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Identification of triggers of U.S. yield curve movements

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Highlights

- The macroeconomic news was the core trigger of U.S. Treasury yield volatility.
- The importance of news associated with capital flight has increased since 2011.
- Capital flight news became the dominant source of movements in the long yields.
- This highlights the growing importance of the U.S. Treasuries as a safe haven.

Abstract

We present new evidence for understanding the sources of daily movements in U.S. Treasury yields. We use a novel narrative approach combined with Bayesian inference to identify news-based triggers of yield movements between 2001 and 2019. We show that the U.S. macroeconomic news was the core trigger of U.S. Treasury yield volatility over most of the period under analysis. However, the importance of non-macroeconomic news associated with capital flight has increased significantly since 2011, and they became the dominant source of movements in the long end of the U.S. yield curve after 2016. This highlights the growing importance of the U.S. Treasuries as a safe haven asset and implies possible partial loosening of the relation between U.S. Treasury yields and the U.S. business cycle.

JEL classification

C38; C58; E43; E44

Keywords

Interest rate; Macrofinance model; Nelson–Siegel; Yield curve

1. Introduction

There is a clear dichotomy in views on U.S. Treasury yields in the literature. From one perspective, since the pivotal works of Ang and Piazzesi (2003) and Diebold et al. (2006), macroeconomic factors are viewed as the main source of volatility in yields. The yield curve is a benchmark for the cost of funds at various maturities, and yields are, therefore, macroeconomic variables directly linked to monetary policy and the business cycle. On the other hand, and simultaneously, a yield is linked to the price of the bond, which is a financial instrument with its supply and demand being affected by various additional factors. The importance of non-macroeconomic factors has been documented, among others, by Bernanke et al., 2004, Craine and Martin, 2009, Dai and Philippon, 2005 or Byrne et al. (2012). This dichotomy may present challenges when interpreting the shapes and dynamics of yield curves. Understanding the factors driving yield curve movements is therefore crucial for their correct interpretation.

To do so, we adopt a novel approach to attribute movements in the U.S. Treasury yield curve to various sources. Using news headlines, we identify prior candidates for dates when yields were affected by news in a certain category: Federal Reserve Board (Fed) announcements, macroeconomic news, Treasury auctions, financial market news and geopolitical uncertainty news that induced cross-border capital flight. Using a Bayesian approach, we update these dates and the magnitude of the impact of the news, which allows us to measure the degree to which the individual categories contributed to the historical variation in the yields.

Our approach is further motivated by several underlying issues. For instance, the interpretation of yield curve inversion as an indicator of a forthcoming crisis implicitly regards a shift in expectations about future monetary policy as the only source of the inversion. This interpretation may neglect the impact of events that motivate international capital flight to U.S. Treasuries as a safe haven, which may be only loosely related to U.S. macroeconomic conditions. The importance of correctly interpreting yield curve movements is also apparent from the historic experience with monetary policy challenges. In 2005, Fed chairman Alan Greenspan expressed the conundrum he faced given the decoupling of movements in short- and long-term yields. Foreign demand for U.S. Treasuries was identified as one of the most important causes of such decoupling (see, for example, Bernanke et al., 2004 or Byrne et al., 2012). Similarly, in 2017, the conundrum was partially revived, when the increase in short-term yields was only loosely followed by the movements in long-term yields. Again, non-macroeconomic forces were mentioned as an important source of decoupling (Bauer, 2017).

We accompany the evidence on the importance of non-macroeconomic causes of fluctuations in U.S. yields from the literature by own narrative news-based observations. As we demonstrate using news headlines, the recent global events inducing uncertainty such as eurozone debt crisis, Brexit referendum or global trade tensions resulted in significant cross-border capital flight seeking U.S. Treasuries as a safe haven. The extent of the international capital flight has been largely debated over the last decade (Avdjiev et al., 2020), closely linked with global search for yield related to the low yield environment (see Ammer et al., 2018, for instance). Similarly, the sensitivity of the cross-border capital flight on non-macroeconomic events increasing the uncertainty has been documented in the literature (Julio & Yook, 2016). All these pieces of evidence serve as the core motivation of our research: to confirm the hypothesis of growing importance of capital flight (and non-macroeconomic events in general) for explaining U.S. Treasury yield movements and to quantitatively evaluate the extent of these linkages.

We analyze triggers of yield curve movements by using a state-space representation, which may be seen as a combination of the dynamic Nelson–Siegel (DNS) model developed by Diebold and Li (2006) and a time-varying parameter regression model. Unlike the DNS model, the innovations in yields are included in our model as exogenous variables in the measurement equation. The transition equation captures the dynamics of the magnitude of how these innovations impact the yields. The innovations (triggers) are considered stochastic, as we combine priors gathered from news headlines with the likelihood of yield curve movements to obtain the posterior distribution of the innovations. Our method may be seen as complementary to the canonical DNS model; whereas the canonical DNS model identifies the "original" orthogonal shocks responsible for the deviation of yields from their steady-state values, our methods identify innovations in the form of triggers of movements related to how the original shock propagates over time into the yield curve.

Our results confirm that both macroeconomic and non-economic events are important triggers of yield curve movements. We assign the movements in the U.S. Treasury daily yield curve between December 2000 and June 2019 to the abovementioned categories. We show that an increasing proportion of the movements in longer yields was triggered by news about geopolitical risk or economic conditions abroad. Most important, over the last decade, these events became the dominant source of yield fluctuations, as they included developments in the eurozone debt crisis, capital flight following the Brexit referendum or international trade tensions.

The remainder of the paper is structured as follows. We position this paper in the literature in the second section. The third section presents data used, stylized facts about recent dynamics in U.S. Treasury yields and the narrative context of the largest movements. We describe our approach to identifying the innovations and evaluating their attribution to U.S. yield movements in the fourth section. The fifth section presents and discusses the results of the quantitative analysis and demonstrates their implications using a counterfactual analysis. Finally, the last section concludes the paper.

2. Literature review

The paper contributes to the term structure literature in two ways. First, it emphasizes that non-macroeconomic variables can also bear an important amount of information unspanned by the yield curve. This section summarizes the background behind this motivation and studies from the literature focused on macrofinancial modeling and the identification of macrofinancial yield curve factors. The most important findings from the literature are that (1) it is justifiable to extend the term structure model by observable factors, but (2) only macroeconomic variables are usually used for the extension. The second contribution of this paper is a novel means of attributing yield curve movements to yield innovations.

In a pivotal work in the macrofinancial modeling of interest rates, Ang and Piazzesi (2003) extend the canonical Gaussian no-arbitrage affine term structure model of Duffie and Kan (1996) to include macro factors and show that this extension provides important additional information about the nature of the yield movements. As an alternative approach lacking the no-arbitrage assumption, Diebold et al. (2006) extend the DNS model of Diebold and Li (2006) by including macroeconomic factors and demonstrate linkages between the macroeconomic factors and the yields.

These works led to the creation of a first generation of macrofinance models. The macroeconomic factors included in the macrofinance models usually represent business activity, price dynamics and a monetary policy rate or monetary aggregate. Ang and Piazzesi (2003) utilize two measures representing inflation and real activity and show that whereas these factors are responsible for most movements at the short end of the yield curve, the long end remains largely unexplained. Diebold et al. (2006) use manufacturing capacity utilization, the federal funds rate and annual price inflation. De Pooter et al. (2010) and Ludvigson and Ng (2009) utilize a large dataset that includes macroeconomic and financial variables and extract the most important principal components representing the common factors. Based on their relation to the original series, De Pooter et al. (2010) show that the first principal component is roughly related to real activity, the second component to price dynamics and the third component to monetary variables. Similarly, Kim and Wright (2005) study the specific role of inflation in explaining yield dynamics. As an additional view, Dai and Philippon (2005) focus on the importance of fiscal policy for explaining the dynamics of U.S. yields.

In an important contribution, Joslin et al. (2011) question the validity of such macrofinance models. The authors demonstrate that without additional restrictions in the transition equation, macrofinance models are equivalent to yield-only models. Therefore, as they argue, the canonical macrofinance models cannot provide additional information important for forecasting yields, as the models contain the embedded assumption that the macro factors are perfectly spanned by the yield curve. Joslin et al. (2014) show that such an assumption is not valid, i.e., there is important information on the macro variables not included in the yield curve. As a solution, Joslin et al. (2014) develop a new family of macrofinance yield curve models with unspanned macro variables that affect the price of risk and show that such models can be used to improve forecasting abilities and in-sample properties compared to yield-only models. Although the validity of the evidence supporting the *unspanned hypothesis* is partially called into question by Bauer and Hamilton (2017), it generally remains acknowledged that it is justifiable to extend the term structure models to include macroeconomic factors using either unspanned macro variables or a set of restrictions on the transition equation. The latter approach is utilized in more recent contributions by Bauer and Rudebusch (2020) and Cieslak and Povala (2015), who show that the yields, risk premia and excess returns may be well explained by models with specific transition equation constraints that permit one to distinguish cycles and trends in inflation and the real rate as yield factors.

Multiple studies have focused on understanding the factors behind the movements in the term premium and bond excess returns instead of capturing the dynamics of the yield curve as a whole. Campbell and Shiller (1991) and Cochrane and Piazzesi (2005) demonstrate the partial predictability of excess bond returns using Treasury yields and forward spreads. These findings underline the importance of term premia for understanding yield dynamics. The possible decoupling of long and short yields due to a variation in term premia was extensively discussed after the testimony of Alan Greenspan in 2005, where the Fed chairman admitted that he faced a conundrum of declining longer yields despite restrictionary monetary policy steps. Backus and Wright (2007) demonstrate that multiple factors were responsible for this decoupling, all of which affected the yields through a decrease in term premia. Ludvigson and Ng (2009) demonstrate that macro factors (output and price dynamics) are responsible for the countercyclicality of the term premia. Similarly, Wright (2011) reveals a linkage between bond risk premia and inflation uncertainty. The relation between the risk premium and economic risks is also inherent in the structural approach to yield curve modeling, as in Rudebusch and Swanson (2012).

Importantly, the literature only rarely contains analyses of the linkages among bond yields, term premia and/or excess returns and non-macroeconomic factors. Of the abovementioned contributions, Dai and Philippon (2005) focus on the effects of fiscal policy. Bernanke et al., 2004, Byrne et al., 2012 and Craine and Martin (2009) all link the decline in term premia underlying Greenspan's conundrum to the effect of international portfolio reallocations towards U.S. Treasuries. Bauer (2017) highlights the decreasing longer-term yields despite increasing federal funds rate between 2015 and 2017 and concludes that the revived conundrum was caused by a combination of decreasing inflation expectations, fiscal policy shocks and geopolitical uncertainty effects, explicitly mentioning the declines in U.S. Treasury yields on days with news headlines about tensions with North Korea.

We build on these latter efforts to emphasize the effects of non-macroeconomic factors when explaining yield movements. In doing so, our aim is to contribute to the literature by providing empirical evidence proving that, similar to the benefits of adding macroeconomic variables into the models, it can also be beneficial to add non-macroeconomic variables, especially for understanding yield variations at higher frequencies.

3. U.S. treasury yield movements and news headlines

This section gathers several stylized facts about daily U.S. Treasury yield movements between December 2000 and June 2019.[3] We identify historical yield movements and summarize related news headlines. We show initial narrative findings related to the density of various categories of factors as mentioned in the headlines, which serves as a motivation for the quantitative analysis in the rest of the paper.

We use daily U.S. Treasury yield data from Fed (2019) for the period between December 4, 2000 and June 28, 2019.[4] This period was selected as optimal given its homogeneous news data coverage, which we demonstrate below. The historical paths of yields for selected maturities are displayed in Fig. 1; basic descriptive statistics are displayed in Table A.1 in Appendix A. Over the period of analysis, the longer yields followed a downward trend. The short-term yields fluctuated around the trend along with the business and monetary policy cycle, including periods of both restrictive monetary policy (2000, 2005–2007, partially since 2017) and monetary loosening (2001–2004, 2008–2016).

The realized or expected changes in monetary policy were an important source of the daily volatility of short-term yields, with the cluster of increased volatility observed over the period 2007–2008 (see Fig. 2) being directly attributable to a period of sizable changes in the federal funds rate (see Fig. 1). Unlike the short-term yields, the spikes in longer yield daily movements were often related to non-macroeconomic events. Increased volatility in longer yields appeared after the outbreak of the Great Recession in September 2008. Most important, the three largest 10Y Treasury daily movements since 2016 were linked to non-macroeconomic news (see Table C.1 in Appendix C and the description of the source of the news reports below). The result of Brexit referendum in June 2016 led to a decline in the U.S. yields that was attributed by news reports to an international flight to quality; the result of the U.S. presidential election in late 2016 was mostly attributed to a combination of expectations about a fiscal impulse and a rise in risk premia, and the May 2018 uncertainty over Italian fiscal sustainability sparked a renewed flight to quality and subsequent decline in U.S. Treasury yields.

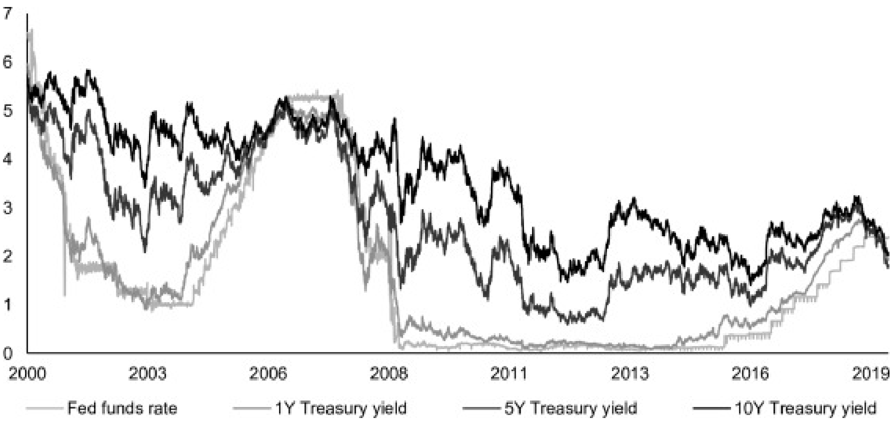

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Fig. 1. U.S. Treasury yields (in %, 2000/12–2019/06).

Fed (2019).

To identify the triggers of the yield movements and measure their importance, we gather economic news headlines through the News Monitor application on the Refinitiv EIKON platform. Specifically, we gather headlines that (i) mention U.S. Treasury bond prices or U.S. Treasury yields, (ii) describe the direction of their movement and (iii) state some source of the movement (for details, see Appendix B). By applying this filtering, we obtain 9,100 news headlines. We further evaluate each headline and remove duplicates and headlines that, despite satisfying the filtering criteria, do not provide sufficient information, which reduces the number of usable headlines to 3,065 that explicitly state causality between some trigger and a direction of the daily movement of the yield or the bond price. Thereafter, by observing the most frequently mentioned sources of the movements, we define five categories of triggers. We once again observe each headline, or even read the text of the article, to correctly assign the trigger of the yield movement to the particular category. The first category gathers the triggers linked to fiscal policy-related events, mostly Treasury auctions. Second, Fed announcements mentioning either conventional or unconventional monetary policy steps are frequently mentioned in headlines as a source of the yield movement, especially when the announcements included a surprise. The third category includes the U.S. macroeconomic news and represents the most common cause attributed to daily yield fluctuations. Events affecting the rest of U.S. financial markets, especially the equity market, were responsible for intra-U.S. flight to/from quality (i.e., the fourth category), whereas international events changing the attitude of global investors towards risk often triggered cross-border safe haven flight into or from U.S. Treasuries (representing the triggers in the fifth category). The list of keywords used to map the headlines to these categories is included in Appendix B.[5]

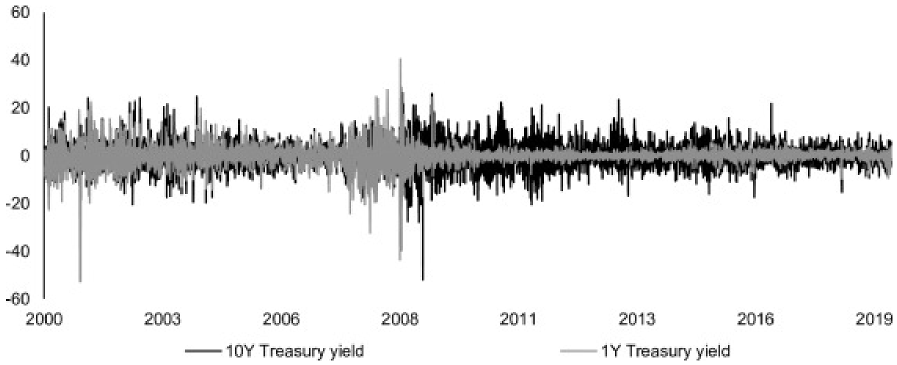

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Fig. 2. Daily changes in U.S. Treasury yields (in bps, 2000/12–2019/06).

Fed (2019).

The frequency of news reports in various categories is shown in Table 1. As the table shows, the frequency of reports was relatively stable over the period of analysis, which is important given the possible changes in news providers or the reach of the source database. Over the period of analysis, at least two headlines were identified almost every week, which may serve as a good basis for covering the most important historical movements in yields. Because we focus on the relative importance of news in various categories, the accuracy of headline filtering is more important than the number of identified events. In other words, we applied rather strict filters, ensuring that the headlines that pass the filters correctly identify the nature of the trigger (i.e.,the category), at the expense of losing some in-sample fit. This has consequences for the results of our quantitative analysis, as we demonstrate in the next sections: the yield movements in periods of less-volatile bond markets and no significant innovations are only partially explained by our model because the news is non-informative over these periods. On the other hand, important events, which triggered large shifts in yields, are believed to be identified by the news headlines with sufficient precision.

The frequency of headline categories shows gradual growth in the triggers related to capital flight over the observed period. This supports the hypothesis proposed by this paper that the factors affecting U.S. Treasury yields through their role in global portfolios became stronger over time. The number of published news items itself does not imply stronger effects in terms of yield movements. However, a detailed examination of the headlines during periods of increased yield volatility further supports the hypothesis. We identify the largest daily gains and declines in the ten-year U.S. Treasury yields each year and find headlines linked to the days of the movements (see Table C.1 in Appendix C). Fed meetings, macroeconomic data announcements and treasury auctions were the topics most frequently linked in news headlines to the largest yield movements between 2001 and 2010. Since 2011, however, non-macroeconomic events triggered some of the largest movements. As an additional evidence, we also evaluate the correlations between the selected yields and the dummies for news headlines on particular days (see Table A.1 in Appendix A). The results show that the correlations between yield movements and presence of news headlines are comparable across all categories under consideration except for the fiscal policy. Therefore, the yields movements may be expected to be triggered by macro news and non-macroeconomic events equally frequently. The remainder of the paper quantitatively evaluates this hypothesis, measuring both the effect of changes in the frequency of various categories of triggers and the linkage between yield volatility and news headlines.

Table 1. News Headline Frequency.

	Fiscal policy	Fed surprise	Macro news	Financial market	Capital flight	Total
Average monthly number of headlines						
2001–2005	0.72	2.17	5.87	4.38	1.55	14.68

	Fiscal policy	Fed surprise	Macro news	Financial market	Capital flight	Total
2006–2010	0.98	1.48	5.08	2.35	1.75	11.65
2011–2015	1.72	2.58	6.93	2.65	2.90	16.78
2016–2019	2.74	3.76	7.05	4.64	5.05	23.24
Share of headlines per category (in %)						
2001–2005	4.88	14.76	39.95	29.85	10.56	
2006–2010	8.44	12.73	43.63	20.17	15.02	
2011–2015	10.23	15.39	41.31	15.79	17.28	
2016–2019	11.78	16.19	30.33	19.98	21.72	
Total number of headlines						
Frequency	320	532	1369	758	584	3563
Share (in %)	8.98	14.93	38.42	21.27	16.39	

Note that the presented total number of headlines for all categories (3565) is larger than the number of originally obtained headlines (3065) since some headlines included keywords from multiple categories and therefore served in the quantitative analysis as multiple priors (see the next section for details).

News Monitor at EIKON — Refinitiv, author's calculations.

4. Methodology

This section summarizes the method we use to quantitatively evaluate the abovementioned intuition and hypothesis. To do so, we use a time-varying parameter regression model with elements of the DNS model. The model consists of three building blocks that link the daily change in yield $y_t(\tau)$ with maturity τ to the presence of an innovation (a trigger), which we obtain from the news headlines.[6]

First, the model reduces the dimension of the yield curve by using several common factors to parametrize the whole yield curve. We obtain the factors using the Nelson and Siegel (1987) representation of the yield curve. This representation is linear in the factors, which allows us to use it directly to capture the dynamics of the first differences of yields, which are our focus, instead of the levels of yields. Therefore, we represent the daily change in the yield curve $\{dy_t(\tau)\}_\tau$ by a change in three common factors $\{dF_{f,t}\}_{f=1,2,3}$ as follows:

$$dy_t(\tau)=\sum_{f=1}^{3} L_f(\tau)dF_{f,t}+\nu_t(\tau) \quad . \tag{1}$$

The factor loadings

$$L(\tau)=\left[1 \quad , \quad \frac{1-e^{-\lambda\tau}}{\lambda\tau} \quad , \quad \frac{1-e^{-\lambda\tau}}{\lambda\tau}-e^{-\lambda\tau}\right] \tag{2}$$

are functions of τ and a fixed parameter λ, which we set to 0.0821 to ensure an optimal fit, minimizing the fitting error $\nu_t(\tau)$. We also considered the value 0.0609 presented in Diebold and Li (2006) and obtained very similar results. Following the functional forms of the factor loadings with respect to the maturity, the factors $F_{f,t}$ can be referred to as a level, a slope and a curvature of the yield curve.

The second building block of the model is the linkage between the changes in factors $dF_{f,t}$ and the observed innovations $x_{c,t}$ for the innovation categories $c=1,2,\ldots,C$. We link them using linear regression with time-varying parameters $\beta_{c,f,t}$:

$$dF_f, t = \sum_{c=1}^{C} \beta_{c,f,t} x_{c,t} + \upsilon_{f,t} \quad . \tag{3}$$

As the time-varying parameters are factor- and category-specific, the total number of these parameters is $3C$. The combination of Eqs.(1), (3) provides the final measurement equation of our model:

$$dy_t(\tau) = \sum_{f=1}^{3} L_f(\tau) \sum_{c=1}^{C} \beta_{c,f,t} x_{c,t} + \epsilon_t(\tau) \quad . \tag{4}$$

The measurement error $\boldsymbol{\epsilon_t} \sim \boldsymbol{N}(\mathbf{0}, \boldsymbol{R})$ is given as a combination of the fitting error $\boldsymbol{\nu_t}$ from Eq.(1) and a sum of the regression errors for the three factors $\sum_{f=1}^{3} L_f \boldsymbol{\upsilon_{f,t}}$ from Eq.(3). For simplicity, we assume the errors to be mutually uncorrelated.

To complete the model, we formulate a transition equation for the time-varying parameters $\{\beta_{c,f,t}\}_{f=1,2,3;c=1,2,...,C}$. We gather the parameters in a $3C$-dimensional vector $\boldsymbol{\beta_t}$ assumed to follow a random walk:

$$\boldsymbol{\beta_t} = \boldsymbol{\beta_{t-1}} + \boldsymbol{\eta_t} \quad , \tag{5}$$

where $\boldsymbol{\eta_t} \sim \boldsymbol{N}(\mathbf{0}, \boldsymbol{Q})$ represents the random disturbances in the transition equation. Together, Eqs.(4), (5) form a state-space representation of the dependency of yield movements on the appearance of an innovation from category $\boldsymbol{c}$. As is common in the state-space framework, we assume the random vectors $\boldsymbol{\epsilon_t}$ and $\boldsymbol{\eta_t}$ to be mutually unrelated.

Our method may be seen as complementary to the canonical DNS model, rather than competitive. In the DNS framework, the yield curve shocks are identified as innovations in processes of the latent or observable factors $\widetilde{\boldsymbol{F}}_t$, which themself enter the transition equation. Since Diebold and Li (2006), the joint dynamics of these factors have typically been specified as a stationary vector autoregression (VAR) process that allows the shocks to propagate gradually. A possible explicit inclusion of macrofinancial series into the joint dynamics of the factors, to explain the macrofinancial linkages, is presented by Ang and Piazzesi, 2003, De Pooter et al., 2010, Diebold et al., 2006 and Joslin et al. (2014). In these works, the inclusion of macro series implies that the model may be specified on a monthly or quarterly frequency, for which the macro series are available. This is useful for considering a macroeconomic perspective of the yield curve, because it, together with the stationary VAR process, allows the researcher to capture the gradual propagation of the initial shock into business cycle dynamics, the monetary policy rate and the gradual response of the yields. However, the financial view of the yield curve may suffer from the use of the monthly data because (i) a liquid financial market, including the treasury market, is expected to adjust prices almost immediately, and (ii) an important part of the information about the yield movements between two end-of-month observations may be lost. In other words, using the monthly frequency may result in an aggregation and a mutual compensation of multiple sources of yield movement within a single month, which would imply an underestimation of the importance of certain events.

Therefore, to be able to evaluate the daily movements of yields, we include the innovations in yields as exogenous variables $x_{c,t}$ in the measurement equation (Eq.(4)). The transition equation (Eq.(5)) then captures the dynamics of the magnitude of how these innovations impact the yields. The need for daily data further explains why we obtain information about innovations from news headlines instead of macro series.

To illustrate the linkage between our and the canonical DNS approach, it can be highlighted that the shocks in the DNS approach (appearing in the transition equation) and the innovations in our approach (i.e.,the triggers of the movements in the measurement equation directly affecting the yields) would be equivalent under three conditions. First, the markets have to be efficient, i.e.,correctly anticipate and price future consequences of the shocks, given the information available at the time of the shock. Second, the maturity of the bond has to be longer than the horizon of the shock propagation. This condition ensures that the expected gradual propagation of the shock in the DNS approach is fully reflected in the change of the yield, equivalently to the one-off adjustment following the innovation in our approach. Third, the yields must not be mean-reverting after the initial impulse, because our model assumes one-off change in yields after the innovation appears, without any future reversal. The third theoretical condition is the most questionable, as the yields are frequently considered to converge to a long-term equilibrium, although this view has been recently questioned(Bauer & Rudebusch, 2020).

For example, an unexpected adverse demand shock may lead to temporary decrease in the monetary policy rate, ceteris paribus. The monetary policy authority may respond with a lag, subject to its policy function and the gradual impact of the adverse shock on inflation. The short end of the yield curve evolves together with the path of the monetary policy rate. In the DNS approach, this evolution would be modeled as a gradual transition of the factors $\widetilde{F}_t$ and, subsequently, of the yields, following the single initial shock to one of the factors. In our approach, the dynamics would be captured as a series of innovations $\{x_{c,t}\}_{t=1,2,...}$ that together represent gradual adjustments of monetary policy rate and other related effects. This is the consequence of the duration of the shock propagation being longer than the maturity of the bond at the short end of the yield curve.

However, in the case of the long end of the yield curve, efficient markets would imply that all the future expected monetary policy rate adjustments and changes in risk premia would immediately be priced in the bond yields, given that the entire transition effect occurred before the maturity of the bond. In both the DNS and our approach, this would imply a one-off jump adjustment in the yield. If the DNS model is specified as stationary, it then implies a gradual return of the yields to their steady state. In our approach, the possible return to the steady state represents new information and is therefore linked to a new innovation x_t.

The view forms our interpretation of the results. Our interpretation focuses on the news headlines as signals of an existence of triggers that influence the yields along the path they follow. For long yields, these triggers may therefore be considered as almost equivalent to the initial shocks, whereas for the short yields, these triggers are rather indicators representing whether the initial shock propagates as expected.

Finally, **the third building block** includes the method of how the innovations $x_{c,t}$ are obtained. We use the news headlines introduced in the previous section. News-based identification of an innovation may be inaccurate due to either an imprecise timing of the article (reports published on a certain day may either reflect the current day or be an ex post commentary on the situation from the previous days) or an incorrect opinion of the analyst regarding the nature of daily yield movements. We therefore view the innovations (the triggers) as stochastic, where the day of the publication of a headline represents the mean value of a prior distribution of the day when an innovation in the given category may appear (i.e.,regarding t in $x_{c,t}$). Using the Bayesian approach, we combine such priors gathered from the news headlines with the likelihood of yield curve movements to obtain the posterior distribution of the *location* of the innovations. Specifically, we use a normal distribution centered on the date that each headline was published with three business days' standard deviation as the prior distribution for each innovation location.

The filtering criteria we apply to gather the sample of headlines allow us to ensure that the sign of the innovation is stated in the headline (see AppendixB).[7] However, the news-based identification of the triggers implies that the magnitude of an innovation is not known, although it is to some extent possible to differentiate news discussing significant movements from news discussing only mild volatility. Therefore, for an innovation $x_{c,t}$ in category c, we know the prior for the time t and the sign, but not the absolute value of the magnitude of the innovation. We solve this problem using a combination of two model elements. First, we estimate the *magnitude of the innovation* in its absolute value within the Bayesian setup. We use a log-normal prior distribution for the absolute value of the magnitude with both mean and standard deviation equal to one. This implies that the mode of the distribution is also equal to one, i.e.,the prior tends to place the magnitude of the innovations close to unit size if the data do not state otherwise. Second, by introducing the time-varying parameters $\boldsymbol{\beta}_t$ as defined above, we model the *impact of the innovations*. The intuition behind including both the *magnitude* and the *impact* variables lies in their different specifications and estimations. The time-varying impact variables $\boldsymbol{\beta}_t$ are estimated within the state-space setup using filtering and therefore have the capacity to show longer-term trends in the importance of innovations in various categories. In contrast, the mutually independent magnitudes of $x_{c,t}$ may be seen as certain "adjustments" of the innovations that help the model fit the naturally varying importance of unique events. Therefore, introducing the magnitude allows us to distinguish between the usual idiosyncratic volatility of yields related to individual events and longer-term trends in volatility and its causes.

We estimate the model using Bayesian updating, utilizing the Gibbs sampling procedure with the Metropolis Hastings step for sampling the location and magnitude of the innovations. The details on the estimation procedure are summarized in Appendix D. The prior distributions of the parameters other than innovation location and magnitude (i.e., the covariance matrices of measurement errors and of random disturbances in the time-varying parameter process) are set as standard in the literature; details are included in Appendix E. Since the Gibbs sampling algorithms for state-space models usually require a large number of iterations to converge, we set the number of burned iterations to 50,000, despite the relatively quick convergence of likelihood and stability of the results. We then save 5,000 iterations, which provides sufficient dimensions for evaluating the posterior probabilities. The results of the estimation comprise the posterior distribution of the location and the magnitude of the innovations $\boldsymbol{x}_{c,t}$, the posterior distributions of the covariance matrices $\boldsymbol{Q}$ and $\boldsymbol{R}$ and the posterior distribution of the time-varying parameters (model states) $\boldsymbol{\beta}_t$.

5. Empirical results

After estimating the models, using the data as described in Section 3, we begin by describing the main results and discuss their implications. Thereafter, we provide further comments and outline the results for individual components of the model. At the end of this section, we also present the results of a counterfactual analysis that offers an additional perspective on the obtained results.

5.1. Main results

The aim of the paper is to measure the importance of various categories of events when explaining the variability in U.S. Treasury yields. To do so, we compare the observed and model-implied daily changes in yields. The model-implied values are obtained from Eq. (4) by plugging in the posterior mean and selected quantiles for $\boldsymbol{\beta}_t$ and $\boldsymbol{x}_{c,t}$. A separation of the model-implied changes into the contributions of individual innovation categories allows us to obtain a measure of the importance of the categories.

We show the results aggregated per year to emphasize the most important findings. The annual changes in yields are calculated as a sum of daily movements over each year. The mean posterior model-implied annual changes of one-year and ten-year yields are presented in Fig. 3. The figure shows several important findings. First, we focus on the triggers related to the monetary policy response to crises. As the results show, the decline in short rates in 2001 was broadly triggered by a Fed announcement, whereas the 2008 rate decrease was expected from macroeconomic news and especially in relation to financial market events, i.e., before to Fed's reaction. Second, focusing on the differential transmission of the Great Recession into short- and long-term yields, we observe that the macroeconomic news triggered the response of short-term yields in 2007, whereas the longer Treasuries priced the macroeconomic conditions gradually between 2007 and 2015. This shows that the depth of the crisis and the extent of the monetary policy response, including quantitative easing, were initially underestimated — otherwise, the longer yields would have adjusted more quickly. Third, capital flight affected the yields mostly in the same direction as did the other categories of innovations, i.e. the flight to/from quality in periods of market uncertainty/optimism served as a multiplier of the other triggers. Finally, the extent of the unexplained movements is significant, although not dominant. This highlights possible further improvements in the news headlines sample (i.e., using body of news articles instead of mere headlines), which we see as an interesting challenge for future research. However, we do not consider this to be a fatal weakness of our model.[8]

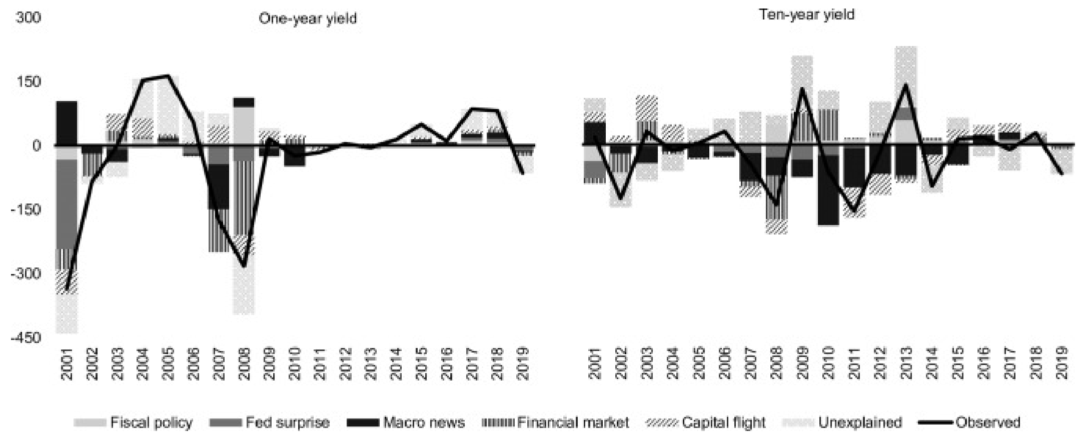

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Fig. 3. Annual yield movements and their decomposition (in bps).

The annual changes may lack a significant amount of information on intra-year movements that may compensate for each other. Therefore, we also calculate the absolute value of the daily movements, both observed and model-implied. The annual sums of the daily absolute movements attributed to each category of innovation, compared to the total model-implied absolute movements, are shown in Fig.4 (for the one-year Treasury yield), Fig.5 (for the ten-year Treasury yield) and Table2.

As it is shown, the events captured by the macro news were historically the most important triggers of yield changes. However, their importance has decreased since the Great Recession in favor of capital flight events that gradually became the most important source of yield changes at the end of the period of analysis. The share of the total model-implied and observed historical variance (bottom-right panels of the figures) was highly volatile, between 20 and 80% of the observed variance (but less than 50% in the case of ten-year Treasury yields). This is mostly a consequence of the presence of less significant "technical" movements and corrections that may have driven the Treasuries market in periods lacking significant innovations and were therefore poorly captured by the news headlines. For the short-term yield, the decreased variance since 2009 (see Fig.2) in a low-yield environment may partially explain the limited robustness of the share of total explained variance.

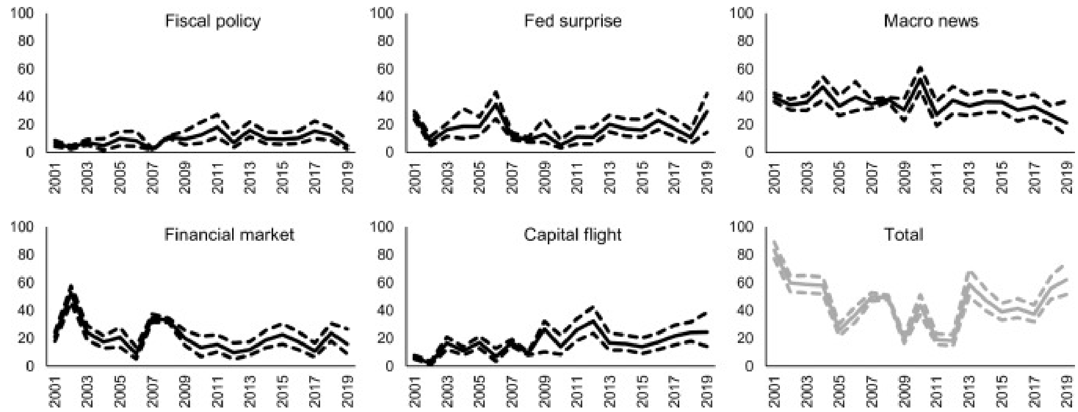

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Fig. 4. Shares of Annual Absolute Yield Movements, One Year (in %). Note that the shares of the five categories are calculated as an annual sum of absolute values of model-implied daily movements in the yield for the given category as a percentage share of the total annual sum of absolute values of model-implied daily movements. The share of the total absolute model-implied changes (bottom-right panel) is calculated as the percentage share of the observed annual sum of absolute values of movements in the yield. The dotted lines represent 10% and 90% credible intervals.

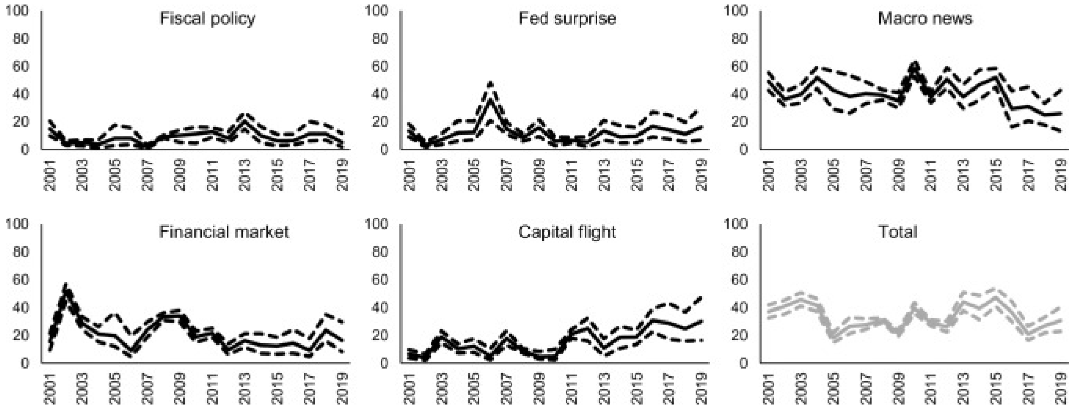

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Fig. 5. Shares of Annual Absolute Yield Movements, Ten Year (in %). See note at Fig.4 for details on the figure.

The presented identified increase in the importance of capital flight events confirms the main hypothesis of the paper. Furthermore, it has implications for the discussion of the spanning hypothesis, i.e.,whether the (macro) factors affecting the yields are perfectly spanned by the yield curve. The literature either rejecting (Joslin et al., 2014, for instance) or supporting (Bauer & Hamilton, 2017, for instance) the spanning hypothesis mostly focuses on macroeconomic variables (see Section2). Our results do not resolve this discussion but hint that the discussion should focus also on the non-macroeconomic factors as an important source of the variation in yields.

Table 2. Relative Shares of Annual Absolute Yield Movements by Category (in %).

	Fiscal Policy		**Fed surprise**		**Macro news**		**Fin. market**		**Capital flight**	
	1Y	**10Y**	**1Y**	**10Y**	**1Y**	**10Y**	**1Y**	**10Y**	**1Y**	**10Y**
2001	6.45	14.91	26.72	13.57	39.61	49.38	21.10	15.48	6.26	6.66
2002	3.44	4.58	7.76	3.32	34.12	36.23	52.65	51.86	2.03	4.01
2003	7.29	5.03	16.31	7.24	35.91	39.86	24.21	28.78	16.73	19.09
2004	4.77	3.72	18.73	12.16	47.09	52.28	17.41	21.34	10.89	10.49
2005	9.95	8.47	18.57	13.15	33.19	44.75	20.69	20.78	16.97	12.84
2006	8.37	8.49	34.42	37.31	39.71	39.69	8.83	9.35	6.87	5.15
2007	2.07	1.74	11.51	15.03	34.76	40.85	34.49	24.23	16.80	18.15
2008	11.03	9.44	9.04	8.76	37.97	39.33	32.98	33.57	9.06	8.91
2009	9.54	10.34	12.99	15.78	30.53	35.29	20.18	34.00	26.66	4.60
2010	12.47	11.39	5.34	6.00	52.32	58.72	13.38	19.04	13.88	4.85
2011	18.14	12.89	11.17	6.69	26.97	37.60	15.57	21.79	26.13	21.04
2012	7.17	8.38	10.95	5.53	37.28	51.10	9.70	9.74	32.29	25.25
2013	15.90	20.69	20.05	13.68	33.35	38.20	11.85	16.34	16.78	11.09
2014	9.82	10.49	17.02	9.40	36.31	47.87	18.80	13.16	16.08	19.09
2015	9.36	6.31	16.04	9.97	36.19	52.27	22.66	12.51	13.85	18.94
2016	10.19	6.63	22.95	17.06	30.47	30.02	17.51	14.81	17.31	31.47
2017	15.33	12.03	17.03	15.01	32.78	32.67	10.77	9.79	21.66	30.50
2018	12.57	11.83	10.87	11.72	26.84	26.03	23.74	24.77	24.26	25.66

	Fiscal Policy		Fed surprise		Macro news		Fin. market		Capital flight	
	1Y	10Y	1Y	10Y	1Y	10Y	1Y	10Y	1Y	10Y
2019	4.84	5.63	29.26	17.14	21.23	27.66	15.87	17.54	24.42	32.03

Note that the median shares of the five categories are displayed. They are calculated as an annual sum of absolute values of model-implied daily yield movements for the given category as a percentage share of the total annual sum of absolute values of model-implied daily movements. Therefore, for each year and each maturity, the sum of the shares equals 100%.

News Monitor at EIKON — Refinitiv, author's calculations.

We further support our findings by a robustness check for the ten-year yield. We split the period of analysis into two sub-samples, separated by the Great financial crisis, and estimate the model for each sub-sample. The results are very close to the full-sample results (see Appendix F), which proves sufficient robustness of our conclusions. Certain differences appear in individual years (the importance of macro news has increased in favor of Fed surprise in 2006 and in favor of fiscal policy in 2013, for instance), but the main trends in the shares remain unchanged.

5.2. Discussion of the estimated parameters

To further understand the results, it is useful to display the elements forming the main results. These are (i) the posterior location of the innovations $x_{c,t}$, (ii) their posterior magnitude and (iii) the posterior distribution of the time-varying parameters. The figures accompanying the text below are included in Appendix G.

The posterior location of the innovations is shifted slightly towards later dates compared to the day when the news was published. The average difference over the full sample was 0.61 business days. We interpret this as indicating that the news is timely, i.e., the model estimation does not generally tend to shift the location into the past, which would be needed if the news were published with a delay. In contrast, the slightly forward-looking nature of the news can be seen as caused by the events that happened after markets closed and, therefore, the news was published before it was priced in on the next business day. The lagged posterior distribution of the innovation location after the news was published also signals a certain momentum in the response of the yields, either because the innovation itself was distributed over time or because the market responded with limited efficiency. The posterior distribution had a heavy upper tail in 2008 and 2011 (see Fig. G.1), which signals certain momentum in the market response over periods with increased uncertainty (the U.S. subprime mortgage crisis and the eurozone debt crisis; see Table C.1).

The posterior distribution of the magnitude of innovations shows that in most years, the average magnitude of the innovations is less than that implied by the prior distribution (see Fig. G.2).[9] The only exception is the year 2008, when the magnitude increased instead (see Fig. G.3). The results thus show that the motivation for including the magnitude parameter was correct, as it allows the model to distinguish periods of increased volatility without the need to introduce a more complex model that would allow for stochastic volatility.

Finally, the values of the time-varying parameters $\beta_{c,t,f}$ – the sensitivity of the latent yield factors $F_{f,t}$ (the level, slope and curvature) to yield innovations $x_{c,t}$ – show some longer-term trends in the impact of the innovations on the yields. As Fig. G.4 shows, the sensitivity of the $F_{1,t}$ factor (the level, i.e., the yield component common for yields to all maturities) increased significantly for the Fed surprise category of events between 2008 and 2010, for macro news events between 2003 and 2006 and since 2010 and for capital flight events between 2011 and 2018. The results suggest that the yield curve as a whole had an increased sensitivity to innovations from the particular categories over these periods. The sensitivity of $F_{2,t}$ factor (the slope, i.e., the yield component with a decreasing weight for increasing maturity) was elevated for financial market events and fiscal policy events first during 2008 and, afterwards, between 2010 and 2015. Over 2008, the short-term rate reached a record low level, mostly following financial market news — the sensitivity of the slope factor especially to the financial market news is therefore justified. Between 2010 and 2015, the short-term rate remained at the low level with limited volatility. Therefore, we interpret the elevated sensitivity of the slope factor to the financial market news in the way that if there was volatility in the short rate over the period 2010–2015, it was linked predominantly to financial market causes.[10]

Note that we do not enforce nonnegativity of the time-varying parameters. The negative values may seem ambiguous, as we handle the sign of the innovation explicitly in the measurement equation by obtaining it directly from the headlines. The negative sign is a consequence of an imbalance between the dimension of the yield curve (a set of maturities) and the number of innovations (a single value for each innovation). Therefore, if different parts of the yield curve respond differently to the innovation (in either magnitude or sign), the negative value in the sensitivity of one of the latent factors allows the yield curve (or its movements) to take various shapes. The benefit of such an approach is the availability of information from the whole yield curve.

Our main conclusion from the detailed analysis is that the hypothesis that capital flight events have become more important for the yield curve movements over the last decade is confirmed. The time-varying parameter linking the capital flight innovations and the level of the yield curve is significantly positive after 2010, with two peaks in 2011 and 2016.

5.3. Counterfactual analysis

To offer an additional view on the implications of our findings, we calculate counterfactual paths for the ten-year U.S. Treasury yield by switching off the innovations of individual categories over selected periods. These hypothetical paths could be considered naive since we do not assume interdependence among the innovations in our model. Analogous to the discussion in Section4, we argue that the counterfactual paths are accurate as long as markets correctly foresee all impacts of the innovations and the transition of an innovation through the economy and into the yields is sufficiently fast. For example, if financial turmoil motivates investors to change their required yield to an extent reflecting not only the expected impact of the news on financial markets but also the impact on the future macroeconomic position and subsequent Fed decisions, then switching this innovation off allows us to accurately draw a “no turmoil” counterfactual path . Although the assumptions of efficient markets and perfect information are strong and generally not fully satisfied, we believe that the counterfactual paths we obtain have the capacity to at least roughly illustrate how the yields would evolve if certain events had not occurred.

The resulting paths are captured in Fig.6. The upper three panels display counterfactual paths of the ten-year yield if financial market or capital flight innovations were not present over the chosen subsamples: the 2008 financial crisis, the 2011 eurozone debt crisis and the events of 2016. Beginning with the former, the absence of negative financial market news during 2008 would keep the ten-year yield above the actual values. The decline in yields during the second half of 2008 would still be present, although of a lesser magnitude than in the case of the actual dynamics. On the other hand, the rebound in the yield during 2009 would be smaller, and therefore, the end of 2009 difference between the actual and hypothetical yield would be limited. This shows that the absence of financial turmoil would result in less volatility over the crisis period, although not a new trend in yields.

The decline in the yield since summer 2011, attributed in the news to a deepening eurozone crisis, would not be present if the capital flight events were turned off (see Fig.6, top-middle panel). The absence of the flight-to-safety behavior transferring capital from the eurozone to the U.S. would result in a U.S. yield 117 basis points above the actual value at the end of 2012. The absence of the Brexit referendum in June 2016 would similarly imply avoiding a minimum yield level of 1.40% from July 8, 2016, which would remain 16 basis points higher (see Fig.6, top-right panel). Nevertheless, the absence of news from this category would result in a lower yield later in 2016 and throughout 2017, which would mostly be attributed to the absence of a positive impact of the result of the 2016 U.S. presidential election on the yield.

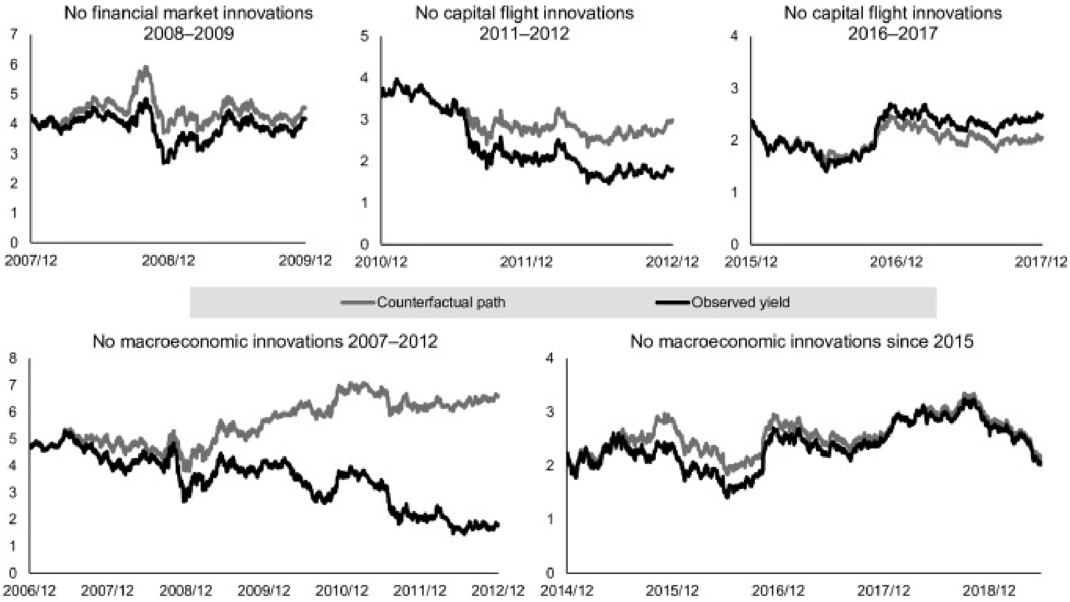

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Fig. 6. Counterfactual paths of ten-year treasury yield (in %). Note that the counterfactual path is calculated as the median path over all posterior draws.

We also display the hypothetical effect of an absence of macroeconomic innovations on the yield in the bottom part of Fig.6. First, focusing on the period 2007–2012, switching off macroeconomic news would imply a lesser downward trend in the yield over 2007–2008, a strong upward trend between 2009 and 2010 and stable yield over 2011–2012. The difference between the actual and counterfactual paths in scenario is substantial, which shows that the macroeconomic position was the dominant source of the downward trend in yields after 2006.

In contrast, the yield would remain mostly unchanged if the macroeconomic innovations were switched off beginning in 2015 (see Fig.6, bottom-right panel). The downward trend in yields in 2016 would be delayed, and the effect of the U.S. presidential election in 2016 would be smaller, but the end-of-period actual and hypothetical yields would be almost identical. Again, this particular result illustrates that the non-macroeconomic events were the core source of the variation in yields over the last decade.

Overall, the results illustrate the magnitude of the impact of events unrelated to the U.S. macroeconomic position on U.S. yields. International capital flight has proven to be an important source of yield variation since 2016. This finding has implications for U.S. monetary policy. The transition of Fed monetary policy adjustments into longer yields may face increasing challenges due to effects of additional yield factors outside the control of U.S. monetary policy. These challenges are relevant especially to the conventional monetary policy using the federal funds rate. However, any unconventional monetary policy tool, except for the direct yield curve targeting, faces such challenges, albeit to a lesser extent.

6. Conclusion

The paper demonstrates the importance of non-macroeconomic events for explaining recent movements in the U.S. Treasury yield curve. The analysis utilizes a Bayesian approach to identify the magnitude and location of innovations related to the stance of macroeconomy and monetary policy, portfolio allocation decisions and Treasury supply. Using a time-varying regression model, we obtain filtered estimates of the impact of innovations in each category on the yields. The results show that the events captured by macroeconomic news were the most important triggers of the yield curve movements over most of the period under analysis. However, the importance of non-macroeconomic events grew over the period. The events related to capital flight became the most important triggers of longer yield movements after 2016, explaining even more than one-third of the variation in longer yields in 2019. These effects were narratively obvious, particularly in relation to events including various phases of the eurozone debt crisis, the Brexit referendum, the U.S. election in 2016 or the trade tensions since 2017. Such results are in line with the discussion of a revival of Greenspan's conundrum due to non-macroeconomic factors, as discussed in Bauer (2017).

The framework presented in this paper also allows us to estimate counterfactual paths of yields. We show that whereas the absence of macroeconomic news would result in a slightly upward trend in the ten-year U.S. Treasury yield over the period 2007–2012, instead of the actual downward dynamics, it would not significantly alter the path of the yield after 2014. The absence of news related to capital flight would prevent the decline in yields over 2011 or in the days following the Brexit referendum. This further illustrates that the non-macroeconomic events became important when explaining yield dynamics.

The implications of the results are straightforward. From a monetary policy perspective, the monetary policy authority should not neglect external factors that may affect the transition of either conventional or unconventional monetary policy steps through the yield curve. Regarding yield curve modeling, the discussion of spanning hypothesis (and, in general, the model selection) could benefit from the presented results. Specifically, it can be expected that an inclusion of non-macroeconomic variables in macrofinance yield curve models could prove beneficial to capture and explain part of the variation in yields.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Descriptive statistics and correlations

See Table A.1.

Table A.1. Descriptive Statistics and Correlations.

	Yield level		Difference of yield	
	1Y	**10Y**	**1Y**	**10Y**
Sample (common to all maturities)				
first observation	12/4/2000			
last observation	6/28/2019			
number of observations	4671			
Descriptive statistics (in % for level, in basis points for difference)				
maximum	5.911	5.837	40.47	26.33
	(12/4/2000)	(3/14/2002)	(9/19/2008)	(10/8/2008)
minimum	0.083	1.400	−54.41	−51.89
	(14/5/2014)	(7/8/2016)	(9/17/2001)	(3/18/2009)
mean	1.68	3.524	−0.086	−0.077
standard deviation	1.562	1.168	4.171	5.848
Pearson correlation coefficient (all observations)				
Fiscal policy			0.043	0.072
Fed surprise			0.099	0.139
Macro news			0.127	0.193

	Yield level		Difference of yield	
	1Y	10Y	1Y	10Y
Financial market			0.119	0.142
Capital flight			0.073	0.120
Total			0.175	0.252
Pearson correlation coefficient (only observations including a news article)				
Fiscal policy			0.248	0.378
Fed surprise			0.298	0.480
Macro news			0.310	0.445
Financial market			0.301	0.466
Capital flight			0.220	0.439
Total			0.283	0.427
Point biserial correlation coefficient (only observations including a news article)				
Fiscal policy			0.284	0.418
Fed surprise			0.338	0.492
Macro news			0.337	0.448
Financial market			0.342	0.502
Capital flight			0.236	0.448
Total			0.327	0.467

Note that the correlation coefficients are calculated between the first difference of yields and the triggers from news headlines (a dummy indicating a presence of a news article with a sign based on the headline). When including all observations, zeros are assigned to the dummies of news triggers for the days where no related article was present in the sample. This leads to relatively low correlations. After removing these observations, i.e. calculating the correlations only for days when a news article was published, the correlations increase.

Fed (2019), News Monitor at EIKON — Refinitiv, author's calculations.

Appendix B. News database filtering

To obtain the headlines that provide sufficient information about U.S. Treasury yield curve movements and their sources, we apply a sequential approach:

1. We filter news articles from News Monitor from Refinitiv EIKON that

   (i) include at least one of the terms U.S. / United States,

   (ii) at least one of the terms Treasury/Yield / Bond/Bill / Note,

   (iii) and at least one of the terms rise/grow / increase/advance / gain/rise / jump/decrease / plummet/decline / shrink/drop / deteriorate/lower / slump

   (or their variations).

2. We gather the headlines and identify certain linking words that divide the part of the headline describing the direction of the movement from the part discussing the cause (for example, the word "after" in the headline *U.S.*

yields plummet after Draghi comments; Fed decision ahead).

3. In one of the parts of the headline, we identify keywords that inform about the direction (see step 1; we carefully divide cases where the headline mentions bond prices or yields, as these imply inverse movements). This defines the sign of the innovation.

4. In the remaining part of the headline, we identify the keyword that allows us to place the news headline into one or more of the five categories.

The lists of keywords to identify the categories were set as follows:

Fiscal policy:

' suppl'; ' auction'; '-suppl'; '-auction'; 'buyback'; 'notes sale'; 'note sale'; 'debt sales'; 'deficit'; 'refunding'; 'u.s. debt'; 'new debt'; '-year sale'; 'tips sale'

Fed surprise:

' fed'; ' bernanke'; 'yellen'; 'powell'; 'greenspan'; '-fed'; '-bernanke'; '-yellen'; '-powell'; '-greenspan'; ' rate'; '-rate'; 'fomc'; 'fomc '; 'tightening'; 'easing'; 'banker comments'; 'trichet'; 'fisher'; 'tapering'; 'stimulus'; 'draghi'

Macro news:

'cpi'; '-cpi'; 'job'; '-job'; 'sales data'; 'home sales'; 'retail sales'; 'confiden'; 'labor'; 'housing'; 'economic data'; 'weak data'; 'strong data'; 'durables'; 'u.s. outlook'; 'ppi'; 'napm'; 'ahead of data'; 'manufacturing'; 'productivity'; 'u.s. data'; 'tepid growth'; 'gdp'; 'consumer'; 'hopes for economy'; 'production'; 'trade report'; 'economic gloom'; 'recovery'; 'economic outlook'; 'wholesale'; 'durable goods'; 'recession'; 'home data'; 'growth rebounds'; 'us growth'; ' pmi '; 'u.s. growth'; 'economy'; 'u.s. rise'; 'price index'; 'econ data'; 'michigan'; 'after data'; 'factory'; 'factories'; 'inflation'; 'chicago pmi'; 'ism services'; 'payroll'; 'on data'; 'economic report'; 'home market'; 'u of mich'; ' ism'; 'outlook and data'; 'retail'; 'business index'; 'ism '; 'layoff'; 'industry'; 'core sales'; 'ism survey'; 'shopper'; 'trade deficit'; 'await data'; 'employment'; 'entiment data'; 'awaits data'; 'house data'; 'business condition'; 'lackulster data'; 'robust data'; 'growth worries'; 'mortgage selling'; 'u.s. output'; 'u.s. weakness'; 'mixed data'; 'claims data'; 'spending'; 'data flow'; 'price data'; 'goods orders'; 'home price'; 'producer price'; 'gloom'; 'homes plan'; 'industrial'; 'home builder'; 'trade data'; 'lukewarm data'; 'tepid data'; 'u.s. decline'; 'data miss'; 'output data'; 'business data'; 'disappointing data'; 'corporate'; 'home resales'; 'wage'; 'import'; 'export'

Financial market:

'profit'; 'stock'; 'stock '; 'stocks'; 'equit'; 'earning'; 'tech sector'; 'nasdaq'; 'enron'; 'book profit'; 'oil price'; 'oil'; 'oil-price'; 'sp 500'; 'fannie'; 'microsoft'; 'bull'; 'bear'; 'dividend'; 'wall st'; 'correction'; 'shares'; 'shares '; 'technicals'; 'technical support'; 'draw buyers'

Capital flight:

'safety'; 'flight to quality'; 'mideast'; 'warning'; 'global growth concerns'; 'argentin'; 'tragedy'; ' attack'; 'uncertain'; ' g7'; 'fear'; 'russia'; 'explosion'; 'iraq'; 'safe-haven'; 'war '; 'war'; 'nervous'; 'geopolitic'; 'blast'; 'hurricane'; 'rita '; 'global tension'; 'baghdad'; 'democrats'; 'saddam'; 'china'; ' alert'; 'u.s. troop'; 'vote'; 'subprime'; 'hungary'; 'bailout'; 'jitters'; 'rescue'; 'stress'; 'greece'; 'aig '; 'speculation crisis'; 'debt crisis'; 'debt concerns'; 'tension'; 'safehaven'; 'risk appetite'; 'global growth'; 'global slowdown'; 'demand for risk'; 'credit rating'; 'downgrade'; 'currency manipulat'; 'greek'; 'budget talks'; 'fiscal'; 'debt ceiling'; 'debt clock'; 'default'; 'ukraine'; 'middle east'; 'global economic'; 'ebola'; 'chinese'; 'riskier'; 'election'; 'trump'; 'syria'; 'brexit'; 'north korea'; 'global market'; 'irma'; 'budget plan'; 'tax'; 'shutdown'; 'sanctions'; 'italy'; 'borrowing'; 'mexico'; 'anxious'; 'tariff'

Appendix C. The largest daily movements

See Table C.1.

Table C.1. The Largest Daily Movements of the 10Y Yield (movements in bps).

Year	Movement	Date	Description of trigger	Headlines on surrounding dates
2001	−17	01/02	Fed expectations	U.S. Treasury notes rise on hopes for lower rates.
2001	24	11/15	U.S. equity market, macro-data	U.S. Treasuries mixed after New York drop.
				U.S. T-bond extends gains to full point after CPI.
2002	−21	11/07	Fed meeting	All ingredients for rally in place: Cuts to U.S. rates, taxes: Bonds poised for a slump that will make stocks attractive
2002	23	11/27	Treasury auction, macro-data	U.S. Treasury yields rise ahead of auction, data.
2003	24	01/02	Macro-data, portfolio allocation (flight from safety)	Canadian dollar jumps on U.S data, bonds pummeled.
				Euro debt-Yields rise above 3-1/2 year lows after U.S. data.
				U.S. Treasuries drift lower as safety bid wanes.
2003	−18	08/06	Treasury auction	S&P 500, Dow, make gains: Telephone stocks rise, Treasuries rebound, but U.S. dollar sinks lower
				U.S. Treasury yields rise, five-year supply looms.
				U.S. stocks gain, aided by solid Treasury note sale.
				GLOBAL MARKETS-Shares, bonds rise after U.S. refunding ends.
2004	25	04/02	Macro-data	U.S. Treasuries plummet after rousing jobs data
2004	−20	06/15	Fed meeting	U.S. Treasuries jump as Fed soothes on rate rise.
2005	15	03/09	U.S. equity market, corporate sector news	GM struggles with debt load: Interest costs rise as bonds near junk status. General Motors had 44% of U.S. market in 1980; that is expected to fall to 24% within five years
2005	−14	08/31	Macro-data	U.S. Treasuries jump on contraction in Chicago PMI
2006	−11	06/02	Macro-data	RPT-Treasuries gain on weak U.S. data ahead of payroll
2006	11	11/03	Treasury auction, macro-data	U.S. bonds lower after payrolls, before auctions
2007	14	09/20	Fed meeting	U.S. Treasury balances at Fed lower on Sept 19
				Hungarian forint firms significantly, bond yields drop after U.S. rate cut
2007	−18	11/26	Macro-data	U.S. yields slump on fresh housing fears BONDS MARKETPLACE by Bloomberg
				U.S. bonds higher after report shows new home sales at a 12-year low; yields decline
2008	26	10/08	Macro-data, U.S. equity market	EURO GOVT-Bonds pare gains after U.S. non-farm payrolls
				U.S. TREASURIES TRIM GAINS AFTER STOCKS CUT EARLY LOSSES
2008	−27	11/20	Macro-data	U.S. TREASURIES ADD SLIGHT GAINS AFTER WEEKLY JOBLESS CLAIMS JUMP TO HIGHEST SINCE JULY 1992
				U.S. Treasuries hold gains after Philly Fed data
2009	−52	03/18	Fed meeting	GLOBAL MARKETS-U.S. stocks surge on Fed move, bond yields slump

Year	Movement	Date	Description of trigger	Headlines on surrounding dates
2009	26	06/01	Treasury auction, macro-data, Fed expectations	Banks beat expectations, TSX jumps 250 points; Dow higher as U.S. bond auction attracts solid demand; home sales, durable goods orders rise
				FOREX-Dlr up on U.S. yield rise, rate expectations
2010	−19	06/04	Macro-data	TREASURIES-Bonds rally as U.S. payroll rise disappoints
2010	22	12/07	Macro-data	U.S. TREASURY OUTLOOK-After rebound, yields may still rise
				GLOBAL MARKETS-U.S. stocks, bond yields rise on recovery outlook
2011	−21	08/09	U.S. equity market, Foreign events (French banks holding Greece debt)	TREASURIES-U.S. 30-yr bond rises a point as stock futures fall
				TREASURIES-U.S. bonds gain on French bank safety fears
2011	21	10/27	Foreign events (Eurozone)	U.S. 30-YR BOND EXTENDS LOSS TO TWO POINTS AS STOCKS GAIN AFTER EURO ZONE DRAFT STATEMENT
2012	17	03/14	Fed statement	TREASURIES-U.S. bonds drop after upbeat Fed statement
2012	−15	04/06	Macro-data	U.S. TREASURIES PRICES ADD GAINS AFTER U.S. JOBLESS CLAIMS RISE MORE THAN EXPECTED IN LATEST WEEK
2013	23	07/05	Macro-data	GLOBAL MARKETS-Stocks, dollar rally, U.S. yields jump on jobs data
2013	−17	09/18	Fed meeting	U.S. mortgage bond prices rise after Fed leaves purchases alone
				Turkish bonds, lira make slight gains ahead of U.S. Fed meeting
				U.S. investors turn to more dealers as bond liquidity declines
2014	10	07/30	Treasury auction	DOLLAR RISES BRIEFLY ABOVE 103 YEN AS U.S. YIELDS EXTEND EARLIER RISE AFTER SOFT 7-YEAR TREASURIES AUCTION
2014	−11	10/01	Portfolio allocation	TREASURIES-U.S. longer-dated bond prices gain more on PIMCO outflows
2015	−16	06/29	Foreign events (Greece debt)	TREASURIES-U.S. bond prices rise on Greece concerns
2015	16	12/03	Fed statement, foreign events (Eurozone — ECB decision)	TREASURIES-U.S. yields rise after ECB disappoints, Yellen speaks
2016	−17	06/24	Foreign events (Brexit)	TREASURIES-U.S. bond prices rise as early Brexit results show 'Leave' leads
2016	22	11/09	Politics (election)	GLOBAL MARKETS-U.S. stocks jump along with bond yields after Trump shock, peso falls
2017	10	03/01	Fed statement	GLOBAL MARKETS-Fed trumps Trump as dollar, U.S. Treasury yields jump
2017	−10	05/17	Macro-data	Global Stocks Fall After U.S. Rout as Bonds Gain: Markets Wrap
				TREASURIES-U.S. bond yields drop as CPI, retail sales data miss forecasts
2018	−15	05/29	Foreign events (Italy debt)	TREASURIES-U.S. 10-year yields post largest one-day drop since Brexit
				TREASURIES -U.S. yields rise as Italy worries ease, for now

Year	Movement	Date	Description of trigger	Headlines on surrounding dates
2018	10	10/03	Fed statement	BUZZ-U.S. banks: Up on Fed's move to ease rules, rise in treasury yields
2019	−9	01/03	U.S. equity market, macro-data	The close: Stocks reverse early drop to end higher, Apple dives in post market on profit warning U.S. 10-year Treasury slips to 11-month low
2019	9	01/04	Macro-data, Fed statement	BUZZ-U.S. big banks: Rises as strong jobs report pushes yields higher
				UPDATE 1-Euro zone yields jump as Fed's Powell triggers U.S. Treasury selloff

Note that news headlines were obtained from News Monitor from Refinitiv EIKON.

Appendix D. Estimation procedure

The estimation procedure utilizes Bayesian updating. The procedure is initialized at the mean of the prior distributions, with the initial state vector and its variance obtained as the mean values from the pre-sample (see AppendixE). The following steps are conducted in each iteration of the updating procedure:

Kalman Filter:

Using the values of parameters from the previous iteration (or the initial values), we evaluate the likelihood of the parameters using the Kalman filter procedure.

Metropolis Hastings for innovations:

The magnitude and location of the innovations $x_{c,t}$ are drawn using proposal densities. For the change in the location of the innovations, we draw a random integer from a Poisson distribution to obtain the number of days to shift the location. We set the distribution parameter $\lambda = 0.5$, i.e.,on average, half of the candidate draws have the location shifted by at least one day. The direction of the shift is also determined randomly. For the magnitude, we draw from a log-normal distribution with both the log-mean and the log-standard deviation equal to one. Thereafter, again using the Kalman filter, we evaluate the likelihood of the model given the drawn innovations. For both the original and the drawn innovations, we evaluate their probability at the prior densities for both the location and the magnitude. We accept the draw if the ratio of prior probabilities (the drawn one over the original one) times the ratio of likelihoods is larger than a random draw from a (0,1) uniform distribution.

Sampling states:

The obtained innovations, either the original or newly drawn, are used to draw the states of the state-space model, which represent the time-varying parameters. To do so, first, the Kalman filter is applied once again, and thereafter, theCarter and Kohn (1994) procedure is utilized to draw the states.

Drawing variance matrices:

Having the innovations and states drawn, we draw the variance–covariance matrices of the random disturbances in the transition equation and of the measurement errors in the measurement equation from the inverse Wishart distribution.

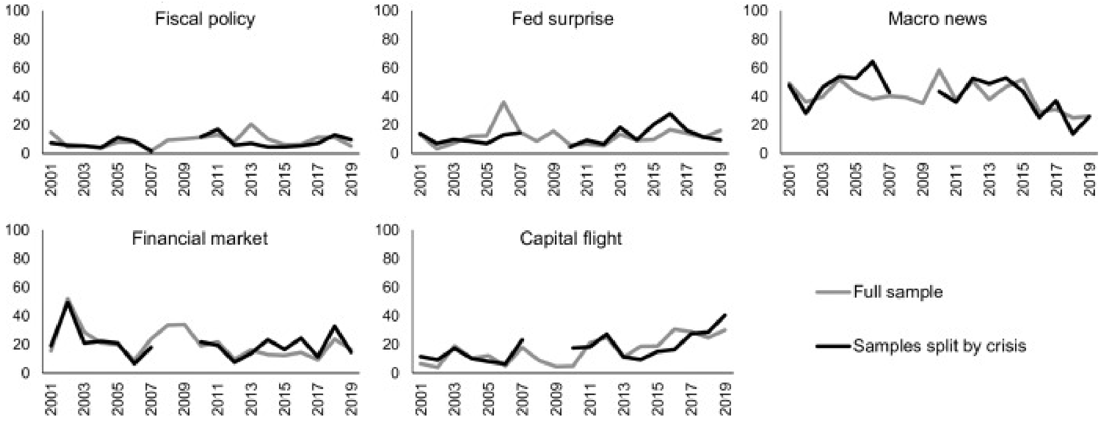

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Fig. F.1. Shares of yield movements, ten year (in %) – Robustness check. Note that gray lines display the original full-sample estimate, whereas the black lines display the results after estimating the model separately on sub-samples split by the Great financial crisis. The shares of the five categories are calculated as an annual sum of absolute values of model-implied daily movements in the yield for the given category as a percentage share of the total annual sum of absolute values of model-implied daily movements.

Appendix E. Details on priors

The priors in the model are of three kinds. First, the innovations are defined by priors about their location. The prior distribution of the location is specified as a normal distribution with the mean at the day of the publication of the headline and a standard deviation of three business days. This standard deviation was set using expert judgment, taking into account the overall density of news: with on average 2–3 headlines per week, using 3 business days ensures that the prior is not too strict and yet that the news articles do not excessively contaminate one another.

Second, innovations are further defined by priors about their magnitude. The log-normal distribution serves as a prior distribution of the magnitude of the innovation, which by the construction of the model needs to be positive (the signs are determined directly from the news headlines). The scale of the distribution may be freely chosen since the time-varying setup of the model ensures that the time-varying parameters adjust such that the observed yield variability is fitted properly. Therefore, we use log-normal(1,1) distribution , which has mode one, implying the common innovation as being of unit size.

Third, since the model assumes that the time-varying parameters follow a random walk, the only remaining parameters of the model are the variance–covariance matrices of random disturbances $\boldsymbol{Q}$ and of the measurement error $\boldsymbol{R}$. We choose the inverse Wishart distribution as the prior distribution for both variance–covariance matrices $\boldsymbol{Q}$ and $\boldsymbol{R}$. The choice of the inverse Wishart distribution is justified since the resulting conjugate prior distribution has many plausible properties (including a possibility to use several hyperparameters with a straightforward interpretation to describe the distribution; seeGelman et al., 2003, for instance).

We set the hyperparameters of the variance–covariance priors using a pre-sample. The pre-sample covers yields over the period 1985–2000. From these yields, we estimate yield factors (the level, slope and curvature) using the dynamic Nelson–Siegel (DNS) model(Diebold & Li, 2006). We set the prior for $\boldsymbol{R}$ from the measurement errors of the DNS model. The mean and variance of the first differences of the pre-sample factors are used as initial values for the states and their variance–covariance matrix. For each yield factor, there are five states: the series of time-varying regression coefficients for each news category. We set the initial values and $\boldsymbol{Q}$ priors identically for all categories. The prior for $\boldsymbol{Q}$ is obtained as this initial variance–covariance matrix multiplied by a small constant. We set this constant at the value 3.5e−04 in line withCogley and Sargent (2005), which is common in the literature using a pre-sample to set the priors. In case of both variance–covariance matrices, the obtained hyperparameters imply only a weakly informative priors. That is in line with our intention to set these priors so that they are not excessively informative, since we have no guidance on setting the prior parameters for the covariance matrices beyond the pre-sample data.

Appendix F. Robustness check

See Fig.F.1.

Appendix G. Figures depicting estimated parameters

See Fig. G.1, Fig. G.2, Fig. G.3, Fig. G.4.

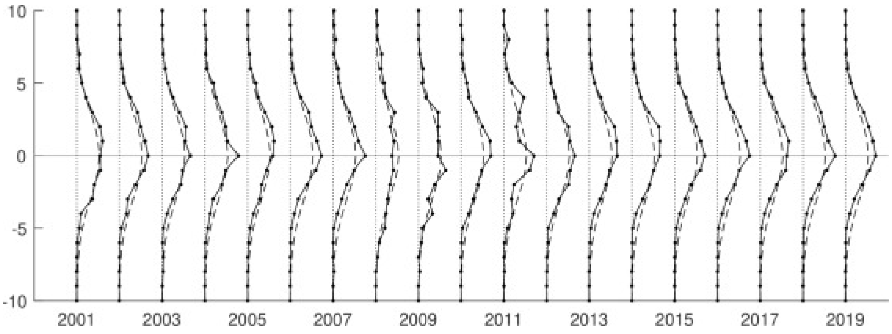

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Fig. G.1. Posterior Distribution of Innovation Location

(difference from the day the news was published,

in business days, mean distribution for each year). Note: The solid lines connect dots that illustrate the number of observations with a given difference in posterior location and the date the day was published. The dashed lines, identical for all years, represent the prior distribution of the location, i.e.,a normal distribution with zero mean (located on the day of publication) and a standard deviation of three business days.

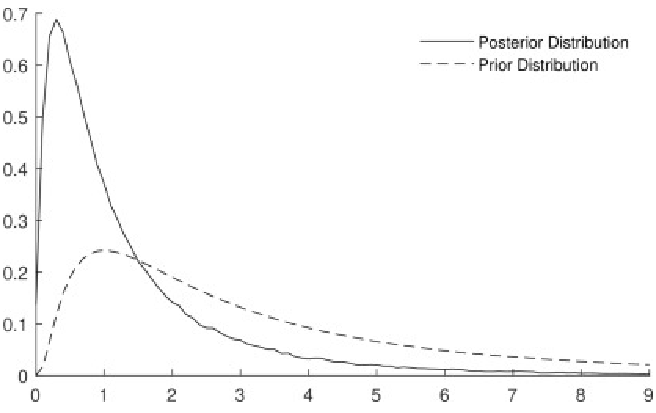

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Fig. G.2. Posterior distribution of innovation magnitude: Aggregate result

(x-axis: magnitude, y-axis: probability density)

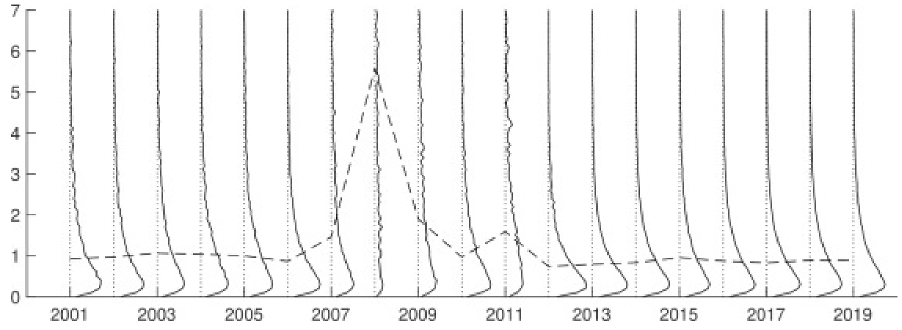

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Fig. G.3. Posterior distribution of innovation magnitude: Dynamic View

(mean distribution for each year). Note that the solid lines illustrate the average posterior distribution of the magnitude of the innovation calculated as a mean distribution for each year. The dashed line shows the mean posterior value (i.e.,the mean of all posterior draws over the particular year).

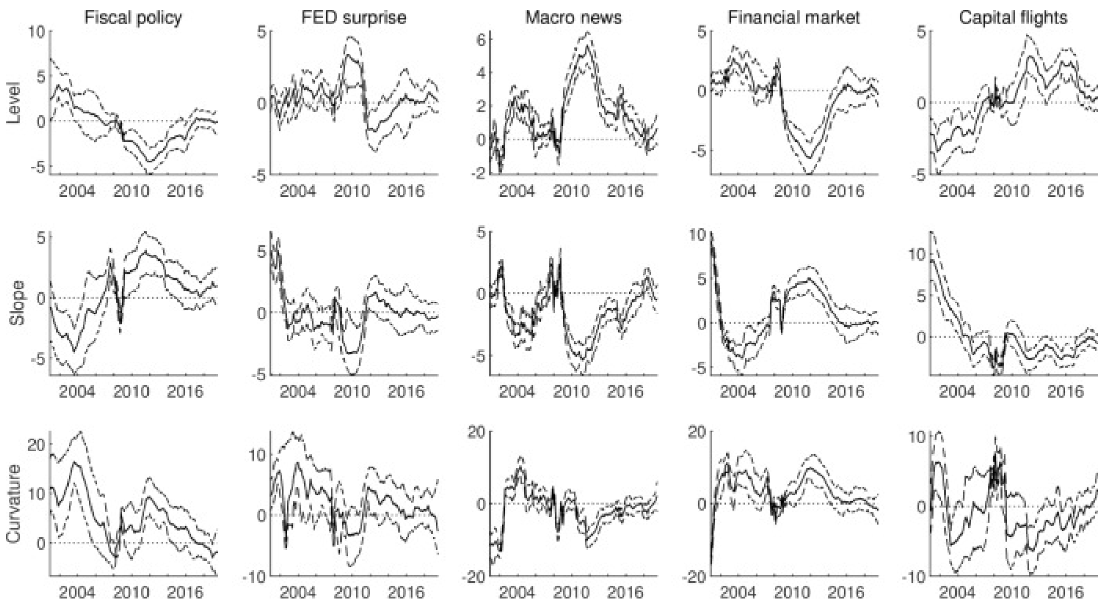

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Fig. G.4. Posterior time-varying parameters. Note that the solid lines illustrate the median posterior distribution, and the dashed lines show the 10% and 90% quantiles.

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1 The views are the author’s own and do not represent the official position of the Czech National Bank.

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3 The short-term yields were close to the lower bound over a significant part of the period of analysis. The lower bound proximity makes the results of canonical yield curve models utilizing symmetric stochastic processes biased. We avoid this by using a different modeling approach (see Section 4) and focusing on the differences of yields instead of yield levels. Therefore, from the econometric point of view, our results are unbiased. The lower bound proximity can, however, bring certain challenges when interpreting the dynamics of the slope factor and its sensitivity to innovations during the low yield periods.

4 Yields were not seasonally adjusted. We expect a possible seasonality in yields to be sufficiently reflected by the corresponding seasonality in the news reports that we use to explain the yield dynamics. The yields were not detrended — possible non-stationarity of the yield time series is addressed by using yields in the first differences instead of levels.

5 Note that one headline may contain keywords for multiple categories. For example, news articles interpreted the surprising result of the 2016 U.S. presidential election as both a macroeconomic trigger and an international capital flight trigger. As we describe below, such headlines represent multiple priors for the triggers (innovations) in each of the mentioned categories.

6 Above, we have used the term “trigger” to describe a new piece of information regarding the cause of a yield movement obtained from the news. In the text below, where we introduce the model, we also use the term “innovation” to highlight the econometric approach we employ to quantitatively estimate the impact of these triggers. Nevertheless, throughout the paper, the two terms are considered equivalent and used interchangeably.

7 In the previous version of the paper, we also attempted to obtain the signs from the yield movements themselves. However, as the yields of various maturities may not always co-move, this led to ambiguous results in some periods when the yield curve rotated. The approach with signs obtained from the headlines is, according to our observations, more robust.

8 See the discussion on the trade-off between the accuracy of the filtering and the in-sample fit in Section 3.

9 The prior log-normal(1, 1) distribution has a mean of 4.48.

10 We omit a discussion on the curvature factor, which allows us to fit the middle part of the yield curve, and its interpretation may not be straightforward.

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