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DOI:
10.57938/2be724d6-2e04-40b0-ad25-803868b7ca58

Published: *01/01/2020*

Document Version:
Publisher's PDF, also known as Version of record

Department of Economics
Working Paper No. 306

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December 2020

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The impact of monetary policy on expectations along the yield curve

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Abstract

This article investigates how market participants adjust their expectations of interest rates at different maturities in response to a monetary policy and a central bank information shock for the US economy. The results show that market participants adjust their expectations faster to changes in interest rates compared to new releases of information by the central bank. This finding could imply that central bank information shocks are more opaque whereas a change in interest rates provides a stronger signal to the markets. Moreover, financial market agents respond with an initial underreaction to both shocks, potentially resembling inattention or overconfidence. Last, we find that the adjustment of expectations for yields with higher maturities takes considerably longer than for short-term yields. This finding is especially important for central banks since in the current low-interest rate environment monetary policy actions mainly consist of policies aimed at the long-end of the yield curve.

Keywords: monetary policy; expectation formation; belief bias.

JEL Codes: C32, D83, D84, E52, E70, G40

Acknowledgments

Maximilian Böck gratefully acknowledges financial support by funds of the Oesterreichische Nationalbank (Austrian Central Bank, Anniversary Fund, project number: 16748).

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1 Introduction

How do expectations of market participants react after a monetary policy shock? Recent advancements in the identification of monetary policy shocks stresses the importance of information effects present when looking at the effects of monetary policy. However, the underlying assumption of rational expectations may not hold and there is ample evidence against it. Yet, it is still unexplored how expectations for treasury yields with different maturities adjust in response to a monetary policy intervention. This paper investigates the possible over- or underreaction of the impact of monetary policy on expectations along the yield curve and discusses its implications.

Macroeconomic models, both of theoretical and also empirical nature, mostly assume one and the same expectation formation mechanism, i.e., rational expectations (Muth, 1961). This assumption, called full information rational expectations (FIRE), is so commonly encountered that it is frequently not even mentioned in applied work. Alternative belief formations can be characterized by the market participant either under- or overreacting when absorbing a newly arrived piece of information. By arguing to utilize survey forecasts to investigate information asymmetries in a seminal article (Coibion and Gorodnichenko, 2012), the same authors developed a few years later a framework to put FIRE to test (Coibion and Gorodnichenko, 2015) finding that the assumption does not hold. This framework has been criticized in a recent contribution, where Kucinskas and Peters (2019) provide a coherent, empirical framework to assess the expectation formation process of market participants by the impulse response function (IRF) of forecast errors in a vector autoregressive (VAR) model. The forecast errors are easily obtained by calculating the difference of a realized value for a variable of interest and the expected / forecast value, which can be collected from survey data of market participants. The IRF of the forecast error is a direct measure of over- or underreaction and can be used to measure systematic deviations from rational expectations nesting several approaches in the literature, such as the sticky-information model (Mankiw and Reis, 2002) or diagnostic expectations (Bordalo *et al.*, 2018).[1]

In this paper, we use the approach of Kucinskas and Peters (2019) to investigate how financial markets adjust their beliefs / forecasts for different segments of the yield curve in response to two monetary policy shocks. More specifically, we look at a conventional monetary policy shock, which is characterized by a change in interest rates, and an information shock, which reflects the central bank's assessment about the economic outlook. In fact, the latter arises due to information asymmetries between the public and the central bank and has been recently dubbed the 'information channel' of monetary policy transmission (Melosi, 2017; Nakamura and Steinsson, 2018). Empirical estimates of monetary policy effects not explicitly controlling for information frictions are likely to be plagued by a mismeasurement which arises through the endogenous response of the central bank to changes in the economy. Hence, we do assume that neither the central bank nor market participants have perfect information. From the perspective of the policymaker, i.e., the central bank, to see how policy actions get absorbed by the markets is of ample importance. We identify the monetary policy shocks using high-frequency data before and after monetary policy announcements of the US Federal Reserve (Fed) following the approach of Jarociński and Karadi (2020). To measure expectations and the forecast error, we use survey data from Blue Chip Financial Indicators, which

[1] In more detail, it nests also models of noisy information, e.g., the rational inattention model studied by Sims (2003) and Mackowiak and Wiederholt (2009) or the imperfect information model in Woodford (2001), misperceived law of motion, extrapolative expectations, adaptive learning, forecasting under adjustment costs and asymmetric loss functions.

is a survey of executives and experts from financial firms. Using the monetary policy and news surprises together with the survey data on expectations, we estimate a Bayesian proxy VAR, similar to the one proposed in Caldara and Herbst (2019).

Our main results can be summarized as follows: First, we find that market participants tend to underreact to both the conventional monetary policy shock and to the central bank information shock. This finding could imply that financial market players are either inattentive or overconfident in their forecasts. Second, most of the adjustment takes place within the first five months after the shock, which provides evidence for significant belief distortions. Put differently, market participants do not act rationally which would imply an immediate adjustment of their expectations to the new information. Third, we find evidence that the adjustment takes considerably longer for higher levels of maturity. This finding is of particular importance since current monetary policy measures are mostly targeted at the longer end of the yield curve. Last and comparing the two shocks, we find a tendency of a longer phase of adjustment in response to the central bank information shock. Taken at face value this implies that a conventional monetary policy shock provides a stronger signal to the market and in turn leads to a faster adjustment.

The remainder of the paper proceeds as follows. In Sec. 2 we provide an overview of relevant literature and Sec. 3 describes the methodological framework to measure biases in expectations. Sec. 4 presents our econometric approach and Sec. 5 the results. Finally, Sec. 7 concludes.

2 Related literature

This paper fits into the recent stream of literature exploring the transmission of monetary policy under informational rigidities. Controlling for different information sets dates back to the introduction of the narrative instrument by Romer and Romer (2004) and is widely discussed in the literature on high-frequency identification (Kuttner, 2001; Cochrane and Piazzesi, 2002; Gürkaynak *et al.*, 2005). A recent article by Jarociński and Karadi (2020) studies the empirical effects of the information effect. Their identification approach rests on the idea to separate monetary policy shocks from information shocks by the combination of high-frequency market surprises in federal funds futures and asset prices and the use of sign restrictions. If surprises in federal funds futures display comovement with stock prices, they take this as indication of an active information channel. Hence, the market interprets interest rate hikes as the central banks internal positive outlook of the economy. Similarly, Andrade and Ferroni (2020) disentangle monetary policy surprises from forward guidance shocks for the Euro area. They also identify an information shock (termed Delphic shock in the context of forward guidance) pushing up inflation and output expectations. Another study tackling the information asymmetries constitutes Miranda-Agrippino and Ricco (2020). The idea of the paper is to build an instrument free of the central banks' internal macroeconomic outlook, i.e., project off the high-frequency surprises the Greenbook forecasts of the Fed. This instrument has shown to be informationally robust with respect to the information set of the central bank and is thus orthogonal to both central bank's projections and to past market surprises. Similar results are found in the event-study analysis of Cieslak and Schrimpf (2019) or again for the Euro area by Kerssenfischer (2019). Nevertheless, all of those studies do not look at the adjustment process of expectations of market participants and hence do not allow for belief distortions.

This brings us to the second stream of literature we connect. The number of studies looking at belief distortions in macroeconomics and finance is growing fast. A large theoretical literature has emerged that tries to explain why economic agents make systematic errors embedded in beliefs.

There are a variety of reasons that the presence of new information is given too much or too little weight, but there is ample evidence against the hypothesis that information is processed rationally.[2] Studies putting the FIRE assumption to test show that it does not hold when tested with survey expectations, e.g., in the influential article by Coibion and Gorodnichenko (2015) and for a broader set of variables in Bordalo *et al.* (2020). While the former article finds evidence for underreaction in macroeconomic variables, the latter finds more mixed evidence also pointing to overreaction in expectation about macroeconomic variables. The latter study differs from the former by not looking at the consensus forecasts, but also utilizing forecasts on the individual level. Closely related to our study is Wang (2019) finding underreaction for the short-end and overreaction for the long-end of the yield curve. Furthermore, this paper develops a theoretical model of autocorrelation averaging along the yield curve. We differ from this study in two important aspects: First, we do not rely on the framework by Coibion and Gorodnichenko (2015) to measure belief distortions, which implicitly does not distinguish between biases in how agents form short- and long-run expectation as has been criticized by Kucinskas and Peters (2019). Second, we look at the impact of monetary policy and its transmission channel in particular due to its importance for policymakers.

3 Biases in expectation formation

We follow Kucinskas and Peters (2019) to measure biases in how agents form expectation about some variable x_t. The bias can be either positive (underreaction) or negative (overreaction). In particular, *underreaction* defines the situation where the agent misjudges the impact of a shock to be smaller than it actually is. In other words, the adjustment of beliefs is too small, which results in a positive bias. Conversely, if the agent reacts too strongly, we have a negative bias since the belief adjustments outweighs the realized value, which is then called *overreaction*.

Using these definitions, Kucinskas and Peters (2019) lay out a framework to empirically estimate the direction, the size and the duration of a belief adjustment. In what follows, we briefly present their theoretical model for the case the time series is driven by a single shock, but the extension to multiple shocks is straightforward.[3]

Suppose that we observe a macroeconomic time series x_t and we remove any deterministic component (e.g., a stochastic or linear trend). Furthermore, we demean the process. Then this variable follows a linear stationary process

$$x_t = \sum_{\ell=0}^{\infty} \alpha_\ell \varepsilon_{t-\ell} \tag{3.1}$$

for some coefficients α_ℓ with $\alpha_0 = 1$ and a martingale difference sequence of shocks ε_t. This means that the expectation with respect to the past is zero (more formally, $\mathbb{E}_t[\varepsilon_{t+1}] = 0$). In each period we observe that an agent makes an one step ahead forecast denoted by $\mathbb{F}_t[x_{t+1}]$. The forecasts are generated by the following linear stationary process

$$\mathbb{F}_t[x_{t+1}] = b_0 + \sum_{\ell=0}^{\infty} a_{\ell+1} \varepsilon_{t-\ell}. \tag{3.2}$$

[2] For a recent survey see also Manski (2018).

[3] The general case with multiple shocks is found in their paper Section 2.1.2 (Kucinskas and Peters, 2019).

In this setup, b_0 denotes a time-invariant bias, while the coefficients a_ℓ capture how subjective expectations react to past shocks. From this representation it should be clear that if $\alpha_\ell \neq a_\ell$, the subjective reaction to past shocks differs from the reaction of the realized process.

In case there is evidence of a systematic error in expectations, we have to define *belief distortions* by taking the difference between the true conditional expectation and the subjective forecast. We denote this bias at time t as

$$\begin{aligned} bias_t &= \mathbb{E}_t[x_{t+1}] - \mathbb{F}_t[x_{t+1}] \\ &= -b_0 - \sum_{\ell=0}^{\infty} \operatorname{sgn}(\alpha_\ell) b_\ell \varepsilon_{t-\ell}, \end{aligned} \tag{3.3}$$

where $b_\ell = \operatorname{sgn}(\alpha_\ell)(a_\ell - \alpha_\ell)$, $\ell \geq 1$ correspond to *bias coefficients*. The expectation process is *unbiased* if the subjective and the objective forecast coincide, i.e., $\mathbb{F}_t[x_{t+1}] = \mathbb{E}_t[x_{t+1}]$. Further, an agent underreacts to a current shock ε_t one period before if $|a_1| < |\alpha_1|$, i.e., if the perceived response is smaller than the true response. Overreaction appears if b_ℓ is positive. In case the bias coefficient is zero the expectation formation process is unbiased.

The main contribution of Kucinskas and Peters (2019) is that the bias coefficients can be directly inferred from the data without knowing the true conditional expectation of the shocks. We denote the *forecast error* as the difference between the realized value and the subjective forecast, i.e., $e_t = x_t - \mathbb{F}_{t-1}[x_t]$. We know that $x_t = \mathbb{E}_{t-1}[x_t] + \varepsilon_t$ and $E_{t-1}[\varepsilon_t] = 0$. This implies

$$e_t = x_t - \mathbb{F}_{t-1}[x_t] = -b_0 - \sum_{\ell=0}^{\infty} \operatorname{sgn}(\alpha_\ell) b_\ell \varepsilon_{t-\ell}, \tag{3.4}$$

which is just the IRF of the forecast errors. Put differently, the bias (i.e., over- or underreaction) can be inferred by investigating the IRF of the forecast errors. In a multivariate time series framework the underlying fundamental economic shocks are not yet identified and hence not observed. In order to transform the model into its structural form, additional assumptions are needed.

4 Econometric framework

In what follows, we describe the data and the empirical strategy. The latter consists of three building blocks: Monetary policy and central bank information shocks identified via high-frequency data (Jarociński and Karadi, 2020), survey data to construct forecasts errors and a Bayesian proxy VAR in the spirit of Gertler and Karadi (2015) and Caldara and Herbst (2019).

4.1 Data

In this section, we shortly introduce the data, focusing on two variables that are key to our analysis, survey data on forecasts and the high-frequency identified monetary policy shocks. We use monthly data spanning the period from February 1990 to December 2016. The sample is constrained to the availability of the high-frequency monetary policy instruments.

More in detail, we use the monthly average of the one-year (TB1Y) and ten-year constant-maturity treasury yield (TB10Y) as short- and long-term interest rates, respectively. By using a rate longer than the targeted federal funds rate we also incorporate the impact of forward guidance. Hence, this rate remains a valid monetary policy instrument during the zero lower bound period

(Gertler and Karadi, 2015). When taking a closer look at the yield curve, we further include data on three months (TB3M), six months (TB6M), two years (TB2Y), five years (TB5Y), and thirty years (TB30Y) yields. As the stock price index, we take a monthly average of the S&P 500 (SP500) in log levels. Real activity and prices are measured with real GDP (RGDP) and the GDP deflator (GDPDEF) in log levels.[4] To include an overall measurement of financial conditions, we use the excess bond premium (EBP, Gilchrist and Zakrajšek, 2012; Favara *et al.*, 2016). This has proven to be useful in adding additional information to small-scale VARs due to the strong forward-looking component of corporate spreads (Caldara and Herbst, 2019). More information on the construction of these variables is available in App. A.

For the identification of the monetary policy and central bank information shocks we rely on high-frequency identification. More specifically, we look at surprises (i.e., price changes) measured in a half-hour windows starting 10 minutes before and ending 20 minutes after the FOMC announcement (Gürkaynak *et al.*, 2005) provided in the dataset of Jarociński and Karadi (2020). This data set consists of asset-price changes around 240 FOMC announcements from 1990 to 2016. In particular, we proxy interest rate surprises by the change in three-months fed funds futures and stock price surprises by the change in the S&P 500.

Last, we include data on expectations using the Blue Chip Financial Indicators (BC) data base. The data were purchased and manually checked for errors before using the data in the analysis. This survey consists of subjective expectations on various financial indicators[5] from executives of financial firms. More specifically, in the survey, respondents are asked each month to form a prediction of the average quarter-over-quarter change of various interest rates for the current quarter and four quarters into the future. To keep the notation clear, we indicate expectations on yields with a superscript e, for instance TB1Y^e.

4.2 A Bayesian proxy VAR

Let $\{\boldsymbol{y}_t\}_{t=1}^T$ denote an M-dimensional time series process. A typical VAR(p) is written as

$$\boldsymbol{y}_t = \sum_{j=1}^{p} \boldsymbol{A}_j \boldsymbol{y}_{t-j} + \boldsymbol{u}_t, \quad \boldsymbol{u}_t \sim \mathcal{N}_M(\boldsymbol{0}, \boldsymbol{\Sigma}), \tag{4.1}$$

with $\boldsymbol{A}_j$ denoting the $M \times M$ coefficient matrix of the jth lag and a Gaussian distributed reduced-form error $\boldsymbol{u}_t$ with full variance-covariance matrix $\boldsymbol{\Sigma}$. For the sake of brevity, deterministics like the constant or the trend are excluded.

Transforming the model into its structural form yields

$$\boldsymbol{A}_0^{-1} \boldsymbol{y}_t = \boldsymbol{A}_0^{-1} \sum_{j=1}^{p} \boldsymbol{A}_j \boldsymbol{y}_{t-j} + \boldsymbol{\varepsilon}_t, \quad \boldsymbol{\varepsilon}_t \sim \mathcal{N}_M(\boldsymbol{0}, \boldsymbol{I}), \tag{4.2}$$

which corresponds to assume that $\boldsymbol{A}_0 \boldsymbol{A}_0 = \boldsymbol{\Sigma}$ holds. We follow the work of Gertler and Karadi (2015) to identify the causal effects of the monetary policy and the central bank information shock.

[4] We directly use the replication data of Jarociński and Karadi (2020) who interpolate real GDP and the GDP deflator to monthly frequency following Stock and Watson (2010). This implies to use the Kalman filter to interpolate the months in between by using a set of monthly variables closely related to economic activity and prices.

[5] Basically, the survey includes not only expectations of treasury yields with different maturities, but also expectations on credit spreads and additional macroeconomic variables. The ones used in this paper can be looked up in App. A.

Let $\boldsymbol{Z}_t$ denote a set of instruments. To be a valid instrument for the policy shock, $\boldsymbol{Z}_t$ must be correlated with the policy shock ε_t^p and orthogonal to all other shocks $\boldsymbol{\varepsilon}_t^{-p}$, such that

$$\begin{aligned} \mathbb{E}[\boldsymbol{Z}_t, \varepsilon_t^p] &= \boldsymbol{\Phi} \\ \mathbb{E}[\boldsymbol{Z}_t, \varepsilon_t^{-p}] &= \boldsymbol{0}. \end{aligned} \tag{4.3}$$

We proceed in two stages: First, we regress the reduced form error u_t^p on the instrument $\boldsymbol{Z}_t$ to isolate the variation in the reduced-form residual. Similar to a two-stage least-squares procedure, we collect fitted values of $\hat{u}_t^p$ and regress them in the second stage regression on the other reduced form residuals. By using the variance-covariance matrix $\boldsymbol{\Sigma}$, we get to an analytical solution to identify the elements in the impact matrix $\boldsymbol{A}_0$ enabling us to trace out the structural response to the shocks under consideration. Derivation and details can be found in App. B. Hence, to identify the model we use the reduced-form errors of the TB1Y and S&P500 as our policy indicators for the two instruments.

Our approach is most similar to the one proposed by Gertler and Karadi (2015) and strongly resembles the identification scheme by Jarociński and Karadi (2020) who directly add the instruments to the VAR. An alternative would be to use local projections (Jordà, 2005), but Plagborg-Møller and Wolf (2019) provide evidence that under an external instruments approach the two methods yield similar results. Caldara and Herbst (2019) discuss a unified framework for a Bayesian proxy VAR in more detail. Basically, any of these approaches can be used since they all yield asymptotically the same IRFs up to a scaling factor as shown by Plagborg-Møller and Wolf (2019).

For reduced-form estimation we use a standard Bayesian VAR similar to Giannone *et al.* (2015). Concerning the prior choices we follow Litterman (1986), but show also that our results are robust to more sophisticated priors such as the Stochastic Search Variable Selection (SSVS) prior (George *et al.*, 2008) or the Normal-Gamma (NG) prior (Huber and Feldkircher, 2019).

5 Results

In what follows, we provide results for two different specifications. First, a baseline model that closely follows Jarociński and Karadi (2020) augmented with expectations on one-year and ten-year treasury bills. This exercise should provide a first impression of the adjustment of expectations on the short- and long-end of the curve. Second, we have a closer look at additional segments of the curve.

5.1 The baseline VAR

The baseline VAR features 12 lags and an intercept as a deterministic term. We report results based on 10,000 draws where we discard the first 5,000 as burn-ins. After the estimation of the model we further discard explosive draws leading to around 88% of stable draws. Convergence of the sampler is achieved and checked with Geweke's convergence diagnostic. The results are depicted in Fig. 1. The figure shows responses to the monetary policy shock in the upper panel and the corresponding responses to a central bank information shock in the lower panel. The figures show the posterior median along with 68% and 80% credible intervals. To facilitate comparison, both shocks are scaled to either yield a 0.25% decrease (monetary policy shock) or increase (information shock) in equity prices (SP500).

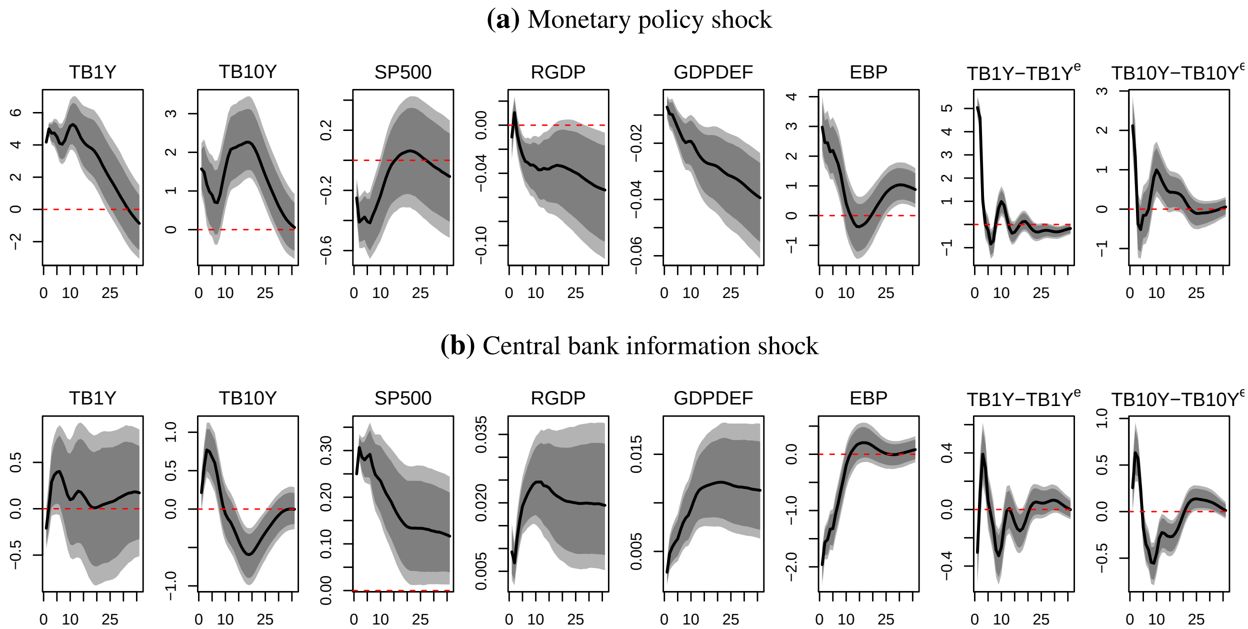


Figure 1: Impulse response functions of the baseline VAR. Black line denotes median response while gray shaded areas denote the 68% and 80% confidence intervals. Interest rates, spreads and forecast errors are in basis points(bp), stock price index, real activity index and prices are in percent.

We first look at responses to the monetary policy shock. Here, the ten-year treasury bill rate increases after a year and stock market prices, real activity, and the GDP deflator all decline. Moreover, financial conditions, as measured by the excess bond premium, tighten. These results are broadly in line with findings of Jarociński and Karadi (2020), which ensures overall confidence in the plausibility of our econometric framework and identification strategy. We now examine how financial market agents adjust their expectations in response to the interest rate shock. For that purpose, we look at the responses of the forecast errors (i.e., the bias coefficients introduced in Sec. 3) in one-year treasury bills (TB1Y-TB1Y^e) and ten-year treasury bills (TB10Y-TB10Y^e). Considering the results depicted in Fig. 1, most of the adjustment takes place within the first five months and takes the form of a significant underreaction to the monetary policy shock. This holds true for both expectations of short-term and long-term yields. The fact that agents significantly underreact could be explained either by a certain degree of inattention or by overconfidence in their own forecasts. Considering the sample of the survey, which consists of executives from financial companies, inattention seems less likely. The period of underreaction is followed by a short period of overreaction to make up for their initial underreaction. In general, the adjustment takes a bit longer for long-term yields compared to short-term yields. Long-term yields are to a large degree determined by movements in short-rates and expected interest rates. If expectations on short-term interest rates adjust slowly, expectations on long-term yields naturally take even longer. Moreover, they depend on further macroeconomic fundamentals such as long-run inflation expectations (Diebold and Li, 2006) which do not immediately react to news / shocks.

Next, we examine results in response to a central bank information shock. Here, we see a positive reaction of the stock market, real activity, and an easing of financial conditions. By contrast, long-term rates increase, which could reflect the uptick in inflation. Looking at the adjustment of expectations, after the initial shock market participants significantly underreact – a finding which is in line with our results on the conventional monetary policy shock. The duration of the adjustment process, however, is considerably longer and especially so for long-term yield where it takes up to 20 months until the bias in expectations vanishes. In contrast to the monetary policy shock, the finding of an immediate underestimation in the context of the central bank information shock relates to a large body of the literature on investigating the effects of forward guidance. Forward guidance in its most basic form can be regarded as a means of the central bank releasing news to the public. Structural models often yield implausibly large effects of forward guidance on output and inflation, a phenomenon called the forward guidance puzzle. Introducing a level of inattention (i.e., underreaction) of market participants is a remedy to the puzzle and renders predictions of dynamic stochastic general equilibrium (DSGE) models more reliable (Christoffel *et al.*, 2020). Our results provide not only an estimate of inattention but also the time profile of adjustment which could further help improving DSGE models in the context of forward guidance.

5.2 A closer look at the yield curve

In this section, we extend the baseline model to include yields with different maturities to get a fuller picture of the reactions along the yield curve. This extended VAR features only 2 lags and an intercept as deterministic term. Again, we report results based on 10,000 draws where we discard the first 5,000 as burn-ins and discard explosive draws leaving us with around 73% stable draws. In particular, we include the 3-months (TB3M), 6-months (TB6M), 1-year (TB1Y), 2-year (TB2Y), 5-year (TB5Y), 10-year (TB10Y), and 30-year (TB30Y) treasury yields along with its respective forecast errors (TB3M-TB3M^e, TB6M-TB6M^e, TB1Y-TB1Y^e, TB2Y-TB2Y^e, TB5Y-TB5Y^e, TB10Y-TB10Y^e, and TB30Y-TB30Y^e). For the sake of brevity, we only report the IRFs of the yields and the respective forecast errors for both shocks. Fig. 2 shows the responses of a monetary policy tightening, while Fig. 3 shows the responses of a central bank information shock. Both shocks are scaled in terms of the S&P500, in particular to a 0.25% decrease and increase respectively.

A conventional monetary policy shock is expected to move the yield curve mostly on the short-end and to a lesser extent on the long-end. The results depicted in Fig. 2 indeed show a more front-loaded response with yields up to two years reacting most strongly. The reaction of yields on the very long-end, in particular the 10-year and 30-year maturity yields, is below 1bp and far less pronounced as on the short-end.

Looking at the adjustment process of expectations, the following results emerge: First and after the initial shock, expectations of all yields along the yield curve respond with an underreaction up to five months, after which expectations revert and overreact. At the short end, market participants adapt their expectations within ten months after which the bias coefficient is no longer significant. For the middle and long end of the curve, adjustment takes considerably longer, namely between fifteen to twenty months. These results corroborate the findings of our baseline model.

Finally, we investigate responses to the central bank information shock, shown in Fig. 3. News and information shocks are often regarded as a form of forward guidance shock, which should mainly impact the middle segment of the yield curve.[6] Considering peak effects of the responses for different maturities indeed indicate stronger effects in the 3-months to two-years segment. Effects

[6] Rogers *et al.* (2014), indicate that forward guidance does typically not affect yields with larger maturity as five years; Brand *et al.* (2010) reports a hump-shaped maturity response pattern of euro area yields to communication. Altavilla

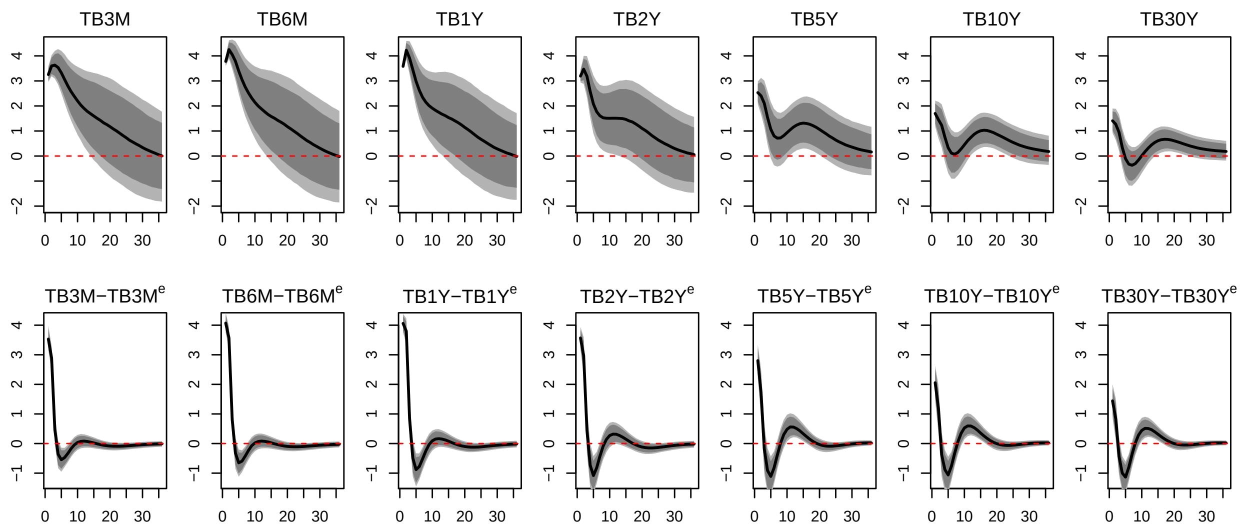


Figure 2: Impulse response functions of a monetary policy shock in the yield curve VAR. Black line denotes median response while gray shaded areas denote the 68% and 80% confidence intervals. All units are in basis points (bp).

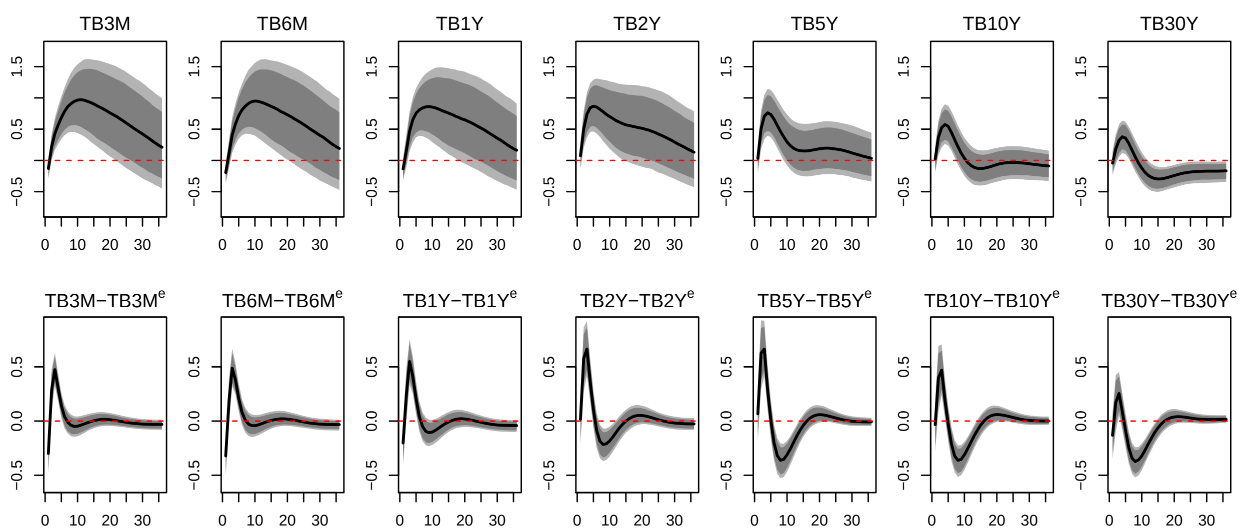


Figure 3: Impulse response functions of a central bank information shock in the yield curve VAR. Black line denotes median response while gray shaded areas denote the 68% and 80% confidence intervals. All units are in basis points (bp).

are significantly smaller for the longer end of the curve. Yields at the very long-end of the yield curve show an even negative reaction after about a year, indicating a compression of the yield curve. Together with the positive reaction on the stock market index (not shown), this behavior is consistent with a positive news shock about the economic outlook. The latter is typically accompanied by a rise in inflation, which could trigger the upward shift in the term structure. When looking at

et al. (2019) using high-frequency identification show that forward guidance affects yields with a maturity over two years most strongly.

the adjustment paths of expectations, we find that at the short-end, after the shock hits, market participants underreact to the news before the bias fades out. This adjustment takes place within the first 10 months after the shock. The picture is more diverse when considering longer-term yields. Here, underreaction is followed by overreaction and with about 20 months, expectations need considerably longer to adjust.

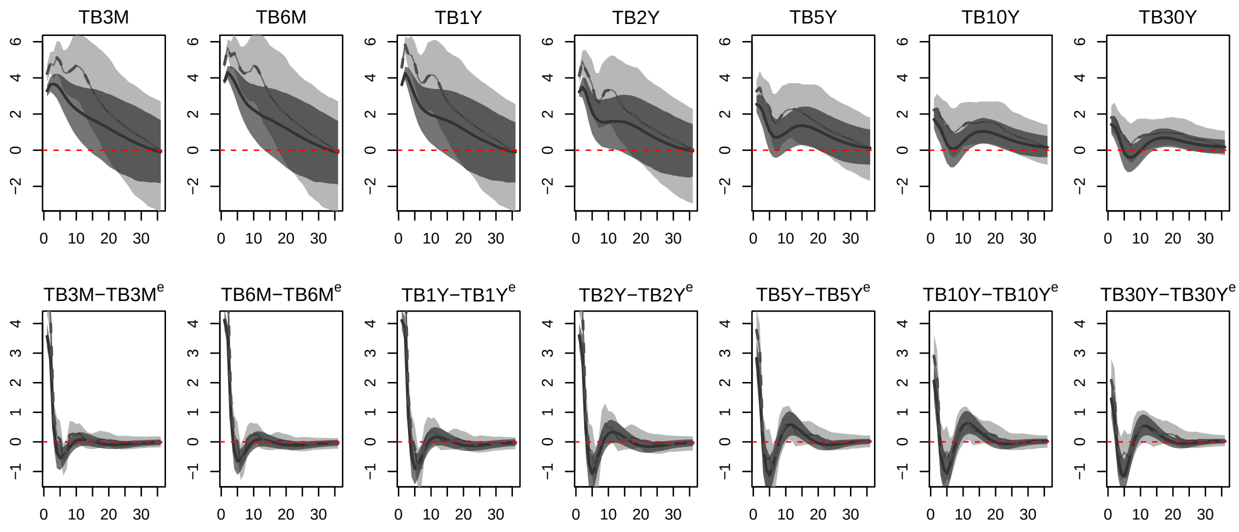
6 Robustness analysis

We perform sensitivity checks of the empirical checks along several dimensions. For this we play around with the specification, in particular choosing the optimal lag length under different Bayesian prior setups and using different indicators. Furthermore, we re-estimate the model with stochastic volatility in the error variances to control for possible heteroscedasticity. More precisely, we rewrite the VAR in its Cholesky form as shown in Carriero *et al.* (2019) and implement stochastic volatility following Kastner and Frühwirth-Schnatter (2014).

As is standard when working with monthly data, we use $p = 12$ in the baseline model. This rather long lag length comes with the drawback that the parameter space increases quadratically. Hence, we moved to use $p = 2$ for the yield curve VAR due the high-dimensionality of the model. We opt for two sensitivity checks here. First, we use different variants of Bayesian shrinkage priors all utilizing the idea to either shrink non-important coefficients to zero or to penalize higher-order lags additionally. Hence, it comes as no surprise that information criteria as the well-known Schwarz criterion point to our preferred lag length since non-important coefficients are shrunk towards zero and do not introduce additional noise. When controlling for heteroscedasticity the results are almost unchanged and qualitatively similar. Despite that, Clark (2011) points to increases in forecasting properties of the model which can be confirmed when looking at information criteria, the structural effects remain close to the original model. To visualize these sensitivity checks, we performed a small sensitivity exercise. We re-run the model outlined in Sec. 5.2 for $p = \{1, 2, \ldots, 12\}$ lags and with and without stochastic volatility resulting in a total of 24 models. After the estimation, identification and calculating the IRFs for each model, we compute the median response of all these models. This median response is depicted in Fig. 4 with the gray dashed line together with the light-gray confidence bounds (the median of the 10/90th quantile of all models). For better comparison, we have also included the results obtained in Sec. 5.2. For both identified shocks, results are rather stable over all those different specifications. The findings concerning the adjustment process of expectations discussed before still hold. It rather seems that some responses amplify further, which is driven by the stochastic volatility specification (not explicitly shown).

Furthermore, we also experimented with different settings of variables. In particular, we have replaced the interpolated monthly real GDP series with industrial production, a commonly used real activity indicator when doing analyses on this frequency, and used the consumer price index instead of the GDP deflator. Again, the structural implications remain the same. We also significantly reduced model complexity for the model used in Sec. 5.2 by replacing yields by the three Nelson-Siegel factors that are frequently used to summarize the yield curve (Nelson and Siegel, 1987; Diebold and Li, 2006): The level factor (β_0), the slope factor (β_1) and the curvature factor (β_2) along with the respective forecast errors of the three factors ($\beta_0 - \beta_0^e$, $\beta_1 - \beta_1^e$ and $\beta_2 - \beta_2^e$). Results show for both shocks reaction along the whole yield curve similar to what we have discussed before. Similarly to our previous findings, the adjustment process for the monetary policy shock takes up to twenty months for the level factor, while it only takes up to 8 months for the slope factor. When

(a) Monetary policy shock



(b) Central bank information shock

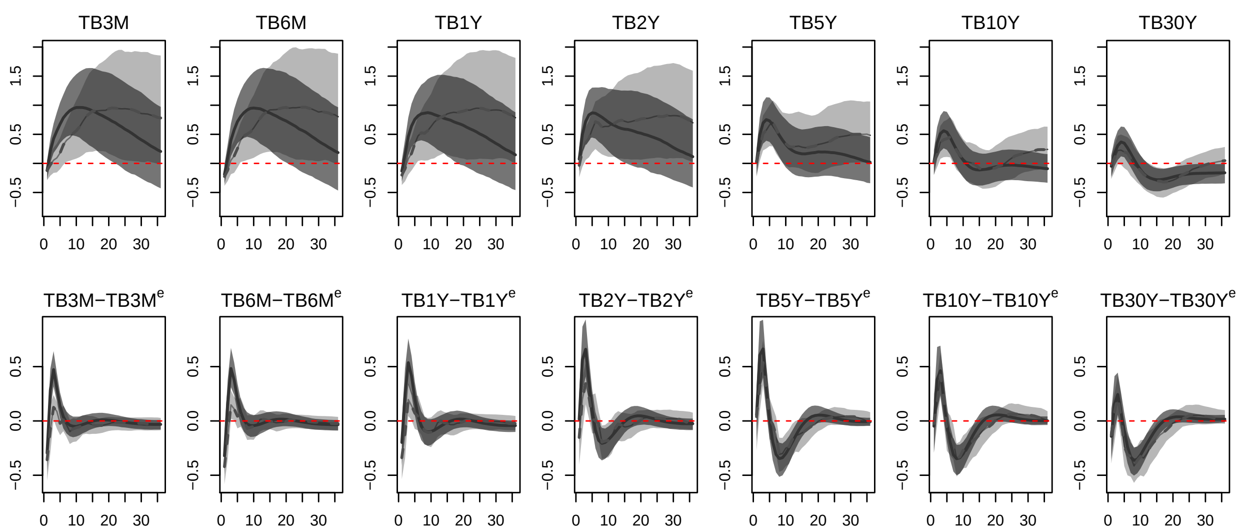


Figure 4: Impulse response functions for sensitivity checks. Lines together with shaded areas denote median with 80% confidence bounds. Black line together with dark-gray shaded area denotes the model in Sec. 5.2 while gray dashed line together with light-gray shaded area denotes median of all models with a different specification. All units are in basis points (bp).

looking at the information shock, adjustment takes longer for the three factors but there may be countervailing forces at work.

7 Concluding remarks

In this paper, we investigate how US market participants adjust their expectations of interest rates at different maturities in response to monetary policy shocks. For that purpose, we rely on the recently proposed framework of Kucinskas and Peters (2019) who show that market agents can either over- or underreact to new information such as a change in the monetary policy stance. Using the difference of realized and expected / forecast values of the US term structure, we show how expectations adjust to either a conventional monetary policy tightening or a central bank information shock – the latter which can also be interpreted as a change in forward guidance.

First, our results indicate that US financial market participants significantly underreact to both conventional monetary policy and central bank information shocks. This underreaction could be either a sign of inattention or a sign of overconfidence in own forecasts and provides evidence against the assumption of rational expectations. Regardless of the underlying cause of underreaction, this implies that monetary policy actions are not fully absorbed in the expectations of market participants. Measures of central banks are to a large degree, though, precisely aimed at aligning central bank actions with market expectations. Second, we find that most of the adjustment of financial market participants takes place within the first five months. This holds particularly true for expectations regarding the short-end of the yield curve. Third, we find that for both shocks the adjustment takes significantly longer for higher maturities. More specifically, at the very-long end, the adjustment process takes up to two years, while on average it takes a year for the shorter end of the curve. Taken at face value, this implies that policies aimed at the longer end do not immediately affect expectations and hence market behavior. These policies are the predominant ones in the current environment of zero interest rates, namely quantitative easing and – to a lesser extent – forward guidance. Last, comparing differences of expectations adjustment in response to the two shocks, we find a tendency of a longer adjustment if the shock arrives in the form of the central bank releasing new information. It seems, market participants have a harder time to adapt expectations in response to the central bank information shock, which by definition is more opaque and can be interpreted in different ways by the public. Our results are qualitatively unchanged if we consider a broader specification of the yield curve and are robust to a range of sensitivity checks.

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A Data

Table A1: Data labels and sources

FRED	
RGDP	Real Gross Domestic Product
INDPRO	Industrial Production
GDPDEF	Gross Domestic Product: Implicit Price Deflator
CPIAUCSL	Consumer prices
SP500	S&P500
TB3M	3-Month Treasury Constant Maturity Rate
TB6M	6-Month Treasury Constant Maturity Rate
TB1Y	1-Year Treasury Constant Maturity Rate
TB2Y	2-Year Treasury Constant Maturity Rate
TB5Y	5-Year Treasury Constant Maturity Rate
TB10Y	10-Year Treasury Constant Maturity Rate
TB30Y	30-Year Treasury Constant Maturity Rate
Blue Chip Financial Indicators	
TB3M^e	Expectation on 3-Month Treasury Constant Maturity Rate
TB6M^e	Expectation on 6-Month Treasury Constant Maturity Rate
TB1Y^e	Expectation on 1-Year Treasury Constant Maturity Rate
TB2Y^e	Expectation on 2-Year Treasury Constant Maturity Rate
TB5Y^e	Expectation on 5-Year Treasury Constant Maturity Rate
TB10Y^e	Expectation on 10-Year Treasury Constant Maturity Rate
TB30Y^e	Expectation on 30-Year Treasury Constant Maturity Rate
Miscellaneous	
EBP	Excess bond premium (Gilchrist and Zakrajšek, 2012)
FF4HF	Surprises in the 3-month Fed Funds futures (Jarociński and Karadi, 2020)
SP500HF	Surprises in the S&P500 (Jarociński and Karadi, 2020)

B Identification based on External Instruments

The identification scheme on external instruments is introduced by Mertens and Ravn (2013) and used by Gertler and Karadi (2015) to identify monetary policy shocks. Generally, it is similar to a two stage least squares procedure, where the reduced form residuals of the structural shock are regressed on the instrument $\boldsymbol{Z}_t$. The fitted values are then regressed on the other reduced form residuals,

$$\boldsymbol{u}_t^{-p} = \boldsymbol{\beta}\hat{u}_t^p + v_t, \quad v_t \sim N(0, \sigma_u^2). \tag{A.1}$$

Therefore, we get an estimate for the ratio $\boldsymbol{\beta}$, which is the structural effect of a unit shock on the other variables in the system. In order to use this, we have to restore the column of $\boldsymbol{A}_0$ with the structural shock, which we denote as $\boldsymbol{A}_0^p$. We do this by partitioning the matrix of the structural coefficients, such that

$$\boldsymbol{A}_0 = [A_0^p \quad \boldsymbol{A}_0^{-p}] = \begin{bmatrix} a_{0,11} & \boldsymbol{a}_{i,12} \\ \boldsymbol{a}_{i,21} & \boldsymbol{a}_{i,22} \end{bmatrix}, \tag{A.2}$$

where the variable to be instrumented is arbitrarily chosen to be the first variable. Furthermore, $a_{0,11}$ is a scalar, $\boldsymbol{a}_{0,12}^\intercal$ and $\boldsymbol{a}_{0,21}$ are vectors of size $M-1\times 1$ and $\boldsymbol{a}_{0,22}$ is a matrix of size $M-1\times M-1$. Furthermore, we partition the reduced form variance-covariance matrix accordingly like $\boldsymbol{A}_0$,

$$\boldsymbol{\Sigma} = \begin{bmatrix} \Sigma_{11} & \boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{21} & \boldsymbol{\Sigma}_{22} \end{bmatrix}. \tag{A.3}$$

Then $a_{0,11}$ is identified up to a sign convention and is obtained by the following closed form solution

$$(A_0^p)^2 = a_{0,11}^2 = \Sigma_{11} - \boldsymbol{a}_{0,12}\boldsymbol{a}_{0,12}^T, \tag{A.4}$$

where

$$\boldsymbol{a}_{0,12}\boldsymbol{a}_{0,12}^T = (\boldsymbol{\Sigma}_{21} - \boldsymbol{\beta}\boldsymbol{\Sigma}_{11})^T \boldsymbol{Q}^{-1}(\boldsymbol{\Sigma}_{21} - \boldsymbol{\beta}\boldsymbol{\Sigma}_{11}), \tag{A.5}$$

with

$$\boldsymbol{Q} = \boldsymbol{\beta}\boldsymbol{\Sigma}_{11}\boldsymbol{\beta}^\top - (\boldsymbol{\Sigma}_{21}\boldsymbol{\beta}^\top + \boldsymbol{\beta}\boldsymbol{\Sigma}_{21}^\top) + \boldsymbol{\Sigma}_{22}. \tag{A.6}$$