The Impact of Monetary Policy on Yield Curve Expectations

MAXIMILIAN BOECK*
Vienna University of Economics and Business

MARTIN FELDKIRCHER†
Vienna School of International Studies

Abstract

This article investigates how US market participants adjust yield curve expectations in response to a monetary policy and a central bank information shock. The results show that in response to both shocks and in the aggregate, market participants initially underreact followed by an overreaction. Most of the general underreaction takes place within five months and is evidence for information rigidities. These could be driven by the way information is absorbed: while market participants directly respond to news disclosed by the central bank, they react less to expectation adjustments from their peers which results in sticky / noisy information at the aggregate level. 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

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*Address: Department of Economics, Vienna University of Economics and Business. Welthandelsplatz 1, 1020 Vienna, Austria. E-mail: maximilian.boeck@wu.ac.at (corresponding author).

†Address: Favoritenstraße 15A, 1040 Vienna, Austria. E-mail: martin.feldkircher@da-vienna.ac.at.

1 Introduction

How do financial market participants react to monetary policy news? Central banks nowadays use policies that affect different segments of the yield curve including its long end. Recent studies also indicate the importance of information effects for monetary policy transmission (Nakamura and Steinsson, 2018). Yet, there is still little research on how yield curve expectations adjust in response to monetary policy news. This paper fills the gap by analyzing how financial market participants adjust their interest rate expectations at different maturities to monetary policy news.

Macroeconomic models, both of theoretical and empirical nature, almost explicitly assume that expectations are formed rationally (Muth, 1961). This implies that agents' expectations are first on average not systematically biased and second that agents collectively use all relevant information. This assumption, often denoted as full information rational expectations (FIRE), has become so predominant in applied work that it is frequently not even explicitly stated and even less so questioned or tested. Nevertheless, there exist alternatives for belief formations: Market participant can either under- or overreact to new information. Theoretical models that explain alternative belief formation processes comprise the sticky-information model of Mankiw and Reis (2002), diagnostic expectations (Bordalo *et al.*, 2018), 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).

The use of survey data as a measure of expectations has spiked new interest in empirical estimates of information asymmetries (Coibion and Gorodnichenko, 2012). In a seminal paper and using a static regression framework, Coibion and Gorodnichenko (2015) empirically reject the FIRE assumption. Recently, Kucinskas and Peters (2019) developed a novel framework that allows to investigate the dynamics of belief formation in response to certain shocks / news. More specifically, they propose augmenting a standard vector autoregression (VAR) with forecast errors – the difference of survey-based forecasts and realized data – and show that the impulse response of these forecast errors are a valid measure of belief distortions. In other words, their approach allows to dynamically estimate the belief adjustment process of market participants. Similarly, Angeletos *et al.* (2021) use this approach to explain the reaction of expectations to shocks. They argue in favor of a *delayed overshooting* behavior where agents initially underreact and then over-extrapolate their expectations.

In this paper, we use the approach of Kucinskas and Peters (2019) to investigate how financial markets adjust their beliefs / forecasts of different segments of the yield curve in response to monetary policy shocks. We look at both a conventional monetary policy shock, which is characterized by a change in interest rates, as well as an information shock. The latter reflects the central bank's assessment about the economic outlook and arises due to information asymmetries between the public and the central bank. This has also been dubbed the *information channel* of monetary policy transmission (Melosi, 2017) and several studies advocate looking at both conventional monetary policy and news shocks jointly (Cieslak and Schrimpf, 2019; Andrade and Ferroni, 2020; Jarociński and Karadi, 2020; Nakamura and Steinsson, 2018). There is an ongoing discussion on the exact nature of this information shock. Nakamura and Steinsson (2018) argue that the Fed information shock is because the Fed observes a stronger signal from the economy than the private sector; hence the private sector infers from a interest rate change that the economy must be stronger than they thought. On the contrary, Bauer and Swanson (2020) argue that the Fed response to news channel is active. Here, news of a strengthening economy causes both the Fed to raise interests rates and the private market to raise their expectations on the economy. How financial market participants adjust their yield curve expectations to these shocks and how adjustments differ depending on the nature of the shock, might be of particular interest to the policymaker. We identify the monetary policy shocks using changes in 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 market expectations, we use survey data from Blue Chip (BC) Financial Indicators, which 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 in the spirit of Gertler and Karadi (2015). Additionally, we perform static error-on-revision regressions that utilize aggregate (Coibion and Gorodnichenko, 2015) as well as individual-level forecast data (Bordalo *et al.*, 2020). This allows us to investigate one general potential source of imperfect expectations, namely the fact that market participants tend to neglect belief adjustments of their peers (Angeletos *et al.*, 2021).

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 pattern is reversed in the long-run where participants tend to overreact. This finding could imply that financial market players are at first inattentive or perceive signals as too noisy, before future outcomes become extrapolative or diagnostic in nature. 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, i.e., with an immediate adjustment of their expectations to new information. These findings on the aggregate level are corroborated when using the static approach of Coibion and Gorodnichenko (2015) to shed more light on the overall belief formation process. Also here, we find underreaction in the aggregate, but strikingly individual-level forecasts point to overreaction. According to Bordalo *et al.* (2020) this finding can be explained by market participants individually overreacting to news, but being ignorant to belief adjustments from their peers, which creates a form of information rigidity / stickiness on the aggregate level. Our dynamic estimates show that this process is also evident at the aggregate level but it takes some time until consensus expectations also point to overreaction. Hence, our results are consistent with the *delayed overshooting* behavior in Angeletos *et al.* (2021). 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, in Sec. 5 we present the results while Sec. 6 offers robustness checks. Finally, Sec. 7 concludes.

2 Related Literature

Our paper is related to two strands of the literature. First, the paper fits into a recent stream of literature investigating the effect of central bank information shocks on monetary policy transmission. The importance of controlling for different information sets when analyzing monetary policy dates back to the introduction of the narrative monetary policy instrument by Romer and Romer (2004). It is also widely discussed in the literature on high-frequency identification (Kuttner, 2001; Cochrane and Piazzesi, 2002; Gürkaynak *et al.*, 2005). In a recent study, Jarociński and Karadi (2020) show that it is of ample importance to separate conventional monetary policy shocks from information shocks in order to receive plausible results. The latter arise due to information asymmetries between the (better informed) central bank and the general public. Their identification strategy relies on a combination of high-frequency market surprises in federal funds futures and asset prices on the one hand and the use of sign restrictions on the other hand. More specifically, a pure monetary policy shock should be accompanied by a negative correlation of interest rates (measured by surprises in federal funds futures) and stock market valuation. A positive comovement is indicative of an information channel. In other words, the public interprets the interest rate increase as the central bank responding to a (future) economic boom, which is good news for the stock market. In the literature dealing with forward guidance, this is dubbed "Delphic" forward guidance (Böck *et al.*, 2021). In this context, Andrade and Ferroni (2020) identify a Delphic forward guidance / information shock by a positive comovement of inflation and output expectations, which is again indicative for a future economic boom. Another study that tackles information asymmetries is the one by Miranda-Agrippino and Ricco (2020). Their approach relies on constructing a measure of monetary policy that is purged from the central banks' internal and markets' forward-looking information. This instrument has been 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), Caldara and Herbst (2019), or Swanson (2021). Nevertheless, none of these studies look at the adjustment process of expectations in response to these shocks.

Second, our paper is related to a number of studies that look at belief distortions in macroeconomics and finance. A growing theoretical literature tries to explain why economic agents make systematic errors in adjusting their beliefs to news. There is a variety of reasons that the disclosure of new information is given too much or too little weight. For a recent and excellent survey, see Manski (2018). Studies investigating the FIRE assumption typically use survey data. Most of these studies show that FIRE does not hold (Coibion and Gorodnichenko, 2015; Bordalo *et al.*, 2020). Coibion and Gorodnichenko (2015) provide evidence for a general underreaction in macroeconomic variables. Bordalo *et al.* (2020) corroborate this finding but only at the aggregate level. At the individual level, findings of Bordalo *et al.* (2020) provide evidence for an overreaction of market participants' beliefs to news. They explain the difference in aggregate and individual belief formation by the mechanism of diagnostic expectations (Gennaioli *et al.*, 2016). Angeletos *et al.* (2021) documents that in response to business cycle fluctuations expectations underreact initially but overshoot later on. By comparing the approaches of Coibion and Gorodnichenko (2015) and Bordalo *et al.* (2020), they find substantial evidence for delayed overshooting in macroeconomic expectations. In the context of yield curve expectations, the study that is closest to ours is Wang (2019). Relying on the empirical framework of Coibion and Gorodnichenko (2015), Wang (2019) demonstrates that market participants underreact to news regarding the short-end of the yield curve and overreact at longer maturities. Our study differs from the one of Wang (2019) since we first look at how market participants respond to monetary policy news and second we use the novel approach of Kucinskas and Peters (2019), which allows for a dynamic analysis of the expectation formation process.

3 Biases in Expectation Formation

We follow Kucinskas and Peters (2019) to measure biases in beliefs for 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.[1] 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

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

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

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

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

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

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

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

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: Identification of monetary policy and central bank information shocks 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) to estimate belief distortions.

4.1 Empirical Specification

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). To take 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. To measure stock prices, 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.[2] To include an overall measure of financial conditions, we use the excess bond premium (EBP, Gilchrist and Zakrajšek, 2012; Favara *et al.*, 2016). Due to the strong forward-looking component of corporate spreads, the EBP adds important additional information to the information set of small scale VARs (Caldara and Herbst, 2019). More information on the construction of these variables is available in App. A. Additionally, we include data on expectations using the Blue Chip Financial Indicators data base. The data were purchased and manually checked for errors. This survey consists of subjective expectations on various financial indicators[3] from

[2] 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.

[3] 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.

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 simple, we indicate expectations on yields with a superscript e, for instance TB1Y^e for the expectation on the one-year treasury bill.

We will work with two main specifications. First, we estimate a VAR which closely follows the specification in (Jarociński and Karadi, 2020) augmented with expectations on the short- and long-end of the yield curve:

$$\boldsymbol{y}_t^{baseline} = \{\text{TB1Y}, \text{TB10Y}, \text{SP500}, \text{RGDP}, \text{GDPDEF}, \text{EBP}, \text{TB1Y}^e, \text{TB10Y}^e\}.$$

In the second specification, we look more closely on the whole yield curve and extend this baseline model with interest rate (expectations) of various maturities:

$$\begin{aligned}\boldsymbol{y}_t^{yieldcurve} = \{&\text{TB3M}, \text{TB6M}, \text{TB1Y}, \text{TB2Y}, \text{TB5Y}, \text{TB10Y}, \text{TB30Y}, \text{SP500}, \text{RGDP}, \text{GDPDEF},\\ &\text{EBP}, \text{TB3M}^e, \text{TB6M}^e, \text{TB1Y}^e, \text{TB2Y}^e, \text{TB5Y}^e, \text{TB10Y}^e, \text{TB30Y}^e\}.\end{aligned}$$

For the identification of the monetary policy and central bank information shocks we rely on high-frequency data. More specifically, we look at surprises (i.e., price changes) in the three-month Federal Funds futures and the S&P 500 measured within an half-hour window around FOMC announcements.[4] The way the surprises are constructed, they measure solely the amount of new information released at an FOMC announcement. For instance, if an interest rate increase has already been fully anticipated in the markets, no change in the futures will be visible. A narrow time windows around the announcements ensures that no other structural shocks confound the surprise measures. We gather the surprise series in the following matrix, $\boldsymbol{Z}_t = \{\text{hf\_MP}, \text{hf\_SP}\}$ where hf_MP refers to the monetary policy surprises while hf_SP refers to surprises in the stock price.

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

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

with $\boldsymbol{c}$ being a $M \times 1$ intercept vector, $\boldsymbol{A}_j$ 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 $\boldsymbol{\Sigma}$.

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] To be precise, the window starts 10 minutes before and ends 20 minutes after the FOMC announcement (Gürkaynak *et al.*, 2005) and the data are provided in Jarociński and Karadi (2020) which covers around 240 FOMC announcements from 1990 to 2016.

Let $\boldsymbol{Z}_t$ denote the set of instruments specified before. In particular, this set of instruments consists of a high-frequency measured surprises series of monetary policy and stock prices. 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

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

While the first is the relevance assumption, the second states exogeneity. Relevance of the instruments is given because the proxies are actual movements of the policy indicators but purged from any endogenous reaction due to the high-frequency measurement. In particular, movements in the Fed Funds future indicate exogenous movements in the monetary policy actions of the central bank. However, stock price movements at FOMC announcements can be attributed to the release of information to the public from the central bank. Exogeneity is given because movements are only measured at the time of the FOMC announcement which constitutes a narrow time interval in which it is unlikely that another structural shock occurs. Hence, to identify the model we use the reduced-form errors of the TB1Y and SP500 as our policy indicators for the two instruments.

We proceed in three steps: First, we estimate the VAR given in Eq. (4.2) and extract the vector of reduced form errors, u_t^p. Second, we regress u_t^p on the instrument $\boldsymbol{Z}_t$ to isolate the exogenous variation in the reduced-form residual. Third and similar to the second stage, in a two-stage least-squares procedure we regress the remaining reduced form errors on the fitted values of $\hat{u}_t^p$. By using the variance-covariance matrix $\boldsymbol{\Sigma}$, we get to an analytical solution to identify the elements in the impact matrix $\boldsymbol{A}_0$, which enables us to trace out the structural response to the shocks under consideration. Derivation and details can be found in App. C.

Caldara and Herbst (2019) discuss a unified framework for a Bayesian proxy VAR in more detail.[5] 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 Main Results

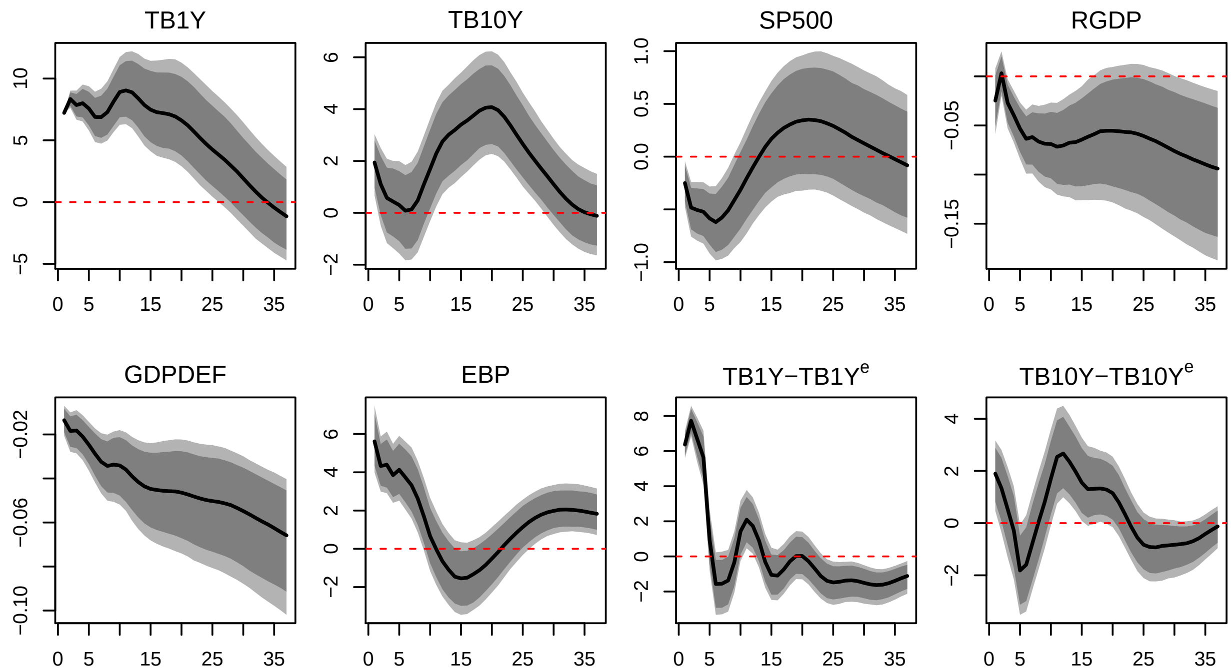
In what follows, we provide results for two different specifications. First, we estimate the baseline model to get a first impression of the effect of monetary policy on expectations on the short- and long-end of the yield curve. Second, we have a closer look at additional segments of the curve. Third and last, we also analyze biases in expectation formation on a disaggregated level.

5.1 The Baseline VAR

The specification of the baseline VAR is closely related to the one by Jarociński and Karadi (2020). Additionally, we include interest rate expectations to analyze belief adjustments. The model is specified as in Sec. 4.1 using the variables in vector $\boldsymbol{y}_t^{baseline}$. The VAR features $p = 12$ lags.

[5] As an alternative to the proxy VAR one could have used the external instruments to compute effects by means of local projections (Jordà, 2005) or added the instruments directly to the VAR (Jarociński and Karadi, 2020). Basically, any of these approaches can be used since they all yield asymptotically the same IRFs up to a scaling factor as shown by **?**.

Figure 1: Monetary Policy Shock of the Baseline VAR.



Note: Impulse response functions to a monetary policy shock, normalized to decrease the stock market index by 25 basis points. 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, stock price index, real activity index and prices are in percent.

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 in App. D. The results are shown in Fig. 1 and Fig. 2. The first figure shows responses to the monetary policy shock, while the second one shows the corresponding responses to a central bank information shock. 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).

We first look at responses to the monetary policy shock and compare them to the existing literature (upper panel of Fig. 1). There is an increase on impact for the one-year Treasury bill rate, while the ten-year treasury bill rate increases after a year. Stock market prices, real activity, and the GDP deflator all decline. The effects on output and prices are rather persistent. Moreover, financial conditions, as measured by the excess bond premium, tighten. These results are in line with findings of Jarociński and Karadi (2020), which ensures overall confidence in the plausibility of our econometric framework and identification strategy. Interestingly, some minor differences with respect to short-term interest rates arise. While the impact response is of similar magnitude (around 5 basis points), the dynamic behavior is different. Here, the response fades out after two years while it fades out relatively quickly in Jarociński and Karadi (2020). Hence, controlling for the responses in expectations alters the dynamic shape of the response. While we discuss the responses of expectations in more detail below, we observe that the response in our setting is more persistent.

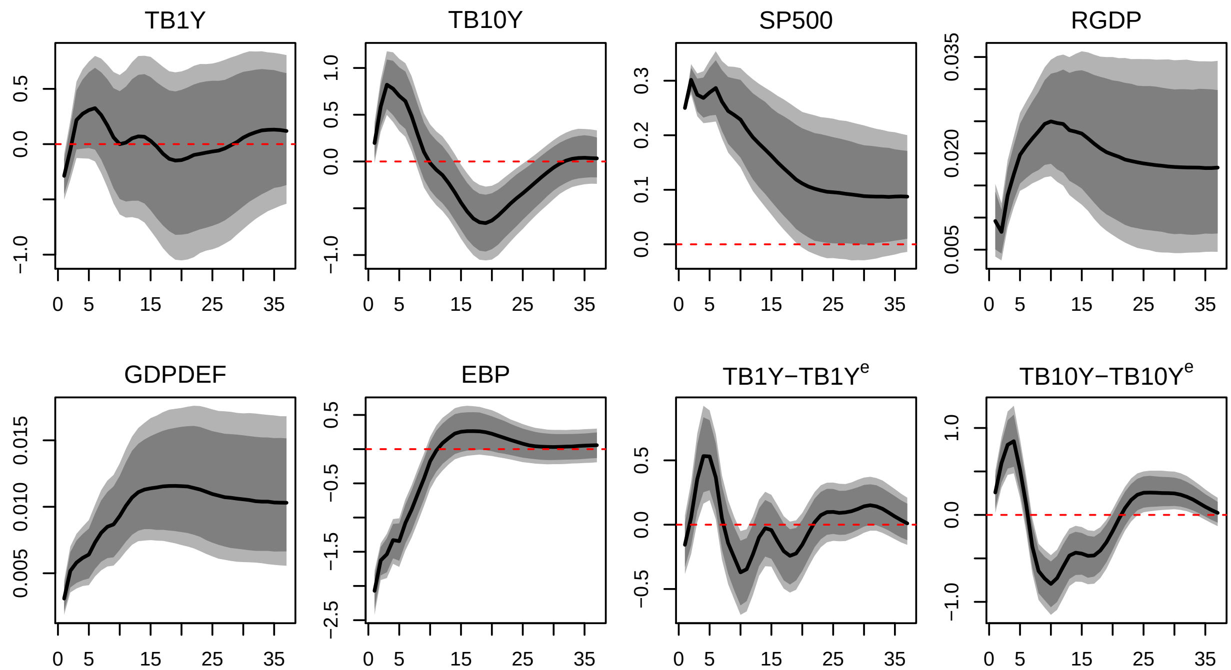
One could interpret this as a more sluggish response of the market to a monetary policy shock which is in line of the observed underreaction in the responses of the forecast errors. Furthermore, our results are also qualitatively aligned to other studies. For instance, Swanson (2021) or Andrade and Ferroni (2020) find similar effects for interest rates of varying maturities in regression-based analysis utilising high-frequency surprises in FOMC statements. The sizable increase in financial conditions following a monetary policy shock is further corroborated by Caldara and Herbst (2019). Overall, our findings are broadly in line with responses to a standard Taylor rule shock in a New-Keynesian (NK) model with financial accelerator (e.g., Bernanke *et al.*, 1999).

Now, we 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.[6] This holds true for both expectations of short-term and long-term yields. The fact that agents significantly underreact could be explained by either a certain degree of inattention or more generally by noisy / sticky information. The period of underreaction is followed by a short period of overreaction to make up for their initial underreaction. This is in line with the findings of Angeletos *et al.* (2021), naming this empirical fact *delayed overshooting*. In an theoretical model, they extend a simple NK model with informational frictions and over-extrapolation accounting for the recovered empirical facts. Similarly to the model proposed by Bordalo *et al.* (2018), over-extrapolation comes from misspecified beliefs about the persistence of macroeconomic fundamentals. 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. Our findings have two policy implications. The first is that strong commitment to a policy rule can decrease the amount of informational frictions (Adam and Woodford, 2012). Second, a leaning against the wind strategy can counteract underreaction caused by informational frictions and induce welfare improvements (Angeletos and La'o, 2020).

Next, we examine results in response to a central bank information shock. Impulse responses are shown in Fig. 2. Here, we see a positive reaction of the stock market, real activity, and an easing of financial conditions. Again, these results are very close to those provided in Jarociński and Karadi (2020). Furthermore, our results are also aligned with event-study analysis such as Cieslak and Schrimpf (2019), Andrade and Ferroni (2020), and Swanson (2021). In contrast to responses to the monetary policy shock, long-term rates increase on impact, which could reflect the uptick in inflation. Again, we observe a distinct difference in the response of the response of short-term interest rates when compared to Jarociński and Karadi (2020). Now, the picture is reversed to the one above. Controlling for the response of expectations to the information shock renders the response of short-term interest rates insignificant while it is clearly significantly positive in their study. This comes as no surprise, since the propagation channel of the information shock runs entirely through expectations. This is also in line with the Fed responses to news

[6] Note that the response of the forecast error on impact resembles the shock on impact of the respective variable. This is simply because it is constructed in this way. Expectations cannot adjust at the same time they are formed.

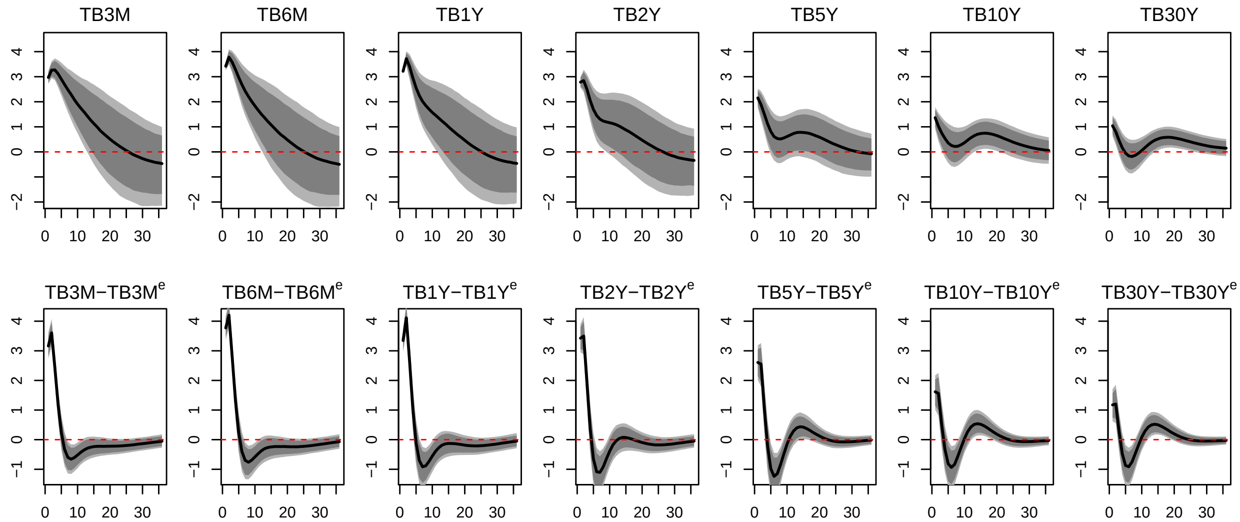
Figure 2: Central Bank Information Shock of the Baseline VAR.



Note: Impulse response functions to a central bank information shock, normalized to increase the stock market index by 25 basis points. 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, stock price index, real activity index and prices are in percent.

channel of Bauer and Swanson (2020). Agents as well as the central bank are just responding to news. Hence, the increase in short-term interest rates after having received positive news from the market is blurred by informational frictions. This is confirmed when 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. Afterwards, overreaction, particularly for long-term rates, is visible. This confirms the *delayed overshooting* behavior of Angeletos *et al.* (2021) once more. The duration of the adjustment process, however, is considerably longer and especially so for long-term yields 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 investigating the effects of forward guidance (Melosi, 2017). This yields another explanation for underreaction besides the aforementioned information rigidities due to noise or stickiness, namely inattention. 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 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 guide the development of theoretical models in the context of forward guidance.

Figure 3: Monetary Policy Shock of the Yield Curve VAR.



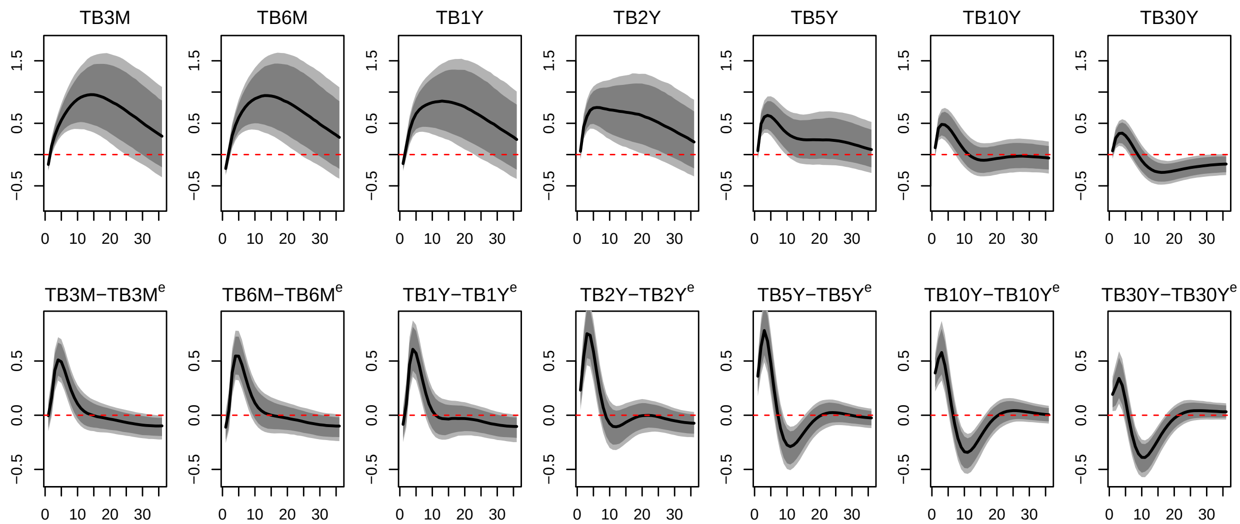
Note: Impulse response functions to a monetary policy shock, normalized to decrease the stock market index by 25 basis points. Black line denotes median response while gray shaded areas denote the 68% and 80% confidence intervals. All units are in basis points.

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 $p = 2$ lags. 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. Convergence diagnostics can be found in App. D. We use the vector $\boldsymbol{y}_t^{yieldcurve}$ defined in Sec. 4. 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 respective forecast errors. For the sake of brevity, we only report the IRFs of the yields and the respective forecast errors for both shocks. Fig. 3 shows the responses of a monetary policy tightening, while Fig. 4 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. 3 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 1 basis points 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. Again, the findings can be seen as a form of *delayed overshooting* behavior (Angeletos *et al.*, 2021). In response to the initial underreaction, we emphasize again

Figure 4: Central Bank Information Shock of the Yield Curve VAR.



Note: Impulse response functions to a central bank information shock, normalized to increase the stock market index by 25 basis points on impact. Black line denotes median response while gray shaded areas denote the 68% and 80% confidence intervals. All units are in basis points.

the proposed policy recommendations. Informational frictions cause underreaction, counteracted optimally by pursuing a leaning against the wind stragegy.

Finally, we investigate responses to the central bank information shock, shown in Fig. 4. 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.[7] Considering peak effects of the responses for different maturities indeed indicate stronger effects in the 3-months to two-years segment. Effects 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 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. Again, this fits into the picture of the *delayed overshooting* behavior.

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

5.3 A Disaggregated View

The results from the previous sections indicate an initial underreaction and hence provide evidence for information rigidities. In this section, we use the disaggregated approach of Bordalo *et al.* (2020) to further shed light on the reason why we find belief rigidities. More specifically, Bordalo *et al.* (2020) suggest that agents systematically overcorrect their own mistakes from the past while being ignorant to adjustments of other market participants. This behavior in turn leads to a rigidity in the aggregate / consensus forecast since information is not fully diffused.

In what follows, we run static error-on-revision regressions in the spirit of Coibion and Gorodnichenko (2015) and more recently used in Bordalo *et al.* (2020). The individual forecast data is from the BC survey. The survey asks each month 40-50 individual financial executives to provide a forecast for the current quarter and up to four quarters ahead. In total, we use data on about 200 individual forecasters with varying sample lengths due to a change in the composition of forecasters in the survey. For a typical forecaster, we observe a median sample length of 35-40 observations (see Column 8 in Tab. 1). Note that this exercise will not tell us how beliefs adjust to monetary policy news. Rather, the results will allow us to assess whether expectations of other market participants in general play a role in forming the aggregate / consensus belief and how mistakes in the past shape individual belief formation.

We denote by $\mathbb{F}_t[x_{t+1}]$ the one-step ahead consensus forecast made at time t for the future value of x_{t+1} of an interest rate with varying maturity. This consensus forecast is constructed with $\mathbb{F}_t[x_{t+1}] = (1/I)\sum_i \mathbb{F}_t^i[x_{t+1}]$, where $\mathbb{F}_t^i[x_{t+1}]$ is the forecast of individual i and $I > 1$ is the number of forecasters. Then we can define the forecast revision at t with $FR_t = (\mathbb{F}_t[x_{t+1}] - \mathbb{F}_{t-1}[x_{t+1}])$ where $\mathbb{F}_{t-1}[x_{t+1}]$ refers to the forecast in the previous period. Predictability of forecast errors is measured by estimating the following regression

$$x_{t+1} - \mathbb{F}_t[x_{t+1}] = \beta_0 + \beta_1 \mathrm{FR}_t + \eta_{t+1}, \quad \eta_{t+1} \sim \mathcal{N}(0, \sigma_\eta^2). \tag{5.1}$$

If forecast errors are not predictable from forecast revisions, we cannot reject the null hypothesis of FIRE. This essentially reduces to testing whether $\beta_1 = 0$. Otherwise, overreaction (underreaction) is implied by a negative (positive) coefficient β_1. For instance, a positive coefficient β_1 together with a positive forecast revision, $\mathrm{FR}_t > 0$, implies that the consensus forecast is not optimistic enough. Bordalo *et al.* (2020) extend this analysis by also analyzing forecast error predictability at the individual level. By using individual forecast revisions $FR_t^i = (\mathbb{F}_t^i[x_{t+1}] - \mathbb{F}_{t-1}^i[x_{t+1}])$ and forecast errors, they pursue estimating a pooled panel regression model,

$$x_{t+1} - \mathbb{F}_t^i[x_{t+1}] = \beta_0 + \beta_1^p \mathrm{FR}_t^i + \eta_{t+1}^p, \quad \eta_{t+1}^p \sim \mathcal{N}(0, \sigma_{p,\eta}^2). \tag{5.2}$$

The common coefficient β_1^p indicates whether the average forecaster under- or overreacts to their own information. If $\beta_1^p = 0$, this implies rational expectations. Last, we also run forecaster-by-forecaster regressions,

$$x_{t+1} - \mathbb{F}_t^i[x_{t+1}] = \beta_0 + \beta_1^i \mathrm{FR}_t^i + \nu_{t+1}^i, \quad \nu_{t+1}^i \sim \mathcal{N}(0, \sigma_{i,\nu}^2), \quad i = 1, \dots, I. \tag{5.3}$$

This yields a distribution of individual coefficients β_1^i, $i = 1, \dots, I$ where we look at the median coefficient. Since this can result in varying sample sizes for the estimation (due to the differ-

Table 1: Error-on-revision regression results

	Consensus			Individual					
Variable	β_1 (1)	SE (2)	Obs. (3)	β_1^p (4)	SE (5)	Obs. (6)	med(β_1^i) (7)	med(Obs.) (8)	I (9)
TB3M	0.22	0.12	321	−0.32	0.01	14,613	−0.27	39.5	216
TB6M	0.38	0.12	321	−0.25	0.01	12,706	−0.18	35.5	200
TB1Y	0.43	0.12	321	−0.23	0.01	12,993	−0.15	35.0	204
TB2Y	0.47	0.10	321	−0.20	0.01	14,796	−0.13	40.0	215
TB5Y	0.44	0.11	321	−0.21	0.01	14,719	−0.14	39.0	216
TB10Y	0.34	0.10	321	−0.24	0.01	15,034	−0.14	39.0	217
TB30Y	0.33	0.11	321	−0.28	0.01	13,999	−0.20	35.5	216

Notes: This table shows coefficients from forecast error on forecast revision regression. Column 1 to 6 show the coefficients of consensus time series regressions and individual-level pooled panel regressions together with standard errors (SE) and number of observations (Obs.). Column 7-9 shows the median coefficients, median number of observations and number of forecasters (I) in forecaster-by-forecaster regressions. For consensus time series regressions and pooled panel regressions, standard errors are Newey-West with the automatic bandwidth selection procedure of Newey and West (1994).

ent lengths of different forecasters in the sample), we keep forecasters only with at least fifteen observations. Furthermore, we winsorize outliers.[8]

Results of the error-on-revision regressions are presented in Tab. 1. We report point estimates and standard errors. For all interest rates, the null of FIRE can be rejected. The standard errors are Newey-West with the automatic bandwidth selection (Newey and West, 1994). Column 1 reports coefficients from the consensus regression. All of them are highly statistically significant. Throughout the regressions, $\beta_1 > 0$ indicates underreaction. This is consistent with the findings in the previous sections. Turning now to the results of the individual-level regressions provided in columns 4 and 7, we see broad-based evidence for overreaction. More specifically, the pooled panel coefficient β_1^p and the median coefficient med(β_1^i) are consistently negative. The panel coefficient is statistically significant. The median coefficient med(β_1^i) is, on average, slightly less pronounced than the pooled coefficient. Hence, both error-on-revision regression results point to overreaction in interest rates. These findings are similar to the one presented in Bordalo *et al.* (2020).[9]

What do these results imply for our analysis on yield curve expectations? In the previous section we provided evidence that belief formation of yield curve data shows strong initial underreaction to monetary policy shocks. Using the static approach of Coibion and Gorodnichenko (2015) corroborates that the consensus expectation formation of market participants underreact to news – irrespective whether these news are related to monetary policy or not. On top of that, this analysis reveals evidence for an overreaction in the individual-level error-on-revision regressions (Bordalo *et al.*, 2020). Since forecasters overreact to their own information relative to a rational benchmark, they concurrently do not react to all the information received by others. Agents simply do not

[8] We follow here the approach taken by Bordalo *et al.* (2020). They exclude forecasts which are five interquartile ranges away from the median. In case there is no variation in the interquartile range, we apply the interquartile range of the previous period. This ensures consistency of the forecasts.

[9] Differences in the exact size of the coefficients accrue to slightly different samples and the chosen forecast horizon. Bordalo *et al.* (2020) estimates coefficients for horizon $h = 3$.

observe the reactions of their peers – or ignore them – which creates a rigidity / stickiness in the consensus forecast. Information diffuses slowly and it takes time until overreaction is identifiable in aggregate outcome – this pattern is nicely provided from the IRF analysis in the previous section. This fits also in the story of delayed-overshooting in Angeletos *et al.* (2021). In particular, they compare implied coefficients of those regressions presented here and also find a combination of informational frictions and over-extrapolation.

6 Robustness analysis

In this section, we perform sensitivity checks along several dimensions. First, we vary the lag length, second, we choose different Bayesian prior setups and third, we use alternative variables in the VAR specification. Last, we re-estimate the model with stochastic volatility in the error variances to control for possible heteroscedasticity.[10]

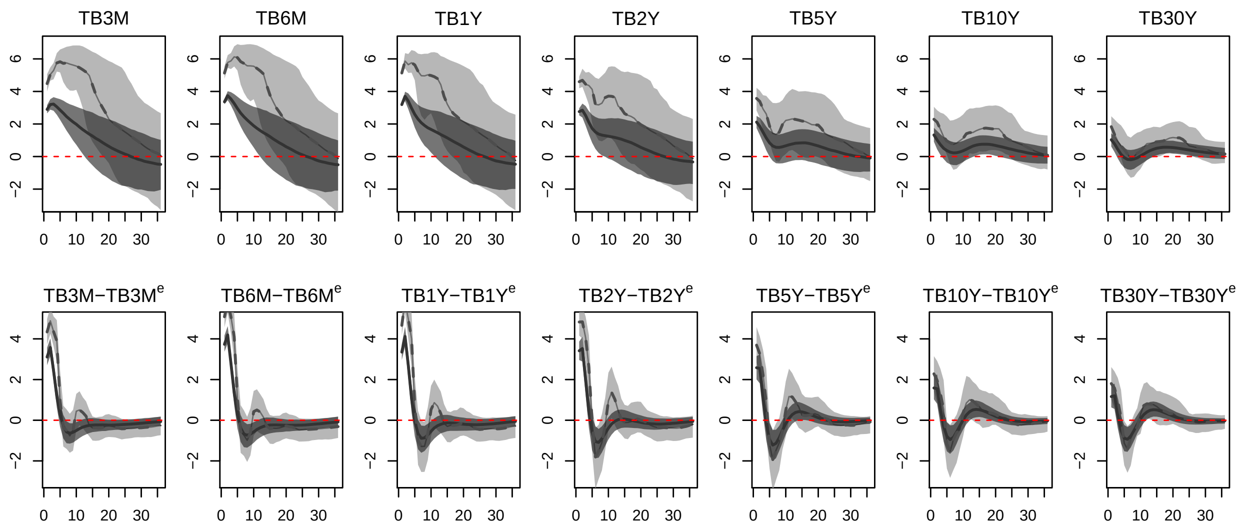
As is standard when working with monthly data, we use $p = 12$ in the baseline model. This rather long lag length comes with the drawback that the parameter space increases quite drastically. Hence, we decided to use $p = 2$ for the yield curve VAR due the high-dimensionality of the model. We opt for 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 to our baseline results. The sensitivity checks are performed for 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 alternative specifications. 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. 5 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 do not change significantly across specifications considered. The findings concerning the adjustment process of expectations discussed before still hold. It rather seems that some responses are amplified, 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, our results do not change qualitatively. We also 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 $\beta_2 - \beta_2^e$). The results show reactions similar to the ones obtained by our baseline specification. More specifically, the adjustment process for the monetary policy shock takes up to twenty months for the level factor, while it only takes up to eight

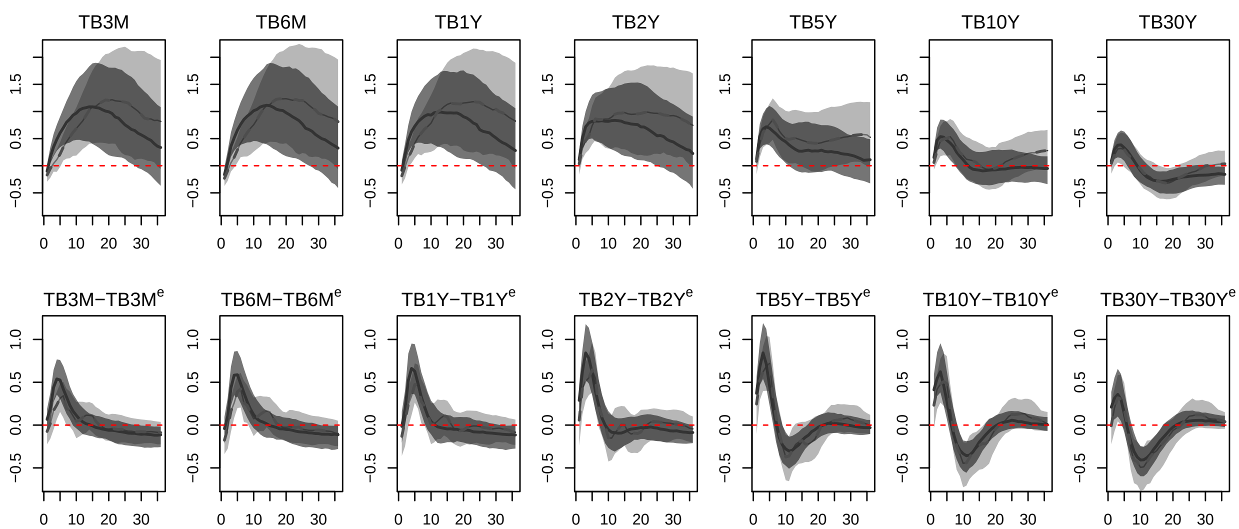
[10] More precisely, we rewrite the VAR in its Cholesky form as shown in Carriero *et al.* (2019) and implement stochastic volatility following Kastner and Frühwirth-Schnatter (2014).

Figure 5: Impulse Response Functions for Sensitivity Checks.

(a) Monetary Policy Shock



(b) Central Bank Information Shock



Note: Upper panel denotes the responses to a monetary policy shock, normalized to a decrease of the stock market index by 25 basis points. Lower panel denotes the responses to a central bank information shock, normalized to an increase of the stock market index by 25 basis points. 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.

months for the slope factor. When 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. Furthermore, we also apply the error-on-revision regression framework of Coibion and Gorodnichenko (2015) to get information on the adjustment process on a disaggregated level. 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 Delphic forward guidance.

First, our results indicate that US financial market participants significantly underreact to both monetary policy shocks on average. After the initial underreaction, we observe a rebound to overreaction, consistent with the findings of Angeletos *et al.* (2021). 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. Our results hence provide evidence against the assumption of rational expectations which 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. Using individual-forecast data, we also provide a potential explanation for the initially observed underreaction: On the individual level, market participants overreact but they are ignorant of responses from their peers. This creates an information rigidity at the aggregate level initially. After information has diffused, market participants tend to overreact also at the aggregate level and consistent with adjustments of individual beliefs. 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.

The empirical results presented in this paper can be used twofold. First, to guide the development of macroeconomic theory. In particular, macroeconomic models should resemble imperfect expectations, as has been exemplified in Angeletos *et al.* (2021). Dynamic stochastic general equilibrium models should thus incorporate a combination of informational frictions and overshooting behavior. Second, to inform optimal monetary policy and give policy recommendations. The literature on designing optimal monetary policy in the face of misspecified beliefs (see inter alia Adam and Woodford, 2012, Angeletos and La'o, 2020) together with the findings of this article helps giving policy recommendations. In order to counteract the strong initial underreactions due to informational frictions, central banks can resort to two strategies. First, a strong commitment to the current monetary policy stance can reduce the amount of uncertainty in the private sphere. Agents are permanently learning a central banks' monetary policy rule, and have to re-learn it again in case of policy shifts. Second, the initial underreaction can be counteracted by resorting to a leaning against the wind strategy. If the central bank tightens monetary policy stronger than necessary at first and relaxes it afterwards, it mirrors the responses in expectations due to *delayed overshooting*. This can then lead to welfare improvements.

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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 Bayesian Vector Autoregression

We estimate the reduced-form VAR(p) within a Bayesian framework. The law of motion of the M-dimensional vector $\boldsymbol{y}_t$ reads

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

where $\boldsymbol{A}_j$ ($j = 1, \ldots, p$) is the $M \times M$ coefficient matrix, $\boldsymbol{c}$ denotes the $M \times 1$ vector of constants and $\boldsymbol{\Sigma}$ is the $M \times M$ covariance matrix. To speed up computation, we use a simple factorization following Carriero *et al.* (2019). The factorization is applied to the covariance matrix $\boldsymbol{\Sigma}$ and reads as follows

$$\boldsymbol{\Sigma} = \boldsymbol{L}^{-1} \boldsymbol{D} \boldsymbol{L}^{-1'}, \tag{A.2}$$

where $\boldsymbol{L}^{-1}$ is a lower-triangular matrix with ones on the main diagonal and $\boldsymbol{D}$ is a diagonal matrix containing the volatilities. This allows us to estimate the vector autoregression equation-by-equation. We purse a Bayesian approach to estimation, because it allows to introduce a priori information to the model. Issues arising when estimating time series models like the small-sample bias and initial value dependence can thus be at least alleviated. Furthermore, Bayesian methods allow for regularization since VAR models are quite heavily parameterized. In the Bayesian paradigm, we have to elicit prior distributions over the parameters. Hence, we stack all coefficients in $\boldsymbol{\beta} = \text{vec}\left((\boldsymbol{A}_1', \ldots, \boldsymbol{A}_p', \boldsymbol{c}')'\right)$ and use the well-known Minnesota prior setup (Doan *et al.*, 1984).

$$\boldsymbol{\beta} \mid \lambda_1, \lambda_2 \sim \mathcal{N}(\boldsymbol{b}, \boldsymbol{V}) \tag{A.3}$$

Most macroeconomic time series seem to be characterized by a unit root (Litterman, 1986). We incorporate this prior belief that each endogenous variable included in the model presents a unit root in its first lags, and coefficients equal to zero for further lags and cross-variable lag coefficients. These translates into $\boldsymbol{b}$ being a vector of zeros except for the entries concerning the first own lag of each endogenous variable which are attributed values of 1.

$$\boldsymbol{b} = \text{vec}\left((\boldsymbol{I}_M, \boldsymbol{0}, \ldots, \boldsymbol{0})'\right) \tag{A.4}$$

For the prior variance-covariance matrix $\boldsymbol{V}$ it is assumed that no covariance between coefficients exist, so that $\boldsymbol{V}$ is diagonal. Also, Litterman (1986) argued that the higher the lag, the more confident we should be that coefficients linked to this lag have a value of zero. Therefore, prior variance gets smaller for higher lags. In particular, we differentiate between setting the variance on the own endogenous lagged variable or on cross-variable lag coefficients and deterministics

$$\boldsymbol{V} = \begin{cases} \left(\frac{\lambda_1}{k}\right)^2 & \text{for } i = j \text{ and the } k\text{-th lag and,} \\ \left(\frac{\sigma_i^2}{\sigma_j^2}\right)\left(\frac{\lambda_2}{k}\right)^2 & \text{for } i \neq j \text{ and the } k\text{-th lag,} \\ \lambda_3 \sigma_i^2 & \text{for the deterministic part of the model,} \end{cases} \tag{A.5}$$

In each case, the variance decreases with higher lag order. The hyperparameter λ_1 governs the tightness on own lag coefficients, while λ_2 governs the tightness on cross-variable lag coefficients. Furthermore, σ_i

denotes the OLS error standard deviations obtained by estimating univariate autoregressive models of order p. The hyperparameter $\lambda_3 = 100$ is for the deterministic part of the model. Since λ_1 and λ_2 are crucial and might exert a powerful effect on the posterior estimates, we infer them from the data. Similar to Giannone *et al.* (2015) we specify Gamma priors on $\lambda_s \sim G(0.01, 0.01)$ $(s = 1, 2)$. These Gamma priors are set to be weakly informative. This allows us to estimate the shrinkage parameters alongside the remaining coefficients of the model.

For the remaining quantities in the model, standard priors are assumed. More precisely, the free elements of $\boldsymbol{L}^{-1}$ follow a uninformative Gaussian distribution, i.e., $[\boldsymbol{L}^{-1}]_{ij} \sim \mathcal{N}(0, 10)\ \forall i < j$. The diagonal elements of $\boldsymbol{D}$ follow a Inverse-Gamma distribution, i.e., $[\boldsymbol{D}]_{ii} \sim G(0.01, 0.01)$. For robustness analysis, we also use the SSVS prior (George *et al.*, 2008) and the NG prior (Huber and Feldkircher, 2019) providing both a different parametrization of Eq. (A.5). For details we refer to the papers.

We briefly sketch the proposed Markov chain Monte Carlo (MCMC) algorithm. While the conditional posterior distributions of the coefficients and variances are available in closed-form and can be sampled from in a Gibbs step, we need an Metropolis Hasting within Gibbs step for drawing from the posterior distribution of λ_s $(s = 1, 2)$. We refer to Koop and Korobilis (2010) as an excellent resource on the estimation of Bayesian multivariate time series models.

C 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,

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

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

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

where the variable to be instrumented is arbitrarily chosen to be the first variable. Furthermore, $a_{0,11}$ is a scalar, $\boldsymbol{a}_{0,12}'$ 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

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

where

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

with

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

D Convergence Diagnostics

In this section, I evaluate convergence of the sampler laid out in App. B. To proceed, we look at three different convergence diagnostics. In an ideal setting, the sampler returns independent draws. The stronger the autocorrelation in the sampler, the more draws are needed. To evaluate the extent of autocorrelation in the chain, we use three different statistics. First, we compute inefficiency factors telling us how much draws we need for drawing one identically and independently distributed draw. Second, we have a look at the Raftery and Lewis's diagnostic statistic (Raftery and Lewis, 1992). It is also a measure of autocorrelation and returns an dependence factor which should not exceed 5 in the ideal setting. Third, we look at Geweke's convergence diagnostic (Geweke *et al.*, 1991). This is a test of equality of the means of the first 10% and last 50% of the MCMC chain. We report the share of Z-scores exceeding the critical value of 1.96.

For both models, convergence is achieved. Only for the hyperparameters λ_s ($s = 1, 2$) higher inefficiency factors and dependence factors are observed. This comes as no surprise since they are not drawn from a closed-form conditional posterior distribution, but with the help of Metropolis-Hasting simulation techniques which usually result in higher autocorrelation of the sampler. Nevertheless, the problem is not severe due to the high number of draws generated for both models. Both models are based on 10,000 posterior draws where we discard the first 5,000 as burn-ins. Furthermore, we discard all explosive draws (defined as the maximum eigenvalue of the companion matrix exceeds unity in absolute terms).

Table A2: Convergence statistics. Mean inefficiency factors and mean dependence factor for specific variable groups.

	$\boldsymbol{\beta}$	$\boldsymbol{\Sigma}$	$\boldsymbol{L}^{-1}$	$\boldsymbol{D}$	λ_1	λ_2	# Draws
Baseline Model							4,341
Inefficiency Factor	1.06	1.07	1.01	1.74	16.47	39.57	
Dependence Factor	1.01	1.02	1.01	1.06	10.00	11.90	
Geweke's Z-scores	0.09	0.00	0.04	0.00	0.00	0.00	
Yield Curve Model							3,506
Inefficiency Factor	1.03	1.03	1.01	1.26	4.90	12.40	
Dependence Factor	1.01	1.01	1.01	1.04	4.48	6.52	
Geweke's Z-scores	0.05	0.13	0.06	0.00	0.00	0.00	