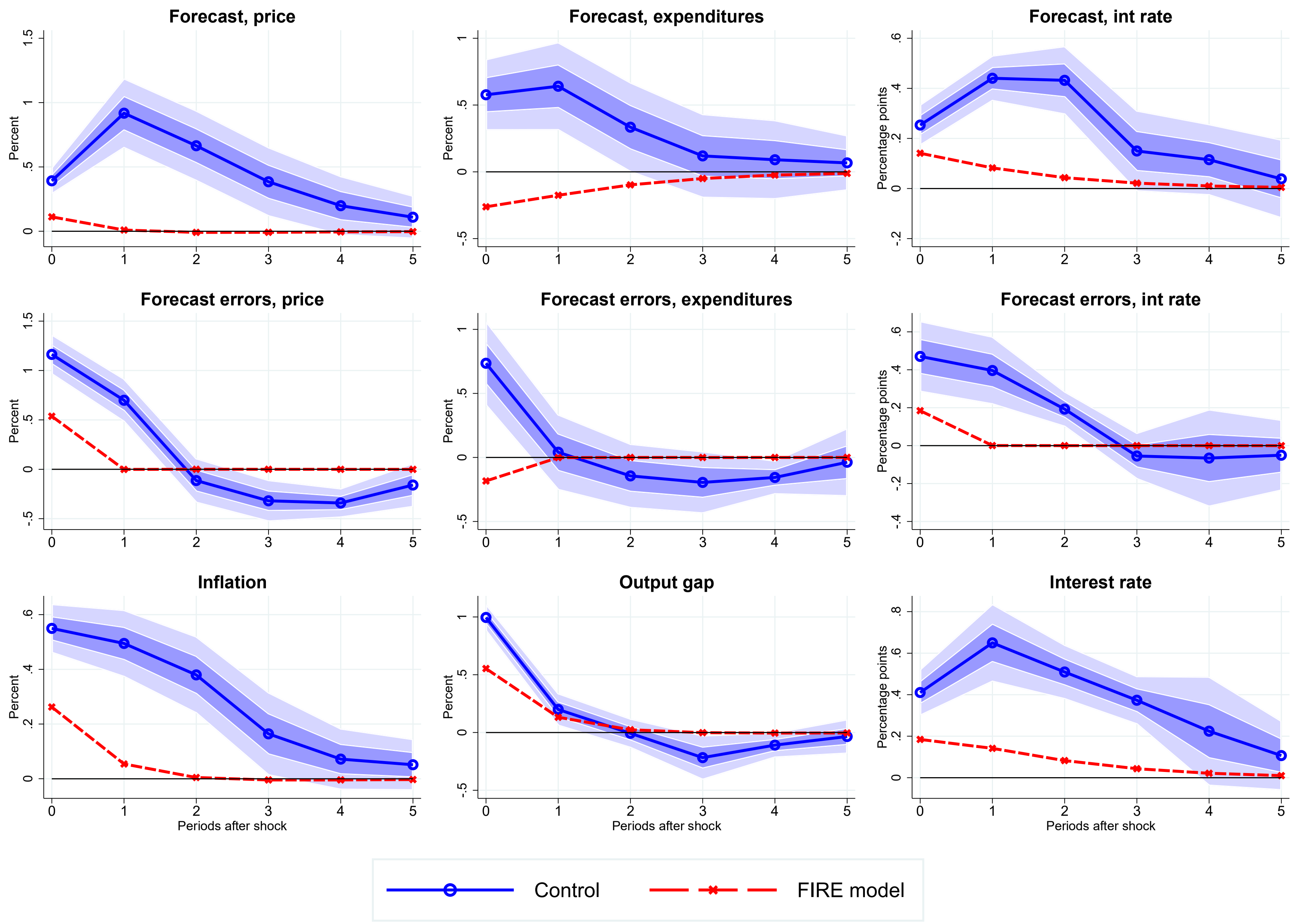
Notes. Panel A provides standard deviations of forecasts and forecast errors for individual price (p^*_{jt}), individual expenditures ($\overline{v}_{kt}$) and interest rate (i_t), expressed relative to standard deviations in their respective levels or relative to aggregate price ($\sum_j p^*_{jt}$), aggregate expenditures ($\sum_k \overline{v}_{kt}$) or interest rate. Panel B provides standard deviations for inflation, output and interest rate, and the fractions of their variance explained by demand shocks and monetary policy surprises. Columns: (1) Model under full-information rational expectations, (2) Control experiment, (3)–(5) Treatment experiments, COM-BACK, COM-FWD, and COM-COMMIT.

Table 2: Aggregate responses

Experiment	Interest rate, ppt		Inflation, %		Output, %	
	coef	*p*-value	coef	*p*-value	coef	*p*-value
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Responses in Control experiment						
period 0	0.41	ppt	0.55		1.00	
period 1	0.65	ppt	0.49		0.20	
Panel B: Treatment effects (Treatment minus Control), ppt						
COM-BACK						
period 0	-0.13	0.06	-0.05	0.30	-0.12	0.18
period 1	-0.16	0.07	-0.06	0.32	-0.04	0.50
COM-FWD						
period 0	-0.09	0.16	-0.04	0.40	-0.03	0.69
period 1	-0.11	0.25	-0.03	0.52	-0.02	0.73
COM-COMMIT						
period 0	-0.13	0.02	-0.09	0.09	-0.04	0.52
period 1	-0.13	0.19	0.01	0.80	0.05	0.41
Panel C: Compensated Treatment effects (Treatment minus Control), ppt						
COM-BACK						
period 0	0.00	0.95	-0.09	0.08	-0.23	0.02
period 1	0.00	0.99	-0.15	0.03	-0.14	0.04
COM-FWD						
period 0	0.00	0.95	-0.07	0.17	-0.09	0.17
period 1	0.00	0.93	-0.09	0.08	-0.08	0.19
COM-COMMIT						
period 0	0.00	0.98	-0.12	0.02	-0.13	0.05
period 1	0.00	0.87	-0.05	0.28	-0.01	0.85

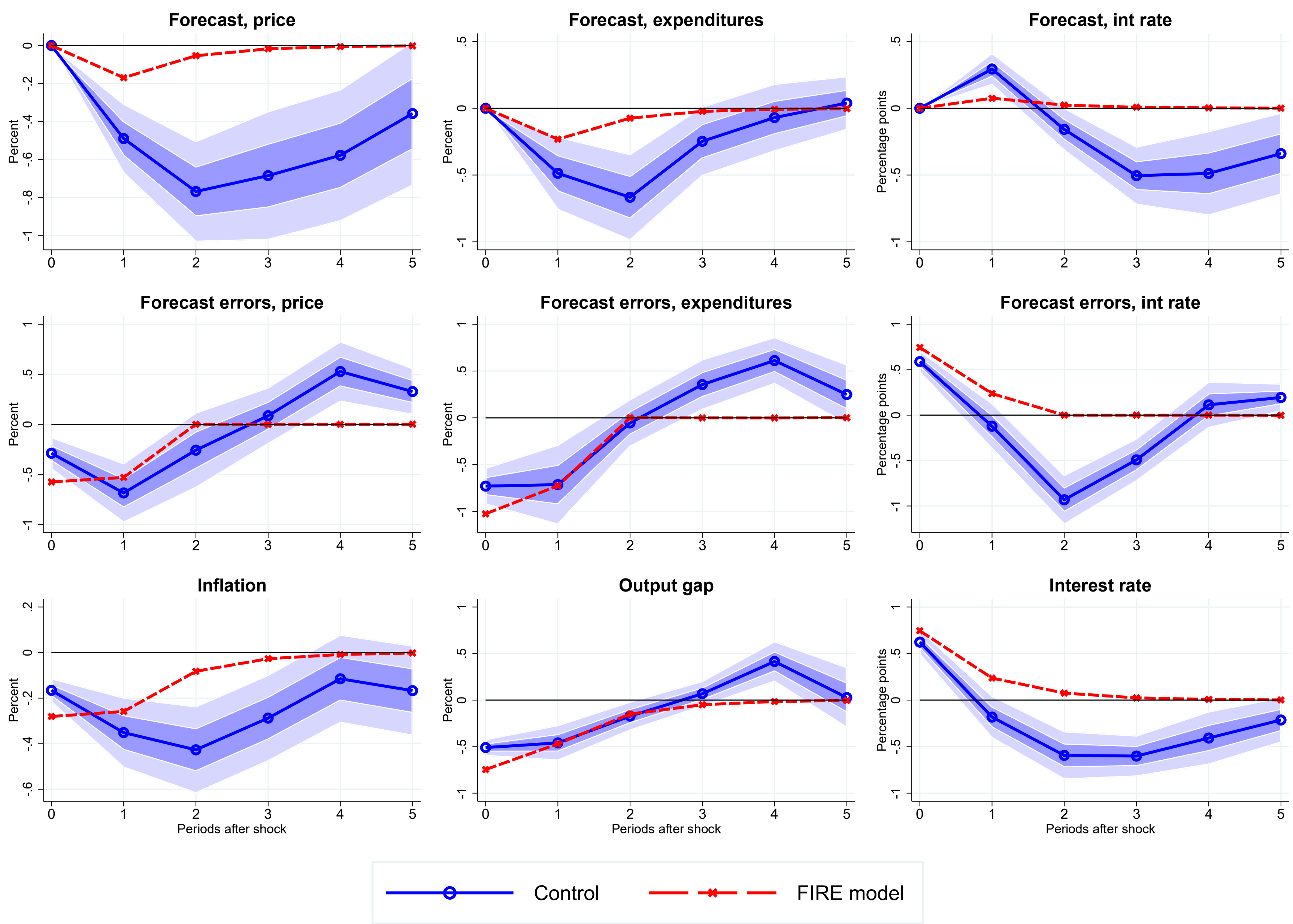
Notes. Panel A provides impulse responses (IRFs) to a +1% demand impulse for periods 0 and 1 after the shock. IRFs are constructed by local projection method using regressions (8). Panel B provides treatment effects (Treatment minus Control) estimated by local projection method using regression 9. Columns (1), (3), (5) provide point estimates for inflation (π_t), output (y_t), and interest rate (i_t); and columns (2), (4), (6) provide corresponding p-values for null hypothesis of zero treatment effects. Panel C provides counterfactual treatment effects and p-values when the interest rate response is kept the same as in the control experiment.

Figure 1: Responses to a +1% demand impulse, control experiment



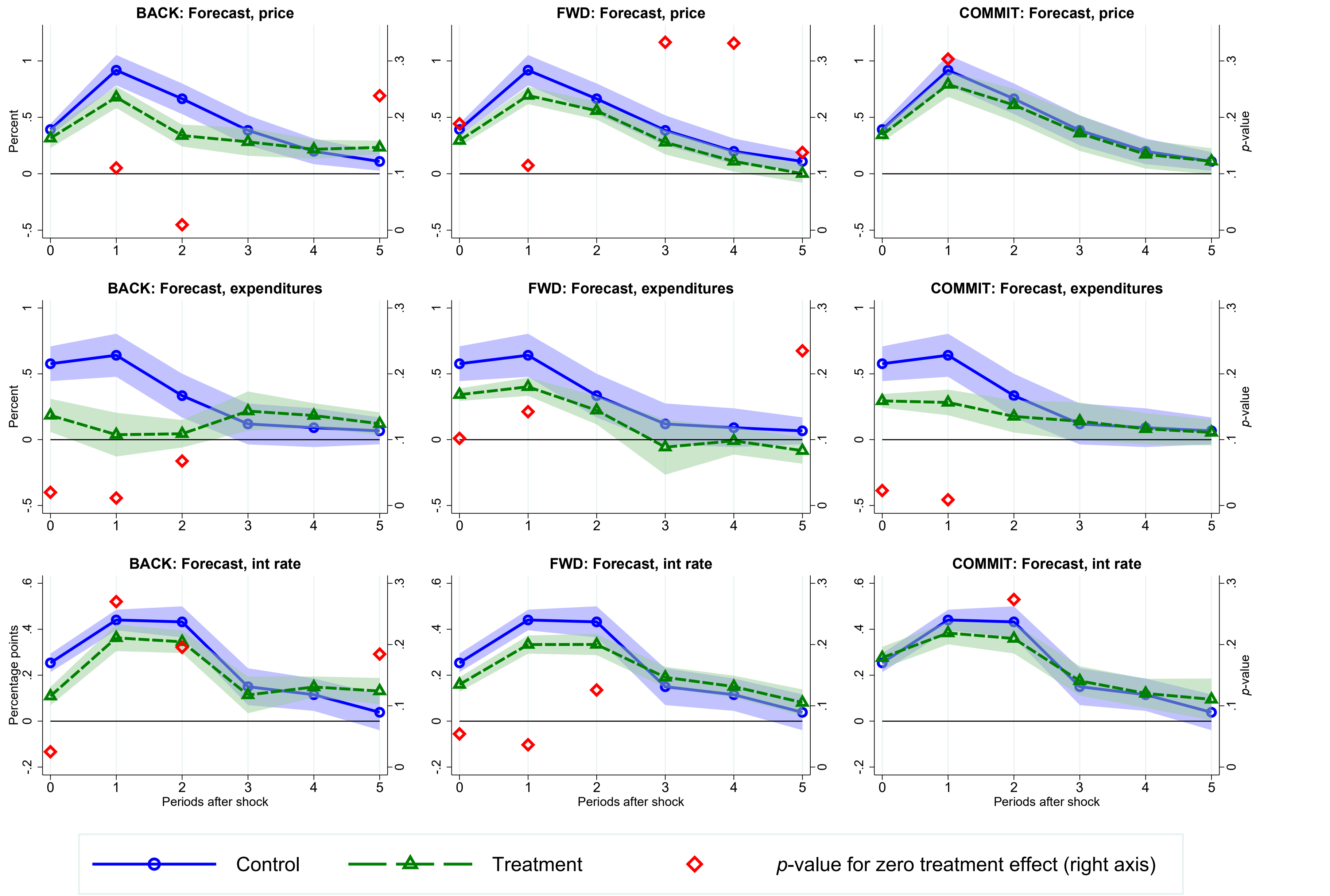
Notes. IRFs in the control experiment are estimated by local projections using regression (8). Shaded areas outline one- and two-standard-deviation bands based Driscoll-Kraay standard errors. IRFs in the FIRE model are estimated by applying the same methodology to time series obtained from simulations of equilibrium dynamics..

Figure 2: Responses to a +1 ppt interest rate impulse, control experiment



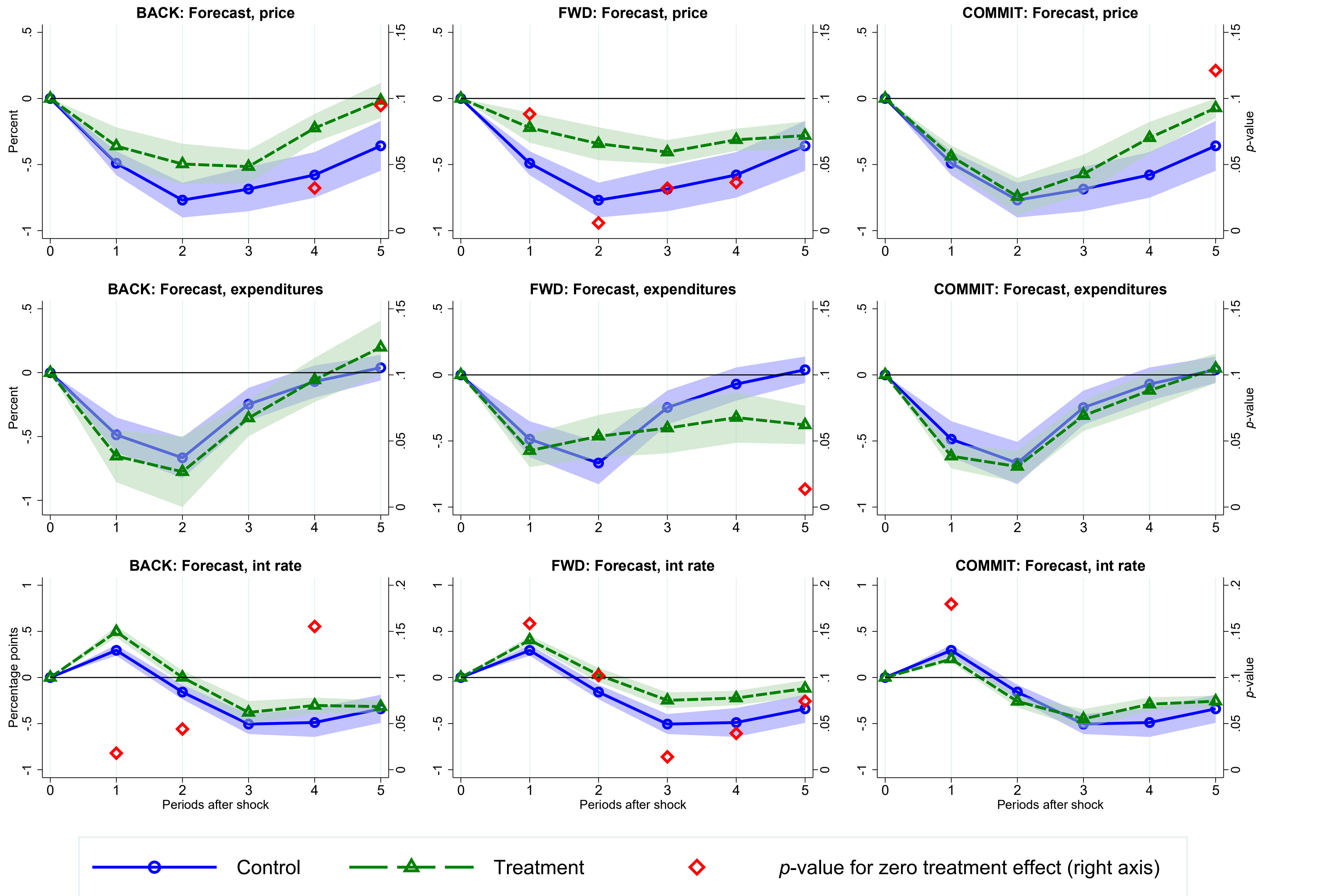
IRFs in the control experiment are estimated by local projections using regression (8). Shaded areas outline one- and two-standard-deviation bands based Driscoll-Kraay standard errors. IRFs in the FIRE model are estimated by applying the same methodology to time series obtained from simulations of equilibrium dynamics..

Figure 3: Forecast responses to a +1% demand impulse



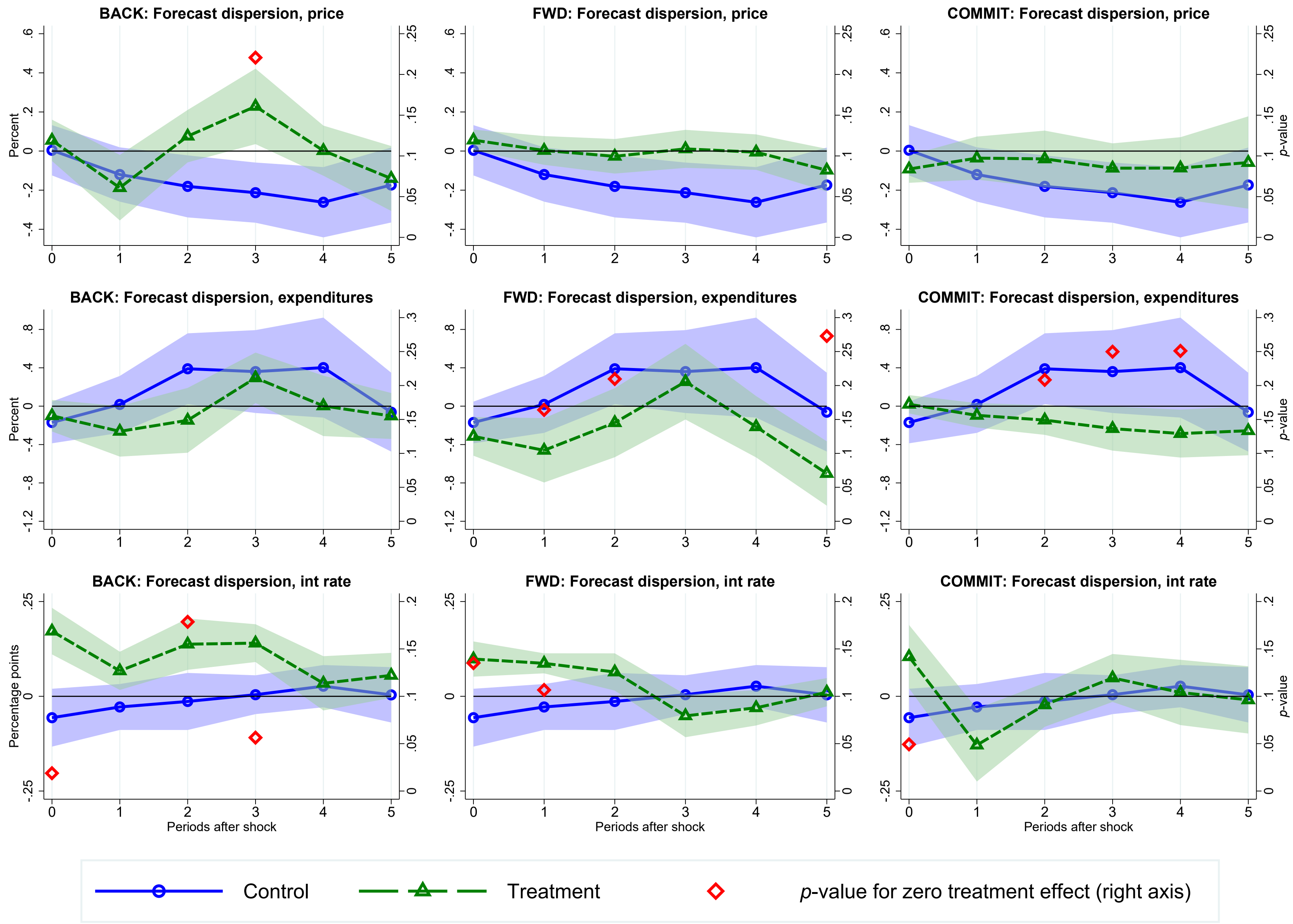
Notes. Figure provides impulse responses to a +1% demand impulse. IRFs are estimated by local projections using regression (8) for the control experiment, and (9) for treatment experiments. Shaded areas outline one-standard-deviation bands based Driscoll-Kraay standard errors. Red diamonds are p-values (right axis) for the null hypothesis of zero treatment effects at horizon h. Top row provides IRFs for forecasts of individual price, $E_{kt}p^*_{kt+1}$, middle row—forecasts of individual expenditures, $E_{kt}\bar{v}_{kt+1}$, and bottom row—forecasts of interest rate, $E_{kt}i_{t+1}$. Columns span treatment experiments: COM-BACK (left), COM-FWD (middle), and COM-COMMIT (right).

Figure 4: Forecast responses to a +1 ppt interest rate impulse



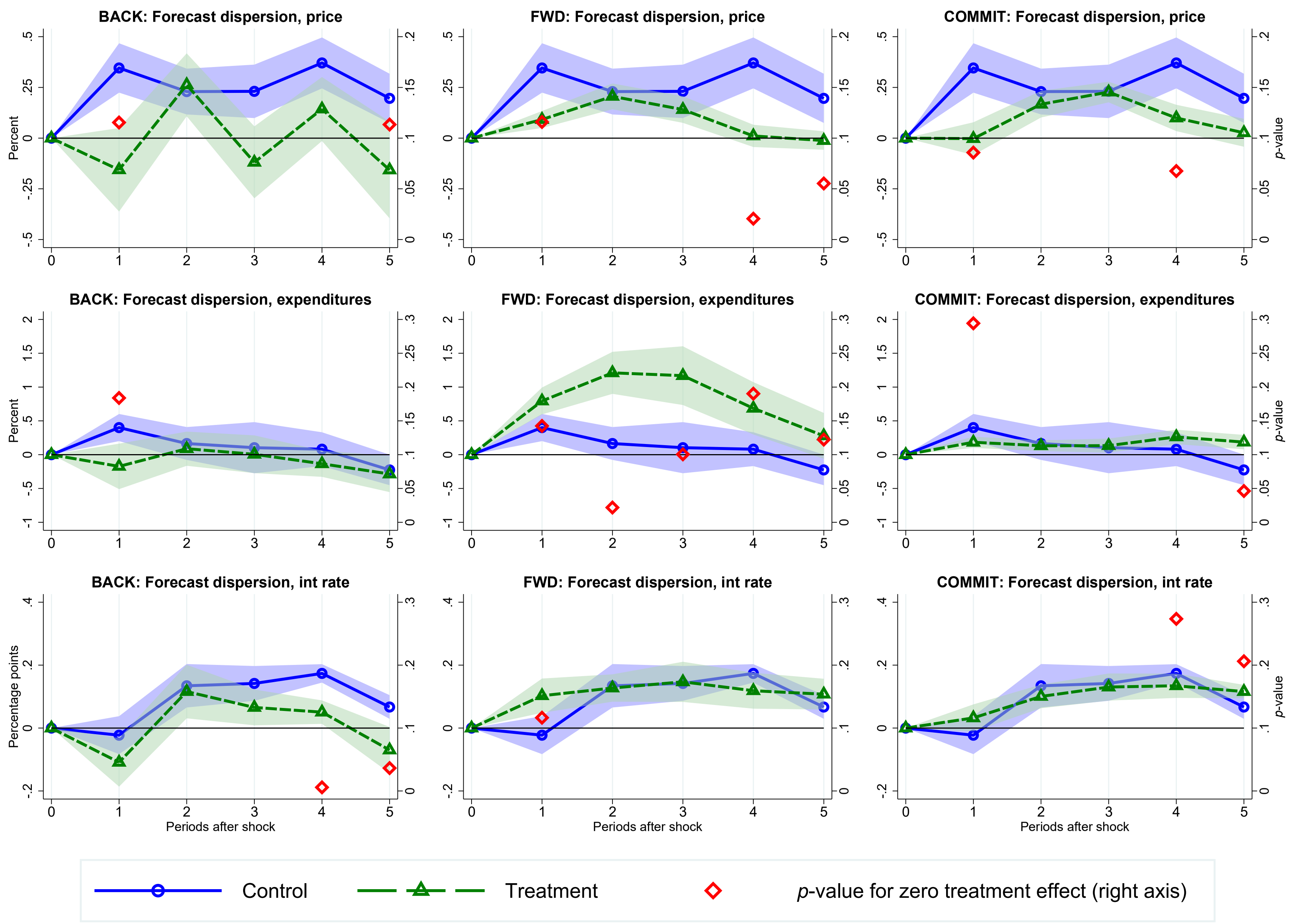
Notes. Figure provides impulse responses to a +1 ppt interest rate impulse. IRFs are estimated by local projections using regression (8) for the control experiment, and (9) for treatment experiments. Shaded areas outline one-standard-deviation bands based Driscoll-Kraay standard errors. Red diamonds are p-values (right axis) for the null hypothesis of zero treatment effects at horizon h. Top row provides IRFs for forecasts of individual price, $E_{kt}p^*_{kt+1}$, middle row—forecasts of individual expenditures, $E_{kt}\overline{v}_{kt+1}$, and bottom row—forecasts of interest rate, $E_{kt}i_{t+1}$. Columns span treatment experiments: COM-BACK (left), COM-FWD (middle), and COM-COMMIT (right).

Figure 5: Response of forecast dispersion to a +1% absolute value demand impulse



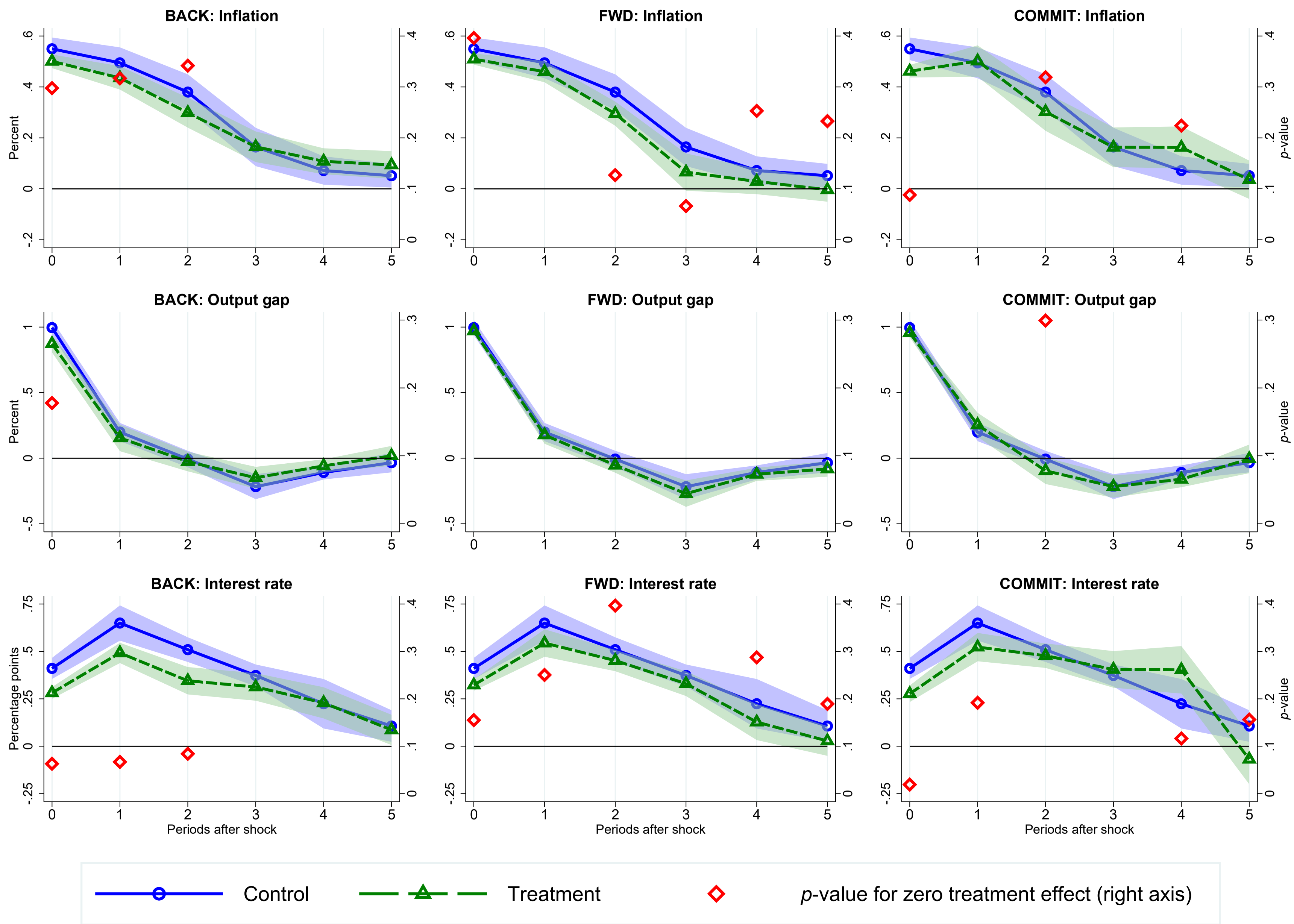
Notes. Figure provides impulse responses to a +1% in absolute value of demand impulse. IRFs are estimated by local projections as explained in Section 4.2. Shaded areas outline one-standard-deviation bands based Driscoll-Kraay standard errors. Red diamonds are p-values (right axis) for the null hypothesis of zero treatment effects at horizon h. Top row provides IRFs for dispersion of individual price forecasts, $E_{kt}p^*_{kt+1}$, middle row—dispersion of individual expenditure forecasts, $E_{kt}\overline{v}_{kt+1}$, and bottom row—dispersion of interest rate forecasts, $E_{kt}i_{t+1}$. Columns span treatment experiments: COM-BACK (left), COM-FWD (middle), and COM-COMMIT (right).

Figure 6: Response of forecast dispersion to a +1 ppt absolute value interest rate impulse



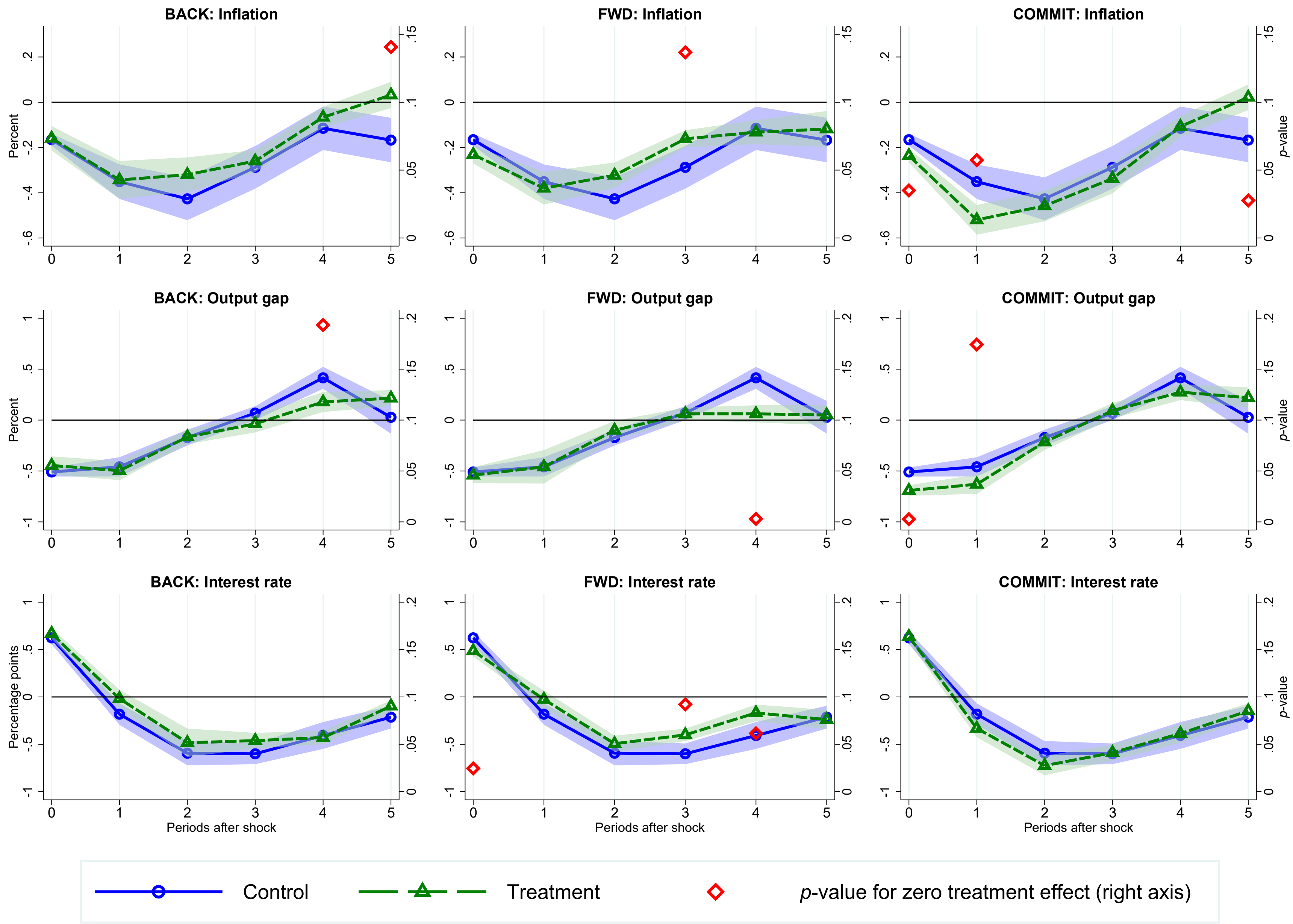
Notes. Figure provides impulse responses to a +1 ppt in absolute value of interest rate impulse. IRFs are estimated by local projections as explained in Section 4.2. Shaded areas outline one-standard-deviation bands based Driscoll-Kraay standard errors. Red diamonds are p-values (right axis) for the null hypothesis of zero treatment effects at horizon h. Top row provides IRFs for dispersion of individual price forecasts, $E_{kt}p^*_{jt+1}$, middle row—dispersion of individual expenditure forecasts, $E_{kt}\overline{v}_{kt+1}$, and bottom row—dispersion of interest rate forecasts, $E_{kt}i_{t+1}$. Columns span treatment experiments: COM-BACK (left), COM-FWD (middle), and COM-COMMIT (right).

Figure 7: Aggregate responses to a +1% demand impulse



Notes. Figure provides impulse responses to a +1% demand impulse. IRFs are estimated by local projections using regression (8) for the control experiment, and (9) for treatment experiments. Shaded areas outline one-standard-deviation bands based Driscoll-Kraay standard errors. Red diamonds are p-values (right axis) for the null hypothesis of zero treatment effects at horizon h. Top row provides IRFs for inflation (π_t), middle row – output (y_t), and bottom row – interest rate (i_t). Columns span treatment experiments: COM-BACK (left), COM-FWD (middle), and COM-COMMIT (right).

Figure 8: Aggregate responses to a +1 ppt interest rate impulse



Notes. Figure provides impulse responses to a +1 ppt interest rate impulse. IRFs are estimated by local projections using regression (8) for the control experiment, and (9) for treatment experiments. Shaded areas outline one-standard-deviation bands based Driscoll-Kraay standard errors. Red diamonds are p-values (right axis) for the null hypothesis of zero treatment effects at horizon h. Top row provides IRFs for inflation (π_t), middle row – output (y_t), and bottom row – interest rate (i_t). Columns span treatment experiments: COM-BACK (left), COM-FWD (middle), and COM-COMMIT (right).