DEUTSCHE
BUNDESBANK
EUROSYSTEM

Discussion Paper

Deutsche Bundesbank
No 27/2018

With a little help from my friends: Survey-based derivation of euro area short rate expectations at the effective lower bound

Felix Geiger
Fabian Schupp

Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-0

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax +49 69 9566-3077

Internet http://www.bundesbank.de

ISBN 978–3–95729–480–7 (Printversion)
ISBN 978–3–95729–481–4 (Internetversion)

Non-technical summary

Research Question

Dynamic term structure models face significant econometric challenges, which are related to the high persistence of interest rates. In the euro area, further difficulties arise from a small sample size and a prolonged period of interest rates at or near the effective lower bound. These data features make the model results and thus the information extracted from the yield curve sensitive to modeling and estimation methods. We aim at developing a euro area term structure model that produces a good model fit and generates economically plausible short rate expectations that can be used for policy analysis.

Contribution

We propose a non-linear ('shadow-rate') term structure model for the euro area overnight index swap (OIS) yield curve which includes a lower bound specification that allows for current as well as future changes in the effective lower bound. Our model also accounts for the spread between the short rate and the deposit facility rate as observed in the data. Most importantly, we incorporate survey information on interest rate forecasts into our model to better pin down the expected future path of the short rate, which is important when decomposing interest rates and deriving monetary policy expectations from the yield curve. We also empirically asses the effects of conventional and unconventional monetary policy measures on the components of the OIS curve by explicitly accounting for the non-linearities associated with the effective lower bound.

Results

The estimated model allows to adequately assess short-term monetary policy expectations. The model-implied most likely path of the short rate follows a trajectory which is in line with survey forecasts and which is consistent with the intended policy rate path of the ECB's Governing Council according to its forward guidance. At more distant horizons rate expectations correlate with an estimated equilibrium nominal short rate. Our analysis also highlights the signaling channel of non-standard monetary policy in the run-up to the Eurosystem's sovereign bond purchases. Our preferred model outperforms alternative modeling specifications in terms of economic plausibility and model fit. Simulations confirm that survey information is key to determine expectations on interest rates priced into the yield curve.

Nichttechnische Zusammenfassung

Fragestellung

Für dynamische Zinsstrukturmodelle stellt die hohe Persistenz von Zinsen eine signifikante ökonometrische Herausforderung dar. Im Euroraum entstehen aufgrund des kleinen Datensatzes und einer anhaltenden Periode von Zinsen an oder nahe der effektiven Zinsuntergrenze weitere Schwierigkeiten. Diese Dateneigenschaften führen dazu, dass sowohl Modellergebnisse als auch die aus den Zinsen abgeleiteten Informationen sensibel auf Modellierungs- und Schätzansatz reagieren. Wir versuchen, ein Zinsstrukturmodell für den Euroraum zu entwickeln, welches eine hohe Schätzgüte produziert und ökonomisch plausible Kurzfristzinserwartungen generiert, die für die Politikanalyse nutzbar sind.

Beitrag

Wir schlagen ein nicht-lineares (Schatten-) Zinsstrukturmodell für die Overnight Index Swap-Kurve des Euroraums vor, dessen Zinsuntergrenzenspezifikation aktuelle und zukünftige Änderungen der effektiven Zinsuntergrenze berücksichtigt. Außerdem trägt unser Modell auch der in den Daten zu beobachtenden Differenz zwischen Kurzfristzins und Einlagesatz Rechnung. Vor allem informieren wir das Modell zudem mit Umfragen über Zinsvorhersagen, um den erwarteten künftigen Zinspfad besser bestimmen zu können, was für die Zerlegung der Zinsen in verschiedene Komponenten und die Herleitung von geldpolitischen Erwartungen von Bedeutung ist. Darüberhinaus untersuchen wir empirisch die Effekte konventioneller und unkonventioneller Geldpolitik auf die Komponenten der Zinsstrukturkurve. Dabei berücksichtigen wir explizit Nicht-Linearitäten in Verbindung mit der effektiven Zinsuntergrenze.

Ergebnisse

Das geschätzte Modell erlaubt eine adäquate Einschätzung der kurzfristigen geldpolitischen Erwartungen. Der modell-implizite wahrscheinlichste Kurzfristzinspfad ist konsistent mit Prognosen aus Umfragen und dem vom EZB-Rat beabsichtigten Zinspfad, wie er gemäß Forward Guidance spezifiziert wurde. Zinserwartungen für die fernere Zukunft korrelieren mit einem geschätzten nominalen Gleichgewichtszins. Unsere Analyse hebt zudem den Signaling-Kanal der unkonventionellen Geldpolitik im Vorfeld der Staatsanleihekäufe des Eurosystems hervor. Unser bevorzugtes Modell übertrifft alternative Modellspezifikationen bezüglich ökonomischer Plausibilität und Modellgüte. Simulationen bestätigen, dass Umfrageinformationen der Schlüssel sind, um in der Zinsstrukturkurve eingepreiste Zinserwartungen zu bestimmen.

Deutsche Bundesbank Discussion Paper No 27/2018

With a little help from my friends: Survey-based derivation of euro area short rate expectations at the effective lower bound *

Felix Geiger
Deutsche Bundesbank

Fabian Schupp
Deutsche Bundesbank

Abstract

The estimation of dynamic term structure models (DTSMs) turns out to be challenging in the presence of a small sample. It is exacerbated if the sample is characterized by a prolonged period of low interest rates near a time-varying effective lower bound. These challenges all weigh heavily when estimating a DTSM for the euro area OIS yield curve. Against this background, we propose a shadow-rate term structure model (SRTSM) that includes a time-varying effective lower bound and accounts for the spread between the policy and short-term OIS rate. It also allows for future changes in the effective lower bound and incorporates survey information. The model allows to adequately assess short-term monetary policy rate expectations and it generates far-distant rate expectations that are correlated with an estimated equilibrium nominal short rate derived from a macroeconomic model set-up. Our results also highlight the signaling channel of non-standard monetary policy shocks in the run-up to asset purchases identified based on a non-linear high-frequency external instrument approach. Our model outperforms DTSM specifications without above modeling features from a statistical and economic perspective. We confirm our findings employing a Monte Carlo simulation.

Keywords: Term structure modeling, short rate expectations, lower bound, survey information, yield curve decomposition, monetary policy, euro area.

JEL classification: E32, E43, E44, E52.

---

*Contact address: Felix Geiger, Deutsche Bundesbank, Wilhelm-Epstein-Strasse 14, 60431, Frankfurt. Email: felix.geiger@bundesbank.de; Fabian Schupp, Deutsche Bundesbank, Wilhelm-Epstein-Strasse 14, 60431, Frankfurt. Email: fabian.schupp@bundesbank.de. We thank Wolfgang Lemke, Martin Mandler, Emanuel Moench, Marcel Priebsch, Jan Scheithauer, Christian Speck, Peter Tillmann, Johannes Tischer, Andreea Vladu, Thomas Werner, Andreas Worms and Dora Xia as well as participants of the Deutsche Bundesbank Research Workshop, 21 March 2018, the ECB CMT seminar, 10 April 2018, the University of Giessen Brown Bag Seminar, 30 April 2018 and the 11th annual SoFiE Conference, 12-14 June 2018 for valuable discussions and comments. We are indebted to Martin Mandler, Michael Scharnagel and Luzie Thiel for sharing their instrument data set in order to identify monetary policy shocks.

1 Introduction

Dynamic term structure models (DTSMs) provide valuable information for policy makers. Such models allow to infer market participants' views on the outlook for monetary policy and at the same time to assess to what extent risk-averse investors demand a risk premium for holding bond instruments in an environment of interest rate uncertainty. In general, however, inference based on term structure models is accompanied by great econometric challenges (Hamilton and Wu, 2012). In essence, these challenges are related to the high persistence of interest rates, which makes the estimation of the model parameters of the underlying data generating process very difficult and sensitive to model specifications. This is especially true in a small sample characterized by low interest rate volatility. With the existence of an effective lower bound (ELB), estimation challenges of term structure models even increase because it introduces non-linearities into the term structure model and estimation process. Due to the absence of closed-form solutions for bond prices, they need to be simulated or approximated analytically within a non-linear filtering framework to extract the risk factors which may impact estimation accuracy (Priebsch, 2013; Wu and Xia, 2016). These considerations all weigh heavily when estimating a term structure model with a euro area data sample which only covers a small sample period and essentially only one complete interest rate cycle (2001-08). Moreover, the sample is characterized by a prolonged period of persistently falling interest rates which approached the ELB in July 2012 when the Eurosystem lowered the deposit facility rate (DFR) to 0 and subsequently adopted negative interest rate policies (NIRP).

Against this background, we develop a DTSM for the euro area OIS yield curve which explicitly accounts for the above features and fulfills two criteria, i.e. (i) a good model fit and (ii) plausible short- and long-term rate expectations that can be used for policy analysis. We find that given the severe small sample problem with a protracted period of low interest rates near the time-varying ELB, a shadow short rate model specification that incorporates actual as well as expected changes of the ELB is important from a statistical and economic point of view. Moreover, by incorporating survey forecasts on short- and long-term interest rate expectations (our 'friends'), the model is able to better pin down the future path of short rates, which is important when decomposing longer-term yields and forward rates.

Our model is able to provide a good model fit of the yield curve across time. In the ELB period the mean absolute fitting error is less than 1 basis point for the 1-month rate and 2 basis points for the ten-year rate, respectively. In contrast to alternative model specifications that do not account for a time-varying effective lower bound, our model is able to replicate the temporarily negative slope of the yield curve which was recorded during the course of 2016 when markets were expecting further DFR cuts. Accounting for expected policy rate changes, therefore, is important to ensure a good model fit at the short end of the yield curve, a finding also documented by Wu and Xia (2017).

The model generates expected short rate paths that do not violate lower bound restrictions. The most likely path of the short rate follows a trajectory which is in line with survey forecasts and which is consistent with the intended policy rate path of the ECB's Governing Council according to its forward guidance. As the possible lift-off of policy rates is linked to the end of net asset purchases of the extended asset purchase programme (APP), changes in the expected duration of net asset purchases should translate into changes of the most likely short rate path. Our model can replicate this hypothesis and it highlights the announcement of asset purchases as a commitment device for future short rates.

In particular, we estimate the impact of monetary policy shocks on the forward curve and its components based on a high frequency external instrument approach. To do so, we employ predictive regressions of the factor innovations on selected monetary policy instruments which allows us to model the reaction of the forward curve in a non-linear way. We identify both conventional as well as unconventional monetary policy shocks. Our model produces a U-shaped response of the forward curve in response to a conventional monetary policy shock which emphasizes the shock's communication / forward guidance character. The median reaction to an unconventional monetary policy shock at the long end is negative and spills over to medium-term maturities. The largest impact on the forward curve stems from the forward premium at the 10-year maturity horizon pointing to the transmission of non-standard measures through duration extraction. At medium-term maturities our model attributes a more prominent role to the expectations component. In the run-up to the start of asset purchases in March 2015 unconventional monetary policy shocks considerably contributed to the drop in long-term interest rates according to our model. Term premia as well as short rate expectations fell in response to these monetary policy shocks thereby also highlighting the signaling channel of non-standard monetary policy measures.

In order to pass judgment on the economic plausibility of the level and the variability of expected short rates, we compare our model-implied expectations component with an estimate of the equilibrium nominal short rate in the medium- to long-term derived from a macroeconomic model (see Holston, Laubach, and Williams, 2017). Indeed, our model estimates resemble the level as well as the dynamics of the equilibrium nominal rate remarkably closely even though the two models do not share any information in the estimation. Thus, long-term forward rates appear to reflect trends in key macroeconomic variables in both real and nominal terms, which play an important role in the formation of longer-term interest rate expectations.

Our benchmark model outperforms alternative specifications in terms of economic plausibility. GATSM estimations generate model-implied short rate expectations that violate lower bound restrictions and imply far-distant short rate expectations that seem too low from an economic perspective or may even become negative. De-meaning the pricing factors in the first place as in Adrian, Crump, and Moench (2013) at least ensures that the unconditional mean of the short rate matches the sample mean which pushes up the level of expected short rates. Still, model estimates fail to range at levels consistent with long-term survey expectations or with far-distant short rate expectations derived from a macro model. Only if surveys are incorporated do GATSMs and SRTSMs generate survey and macro consistent short rate expectations. Interestingly, despite the small euro area sample, our findings indicate that with respect to the considered euro area yield curve sample, estimated DTSMs always produce a very high persistence of the short rate process under the $\mathbb{P}$-measure. Therefore, the difference between non-bias- and bias-corrected estimates are not substantially large. Insofar, short rate expectations in a bias-corrected $GATSM$ do not exhibit implausible large time variation compared to a non-bias-corrected $GATSM$ as partly documented for bias-corrected estimates based on US data (Wright, 2014).

To cross-check our results, we conduct a Monte Carlo exercise in which we simulate yield curve data sets. We ensure that that these samples include an extended period (more than 12 months but less than 60 months) of interest rates stuck at the effective lower bound. In our analysis we compare performance across models in identifying the unconditional mean and persistence of the data generating process. The exercise confirms our previous findings. Only the model specifications including surveys are able to pin down the unconditional mean of the data generating process fairly close while producing high persistence in model-implied interest rates.

Our paper is related to various strands in the literature. SRTSMs which focuses on US, UK and Japanese yield curve data typically assume a constant ELB set or estimated to be close to zero. For the US, see Krippner (2015b); Christensen and Rudebusch (2015); Bauer and Rudebusch (2016); Wu and Xia (2016); Priebsch (2013). SRTSMs based on Japanese data are Ichiue and Ueno (2013); Kim and Singleton (2012); and for UK data, see Andreasen and Meldrum (2015). For the euro area some models likewise implemented SRTSMs based on a fixed, but estimated ELB (see the online implementations of Wu and Xia, 2016; Krippner, 2015b). However, given the NIRP and the subsequent steps of the DFR into negative territory, more recent applications for the euro area implemented a time-varying ELB (Lemke and Vladu, 2016; Kortela, 2016; Wu and Xia, 2017). With respect to the modeling of the time-varying ELB, our model is closely related to Wu and Xia (2017), who allow for time-varying expectations of future DFR cuts in agents' bond pricing.

Our work also relates to the vast amount of research that documents the challenges with respect to the estimation of term structure models. In essence, these challenges are first and foremost related to the very high persistence of interest rates, which in combination with small samples, impedes the estimation procedure and consequently the robust revelation of the mean-reverting characteristics of the short rate process (Kim, 2008; Duffee, 2011; Duffee and Stanton, 2012). Research has addressed this issue by improving and speeding up the estimation process (Joslin, Singleton, and Zhu, 2011; Christensen, Diebold, and Rudebusch, 2011; Hamilton and Wu, 2012; Adrian et al., 2013), applying bias correction (Bauer, Rudebusch, and Wu, 2012) for $GATSMs$ or incorporating survey information into the estimation process (Kim and Orphanides, 2012).

There are also many studies that examine the impact of monetary policy shocks on the yield curve based on high-frequency identification schemes (Kuttner, 2001; Cochrane and Piazzesi, 2002; Gurkaynak, Sack, and Swanson, 2005; Gertler and Karadi, 2015; Abrahams, Adrian, Crump, Moench, and Yu, 2016; Crump, Eusepi, and Moench, 2017). Studies that focus on APP announcements on the euro area yield curve are Motto, Altavilla, and Carboni (2015); Lemke and Werner (2017).

The paper is structured as follows: Section 2 introduces our preferred benchmark model with a focus on modeling the time-varying ELB. Section 3 discusses our estimation strategy. In Section 4 we present our main results with a focus on the above defined criteria, i.e. (i) model fit and (ii) plausible short- and long-term rate expectations that can be used for policy analysis. We then assess the impact of monetary policy on the forward curve based on our benchmark model. Moreover, we compare our model estimates to alternative $DTSM$ specifications and check our results in terms of robustness and the impact of modeling choice. Finally, we present implications for the various estimation and model variants based on a Monte Carlo simulation study using simulated yield curve data sets that are characterized by a protracted period in which the ELB is binding. Section 5 concludes.

2 Model

The class of SRTSMs introduces the concept of a (time-varying) effective lower bound, l_t, together with a shadow short rate, $si_{1,t}$. Similar to standard GATSMs, it is assumed that the pricing factors X_t follow a first-order Gaussian vector autoregressive process both under the risk-neutral ($\mathbb{Q}$) and the historical ($\mathbb{P}$) probability measure

$$X_t = \mu^{\mathbb{Q}} + \rho^{\mathbb{Q}} X_{t-1} + \Sigma u_t, \qquad u_t \sim N(0, I) \tag{1}$$

$$X_t = \mu^{\mathbb{P}} + \rho^{\mathbb{P}} X_{t-1} + \Sigma u_t, \qquad u_t \sim N(0, I). \tag{2}$$

The shadow short rate, $si_{1,t}$, is an affine function of the pricing factors and it holds

$$si_{1,t} = \delta_0 + \delta_1' X_t. \tag{3}$$

The short rate, $i_{1,t}$ is then described as the maximum function

$$i_{1,t} = \max(si_{1,t}, l_t). \tag{4}$$

By assumption, the short rate corresponds to the shadow short rate as long as the latter is above the lower bound. If, however, the shadow short rate falls below the lower bound, the short rate is constrained by the lower bound. This set-up allows for the possibility that the expected path of the short rate remains at this lower bound for an extended period of time, provided that the shadow short rate is expected to prevail below l_t.

Under the condition of no-arbitrage, the price of a zero-coupon bond with residual maturity n is defined as

$$P_{n,t} = E_t^{\mathbb{Q}} \left[\exp \left(- \sum_{i=0}^{n-1} i_{1,t+i} \right) \right] \tag{5}$$

and continuously compounded spot rates thus as

$$i_{n,t} = -n^{-1} \ln P_{n,t}. \tag{6}$$

Given the lower bound restriction, the mapping of pricing factors into interest rates is non-linear and in this case no closed-form solutions for bond prices exist. Therefore, we follow Wu and Xia (2017), who show that generally, implied one-period forward rates h periods ahead, $f_{h,t}$, can be expressed as

$$f_{h,t} \approx \int \left(l_{t+h} + \sigma_h^{\mathbb{Q}} g \left(\frac{sf_{h,t} - l_{t+h}}{\sigma_h^{\mathbb{Q}}} \right) \right) P_t^{\mathbb{Q}}(l_{t+h}) \, \mathrm{d}x \tag{7}$$

where $g(x) = x\Phi(x) + \phi(x)$ with $\Phi(x)$ the standard normal cdf, $\phi(x)$ the standard normal pdf and $\sigma_h^{\mathbb{Q}}$ the conditional variance of future shadow short rates. The variable $sf_{h,t}$ is the shadow forward rate h-periods ahead. It is affine in the pricing factors with loadings $\tilde{a}_h$ and $\tilde{b}_h$ and computed as $f_{h,t} = \tilde{a}_h + \tilde{b}_h X_t$. Notice that in this general form, the forward rate is calculated as the average of future short rates with l_{t+h} weighted by the risk-neutral probability of l_{t+h}.

With respect to the lower bound, we want to account for several stylized facts which can be observed for euro area OIS rates linked to the EONIA, one of these being that the latter can be considered as bound by the DFR.[1] However, it is important to note that the DFR does not necessarily constitute the ELB, as typically the EONIA stays a few basis points away from the DFR even in times of very high excess liquidity.[2] Therefore, the ELB can be thought of as the sum of two elements, the DFR and the minimum spread between EONIA and the DFR. The DFR itself is subject to discrete changes over time as documented, e.g., by subsequent cuts into negative territory in the course of 2014-2016, which were to some extent expected as documented by survey evidence (see Lemke and Vladu, 2016). Finally, the dynamics of forward rates during this period hint at the fact that markets might have expected even further DFR cuts over and above the DFR cuts that were largely anticipated of the next respective Governing Council meeting.

To account for these features and to preserve an approximate analytical solution for bond prices, we specify the time variation in the ELB in the following way:

$$l_{t+h} = \begin{cases} 0 & \text{if prior to ELB period and } \forall h = 0, 1, 2, \dots \\ \gamma_t i_t^{DFR} + (1 - \gamma_t) i_{t+1}^{DFR} + sp_t & \text{if ELB period and } h = 0 \\ \min(l_t, \bar{f}_t) & \text{if ELB period and } \forall h = 1, 2, \dots \end{cases} \tag{8}$$

with $\bar{f}_t = \min(f_{t,h})$ for $h = [1, 2, \dots, N]$. In the period before reaching the ELB, we set the current and expected ELB to zero. Following Wu and Xia (2017), from then onwards, the current ELB, l_t, equals the weighted average of the DFR in period t and the expected DFR in period $t+1$, which in our specification is treated as known in period t, where γ_t is the fraction of days between the end of month and the next Governing Council meeting in the following month. Moreover, in order to allow for further DFR cuts to be expected by agents in the following months, we approximate the expected ELB as the minimum of the current ELB and the minimum forward rate 1 to N periods ahead observed in period t. Notice that we do not explicitly model the DFR expectations process in an internally consistent way as in Wu and Xia (2017).[3] However, we think that our modeling approach is a reasonable shortcut to produce a very good fit of the yield curve at shorter tenors during the ELB period and to be able to generate short rate paths that do not violate lower bound restrictions and are broadly in line with survey evidence (see Section 4 in

[1] Transactions underlying the computation of EONIA take place between counterparties that all have access to the deposit facility of the Eurosystem. Thus, they are expected to have no incentive to lend below that rate.

[2] In times without excess liquidity, EONIA closely follows the main refinancing rate set by the Eurosystem. Then, with increasing excess liquidity, however, EONIA moves away from that rate and non-linearly approaches the deposit facility rate offered by the Eurosystem (Deutsche Bundesbank, 2014).

[3] In order to preserve an approximative analytical solution, Wu and Xia (2017) specify $P_t^{\mathbb{Q}}(l_{t+h})$ within a regime-switching model in which the lower bound is modeled as two-state Markov chain to describe the persistence and the momentum of the policy lower bound and to allow agents to be forward-looking with respect to future lower bound changes that affect bond pricing.

this repsect). With this deterministic lower bound specification we follow Wu and Xia (2016) and Equation 7 can then be approximated analytically as

$$f_{h,t} \approx l_{t+h} + \sigma_h^{\mathbb{Q}} g\left(\frac{sf_{h,t} - l_{t+h}}{\sigma_h^{\mathbb{Q}}}\right). \tag{9}$$

Further, as discussed above, the high persistence of yields which are only available in short samples for the euro area leaves the model with only little information about the data generating process $\mathbb{P}$ as well as the drift in far-distant short rate expectations. To possibly arrive at more precise estimates of the parameters under the $\mathbb{P}$-measure, we link model-implied expectations to survey forecasts on short rate expectations as a further central feature of our model following Kim and Singleton (2012). Given the well known potential drawbacks that may come with incorporating survey forecasts, we add measurement errors when we align model-implied expectations with the corresponding survey forecasts.[4] For any given survey interest rate forecast with residual maturity n in j-periods ahead, we add the following equation to our model set-up

$$i_{n,t+j}^{survey} = E_t^{\mathbb{P}}\left[i_{n,t+j}\right] + e_{n,t}^{survey} \tag{10}$$

where $e_{n,t}^{survey}$ is the measurement error.

3 Estimation

For estimation purposes, we cast our benchmark model $SRTSM_B$ in state space form with the transition equation given by Equation 2

$$X_t = \mu^{\mathbb{P}} + \rho^{\mathbb{P}} X_{t-1} + \Sigma u_t, \qquad u_t \sim N(0, I). \tag{11}$$

The measurement equation takes the form of

$$\hat{Y}_t = Y_t + e_t \tag{12}$$

in which Y_t is the J-vector of model-implied interest rates with $Y_t = g(X_t, \mu^Q, \phi^Q, \Sigma, \delta_0, \delta_1, lb_t)$ and $\hat{Y}_t$ corresponds to the J-vector of observed interest rates as well as survey forecasts adjusted for a vector of measurement errors e_t with standard deviation σ^i for yields[5] and

[4]First, as pointed out by Kim and Orphanides (2012), surveys report average expectations, while market prices are driven by marginal expectations on interest rates – a problem that might be exacerbated by relatively low numbers of participants compared to the number of participants in the market. A further explanation why survey-based expectations may only be an approximate reflection of market expectations may be the potential variation in the information available to participants and the point in time at which they submit their answers. Therefore, it can be assumed that the subjective expectations of survey participants deviate from the objective statistical expectations held under the $\mathbb{P}$-measure. Second, there might be incentives for survey participants not to reveal their true expectations, leaving surveys biased themselves, making them an inaccurate measure of participants' true expectations (Cochrane and Piazzesi, 2008; Chernov and Mueller, 2012).

[5]We assume that the measurement errors of yields are the same across the maturities considered.

σ_n^{survey} for survey expectations[6] (for GATSMs it holds that $Y_t = A + B'X_t$). As the mapping between interest rates and pricing factors in the measurement equation is non-linear, we apply the non-linear extended Kalman filter when maximizing the likelihood function. [7] With respect to the model identification, we closely follow Bauer and Rudebusch (2016) and estimate our model with $L = 3$ latent pricing factors based on the normalization of Joslin et al. (2011) with $\rho^{\mathbb{Q}} = diag(\rho_1^{\mathbb{Q}}, \rho_2^{\mathbb{Q}}, \rho_3^{\mathbb{Q}})$ and in Jordan form, $\mu^{\mathbb{Q}} = [k_\infty^{\mathbb{Q}}, 0, 0]'$, Σ is lower triangular and $\delta_0 = 0, \delta_1 = [1, 1, 1]'$.

In order to make the interpretation of latent pricing factors derived from our model easier, we can also transform the factors to an equivalent representation with new latent pricing factors P_t that resemble principal components in terms of level and dynamics along the procedure sketched out in Lemke and Vladu (2016).[8] This transformation makes it possible to directly compare estimated parameters with those of estimated $GATSMs$ based on principal components used as pricing factors. Therefore, we also report parameter estimates in terms of $\delta_{0,P}, \delta_{1,P}$ and μ_P, ρ_P, Σ_P both under the $\mathbb{P}$- and $\mathbb{Q}$-measure.

In our estimation, we use monthly overnight index swap (OIS) rates based on EONIA for the period January 1999 to October 2017 covering the maturities M in 1,3 and 6 months as well as 1,2,3,5,7 and 10 years. Hence, our yield curve data consist of $T = 226$ months for $J = 8$ maturities of interest rates. As these rates are reliably available only from July 2005 onwards, we follow Lemke and Vladu (2016) and augment our data set with spread adjusted zero-coupon rates based on EURIBOR swaps prior to 2005. Moreover, we follow the authors' specification of defining the ELB period from July 2012 onwards when the DFR hit the zero bound. We focus on the OIS term structure as in our view OIS interest rates represent the yield curve in the euro area with the closest link to expected monetary policy actions priced into interest rates. First, it is risk-free in the sense that it does not carry sovereign credit risk, the pricing of which might change over time and might distort the decomposition of interest rates. Second, as OIS rates are swap contracts in which cash flows are swapped, they do not serve as a store of value and thus should not be influenced by flight-to-safety and -liquidity investors to the same extent as sovereign bonds. And finally, the OIS curve is intrinsically linked to (one of) the monetary policy instruments(s) which the Eurosystem directly controls, as one leg of the contract is associated to the EONIA path which usually closely follows the MRO or - in times of large excess liquidity – the DFR of the Eurosystem.

With respect to modeling the time variation in the ELB, we specify Equation 8 the following way. First, as confirmed by survey and estimation evidence, the DFR cuts in June 14, December 15 and March 16 were largely expected by market participants, while the cut in September largely came as a surprise (Lemke and Vladu, 2016; Wu and Xia, 2017). Therefore, we allow the current ELB, l_t, to already incorporate these DFR cuts in the respective months previous to their realization by weighting the DFR cut with the

[6] In contrast to yield measurement errors, we allow the measurements errors of survey expectations to differ for each survey horizon.

[7] Alternative non-linear filters include the iterated extended as well as the unscented Kalman filter (Kim and Singleton, 2012; Priebsch, 2013; Krippner, 2015c).

[8] An affine transformation of the latent factors X_t to the pricing factors P_t implies that $P_t = AW + WBX_t$ where W is the weighting matrix which maps the set of observed yields into the first three principal components; A and B represent the affine loadings from an estimated $GATSM$ based on Joslin et al. (2011). It then holds that $\mu_P = WB\mu - WB\rho(WB)^{-1}$, $\rho_P = WB\rho(WB)^{-1}$, $\Sigma_P\Sigma_P' = WB\Sigma\Sigma'(WB)'$, $\delta_{0,P} = \delta_0 - \rho'(WB)^{-1}WA$ and $\delta_{1,P} = ((WB)^{-1})'\rho$. See Joslin et al. (2011).

parameter γ_t. Second, for the dynamics of the ELB h-periods ahead, we choose l_{t+h} to be the minimum observed one-month forward rate in 1 to 24 months.[9]

With respect to the use of survey information, we rely on selected Consensus Economics interest rate forecasts of the 3-month Euribor in 12- and 24-months time (available quarterly and semi-annually). Moreover, we also add to the survey measurement equations the long-horizon forecast for the average 3-month Euribor in 6 to 10 years which is available on a quarterly basis since September 2016. Survey data up to the 2-year horizon are adjusted by the Euribor-OIS spread, respectively. We exclude other available survey information at very short horizons and intermediate horizons. We do so because survey information might only be biased approximations of model-implied expectations and we want to let the yield curve data speak for itself as much as possible on the parameters governing the $\mathbb{P}$-measure.

4 Results

4.1 Goodness of fit

Overall, our benchmark model ($SRTSM_B$) performs well in terms of model fit (see Table 1, parameter estimates are reported in Table A.1). The mean absolute fitting error (MEA) of yields over the complete sample is 3 basis points and around 18 basis points for short-term surveys, which is comparable in size with other SRTSM estimates including survey information (see Priebsch, 2017, for US results). Notice that during the ELB period, both the yield and survey fit improves. The MAE for the 1-month rate is 1 basis point and the fit of short-term surveys is between 6 and 10 basis points, while the MEA of long-term surveys ranges at 15 basis points.

This good average model fit is largely confirmed when depicting the model-implied yield curve at selected dates and comparing it to observed yields (see Figure 1). However, during the ELB period the model fit somewhat varies depending on the specific observation dates. For instance, in October 2012 and July 2015, when the short end of the yield curve was very flat, our model is able to replicate this feature to a very good extent. In February 2016, when market participants were broadly expecting a further DFR cut, our model is able to replicate a downward sloping yield curve, but delivers higher fitting errors up to the 2-year maturity horizon.

Our analyses show that with respect to the short rate, even small fitting errors may generate an economically significant impact on the expected and most likely short rate path and, thus, on assessing monetary policy expectations. Therefore, fitting the short rate is important when evaluating the future short rate distribution over time. In order to do that, we explicitly allow the current spread between EONIA and the DFR in addition to expected DFR shifts to enter the ELB in l_t. This leads to a very good model fit of the short rate during the ELB period (see Figure 2). Closely related to this, our model implies a shadow short rate which is less prone to other modeling specifications. This finding is again mostly related to the incorporation of the spread into the ELB definition, which ensures that the ELB is binding for the model-implied short rate during the ELB period by construction. This modeling strategy thus makes the timing of when the shadow short

[9] $\bar{f}_t = \min(f_{t,h})$ for $h = [1, 2, \ldots, 24]$ months.

Table 1: In-sample model fit of yields and survey forecasts

maturity in months	1	3	6	12	24	36	60	84	120	avg
yields										
total sample:	4	3	3	3	2	3	3	2	3	3
pre-ELB sample:	5	4	3	4	3	3	3	1	3	3
ELB sample:	1	2	2	1	1	2	3	2	2	2
expected 3-month rate in months	12	24	60 − 120							
surveys										
total sample:	12	24	15							
pre-ELB sample:	15	30	−							
ELB sample:	6	10	15							

Note: This table shows the mean absolute errors (MAE) of model-implied yields and short rate expectations compared to observed yields and survey forecasts for selected sample periods in basis points. The total sample covers the period January 1999 to October 2017 while the pre-ELB sample covers the period January 1999 to June 2012 and the ELB sample the period July 2012 to October 2017.

rate first moves below the ELB insensitive to other modeling specifications which may affect the dynamics of the pricing factors (see Figure A.1).[10]

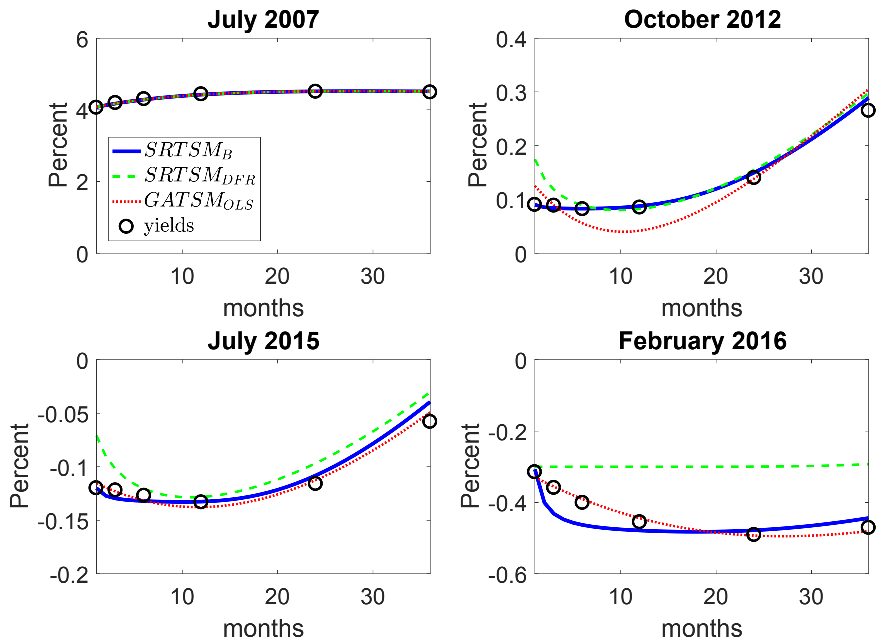
4.2 Model-implied short-term rate expectations

We start our analysis on model-implied interest rate expectations by decomposing forward rates into short rate expectations as well as forward premia for selected short-term and long-term maturities (panel(a) of Figure 3) based on our benchmark model. At the 1Y1Y forward horizon (see panel a), most of the variation in forward rates stems from changes in short rate expectations. Prior to the ELB period, forward premia ranged between 0 and 1%. Note that forward premia turned slightly negative by mid-2011 and remarkably remained anchored at this level from 2012 onwards. The prominent role of short rate expectations can also be identified when conducting a variance decomposition for the variation in the level and the change of the $1Y1Y$ rate. As shown in Table A.2, about 88% of the variation in the level is due to the expectations component over the total sample. During the ELB period, it even accounts for over 111% of the variation in the monthly change of the 1Y1Y forward rate.

To add to this finding, we depict 1-month forward premia for the $1, 3, 6$-month as well as 1 and 2-year horizon (panel (b) of Figure 3). For comparability, forward premia

[10]For a detailed discussion on the impact of model specification on the derivation of a shadow short rate, see Krippner (2015a).

Figure 1: **Yield curve model fit at selected dates**

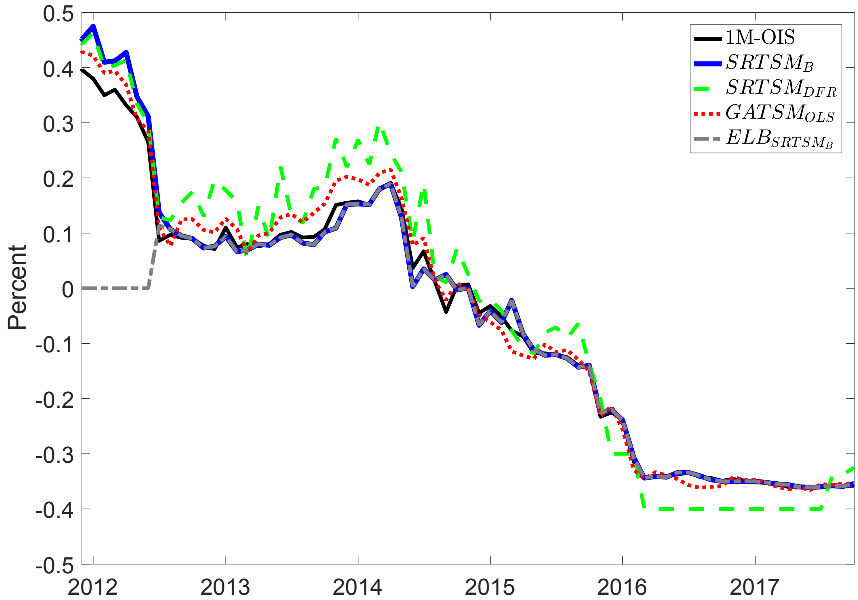


Note: This figure plots the model-implied yield curve based on various term structure model specifications including $SRTSM_B$, $SRTSM_{DFR}$ and $GATSM$ up to 3 years based on selected dates.

are scaled to unit per month and reported in basis points. The figure shows that after turning negative in 2011, term premia for shorter maturities reduced to 0, where they have stuck since the DFR cut to zero. Simultaneously, forward premia up to the 1- and 2-year horizon have stayed slightly negative with very low volatility compared to the time before 2011. These model-implied results can be seen against the background of a deterioration of the macroeconomic outlook with severe downside risks to price stability and an increasing probability of a deflationary scenario. The Eurosystem responded to these risks by introducing NIRP, strengthening its policy rate forward guidance as well as preparing and implementing its various asset purchase programmes. In this context, model-implied forward premia for shorter horizons show that the Eurosystem was able to anchor short-term interest rate expectations extremely well. Moreover, our results also seem to suggest that in addition to policy rate forward guidance, which has been in place since as far back as July 2013[11], signalling its willingness to dive deeper into non-standard monetary policy measures has been also important to steer short-term rate expectations and to reduce interest rate uncertainty priced in forward premia. In this respect, our

[11]The Eurosystem's Governing Council introduced its interest rate forward guidance in July 2013 by expressing its expectations that "key interest rates will remain at present or lower levels for an extended period of time". In June 2014, the Governing Council decided to delete the word "lower" from its forward guidance. This was only reintroduced when the Council decided to link its interest rate forward guidance to its expanded asset purchase programme (APP) by stating the expectation that "the Governing Council expects the key ECB interest rates to remain at present or lower levels for an extended period of time, and well past the horizon of our net asset purchases."

Figure 2: **Model fit of the short rate**



Note: This figure plots the model-implied short rate based on various term structure model specifications including $SRTSM_B$,$SRTSM_{DFR}$ and $GATSM$ together with the effective lower bound (ELB) of the $SRTSM_B$ model.

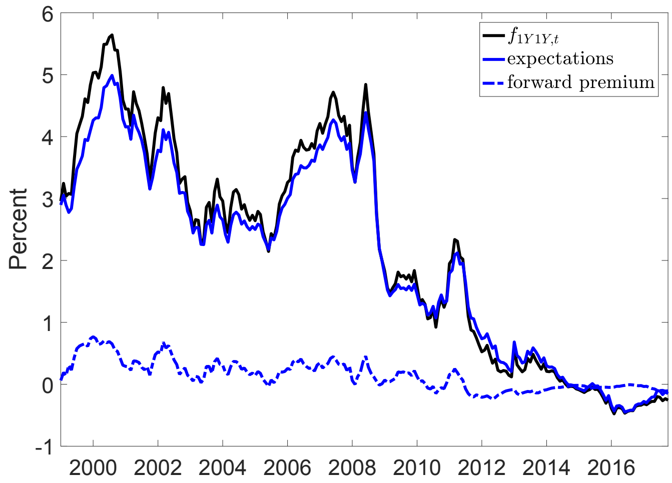
results also emphasize the signaling channel of non-standard monetary policy measures including asset purchases which affect both short rate expectations and risk compensation demanded by market participants (see Bauer and Rudebusch, 2014, for US evidence).

Given the asymmetry of the distribution of future short rates during the ELB period, our model also accounts for the wedge between the *mean* and the *mode*, i.e. the most likely future short rate path which is eminent at short- and medium-term horizons where the ELB implies a truncated distribution. The wedge between these two statistical numbers is important when assessing monetary policy expectations that are priced into the yield curve. The bigger the wedge the tighter the ELB constraint binds for the yield curve (Swanson and Williams, 2014; Bauer and Rudebusch, 2016).[12] To illustrate this point, we plot the dynamics of the mean and the mode of the future short rate for a fixed-horizon forecast in March 2019 together with the corresponding forward rate path and the expected ELB (panel (a) of Figure 4). The figure highlights the bias when relying on the forward rate or the expected short rate path during the ELB period. First, the forward rate path is biased due to the existence of substantial time variation in forward premia. Second, due to the asymmetry, the expected short rate path shows a constant upward bias. Correct inference with regard to monetary policy expectations can only be drawn from the modal path of the short rate which represents the optimal forecast under absolute error loss (Bauer and Rudebusch, 2016). Closely related to this, the model can

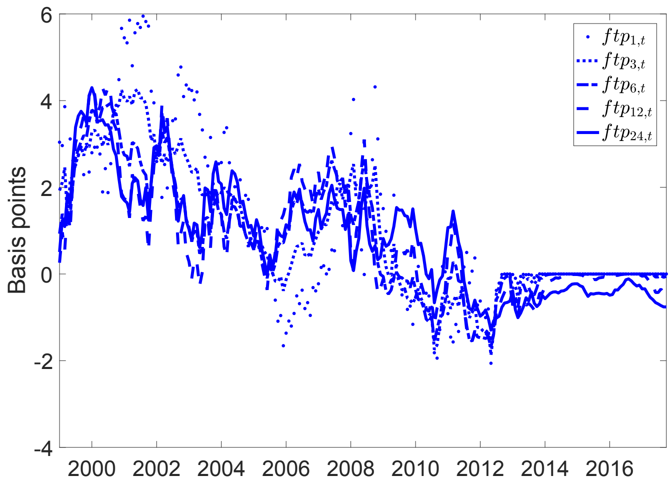
[12]In line with Bauer and Rudebusch (2016), we define the *mode* of the short rate path as $\max(E_t[si_{1,t+i}], lb_{t+i})$.

Figure 3: **Short-term forward rate decomposition**

(a) 1Y1Y forward rate



(b) (Normalized) short-term forward premia



Note: Panel (a) plots the time series of the decomposition of the 1Y1Y forward rate. Panel (b) plots the time series of normalized 1-month forward premia at the $1, 3, 6, 12$ and 24-months horizons. Forward premia are normalized by maturity in months. End-of-month values for January 1999 to October 2017.

inform on the median of the lift-off distribution of the short rate which measures the time at which the short rate is likely to cross a certain threshold level.[13] Panel (b) of Figure 4

[13]The lift-off distribution is calculated by simulating a large number of short rate paths under the $\mathbb{P}$-measure and then saving the future horizon at which each single path rises above a certain threshold.

depicts the lift-off horizon based on the modal path as well as the lift-off distribution for a specification that gives an idea about the point in time at which market participants regard a first 10 bp rate hike as most likely. Both indicators move fairly close to each other. With the transition to the ELB period, the crossing time constantly moved out further. For instance, in summer 2016, market participants did not believe they would see a first 10 bp rate hike before 2020. Since then and going forward in time, both indicators signaled a gradual reduction in the number of months until a first DFR hike is regarded as most likely. For the end of the sample in October 2017, this assessment implies a first DFR hike in the summer of 2019.

4.3 Model-implied longer-term rate expectations

In this Section, we turn to the implications of model-implied intermediate and long-term expectations as well as term premia based on our benchmark model. To start with, in Table 3 we report summary statistics for the (shadow) short rate based on the $\mathbb{P}$-measure. The model is estimated with an unconditional mean of 4.55% and a fairly high persistence of the pricing factor process of the transition matrix, which is expressed by a largest eigenvalue of 0.990 in $\phi^{\mathbb{P}}$. Indeed, a shock to the most persistent pricing factor has a half-life of roughly 5.75 years. Although our model implies that the short rate will converge to a constant in the very long run, according to the short rate summary statistics, our model also implies a substantial time variation of far-distant short rate expectations up to the 10-year horizon.

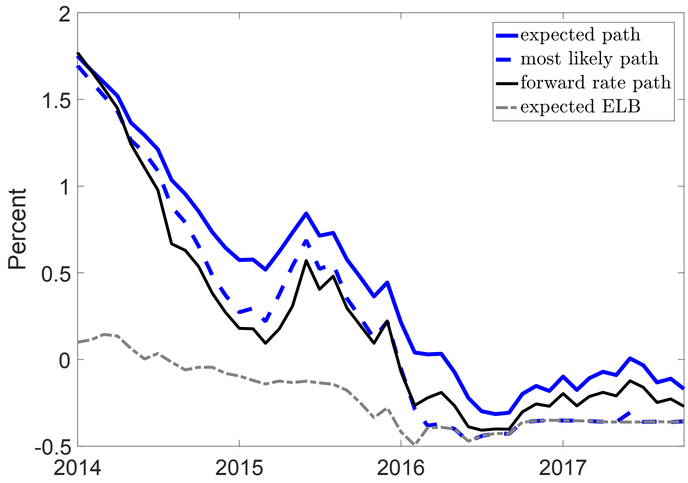
To see this, we plot the 9Y1Y forward rate together with its decomposition into the expected short rate and forward premium component in panel (a) of Figure 5. A high degree of the variability in forward rates can be attributed to the forward premium which exhibits a marked decline over the sample period from close to 2% into negative territory, standing at about -89 bp at the end of the sample. In particular, a first large drop can be observed in the wake of the Greenspan conundrum between June 2004 and June 2006. Following a short upward movement, it then began to follow a lasting downward trend after the outbreak of the financial crisis in 2008. The market's anticipation of widespread asset purchases since the beginning of 2014 then triggered another sharp drop leading the premium into negative territory, where it has remained since, although its downward trend came to a halt. This time variation of forward premia is also reflected at more intermediate horizons (see panel (b) of Figure 5). Note that at these intermediate to long-term maturities, forward premia co-move more linearly than at shorter maturities (see panel (b) of Figure 3). However, the decline in the long-term forward rate reflects also the time variation in far-distant short rate expectations which have trended downwards since the height of the financial and economic crisis in 2008.

A variance decomposition for the 9Y1Y forward rate confirms that over the total sample roughly 56% of the variation in the level of the $9Y1Y$ rate is due to the forward premium component (see Table A.3). In the ELB period, the share of the forward premium

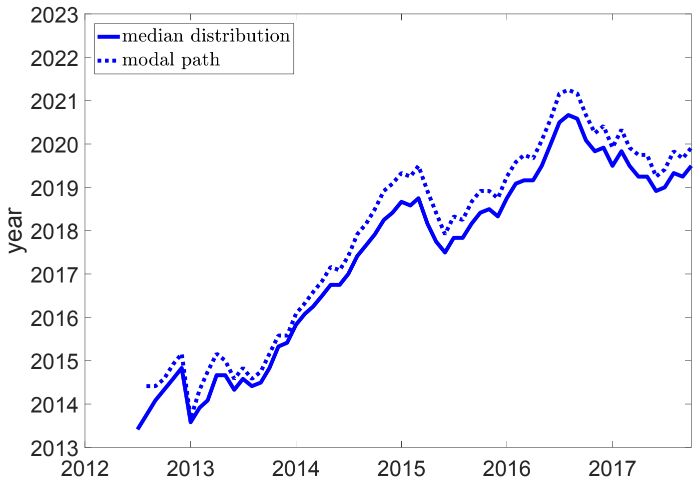
While determining these future horizons, the fact can be accounted for that some paths cross the threshold due to shocks, but then may again fall back below. This is done by requiring a path to stay above the threshold to be chosen for a certain amount of time, e.g. 12 months. This way, it is ensured that the inspected path has really lifted off. Ideally, the median of that distribution corresponds to the future point in time at which the modal path crosses the threshold, but it might deviate if enough paths fall back below the threshold too quickly after lifting off for the first time (Bauer and Rudebusch, 2016)

Figure 4: **Distribution of short rates**

(a) Future short rate in March 2019



(b) First +10 bp DFR hike

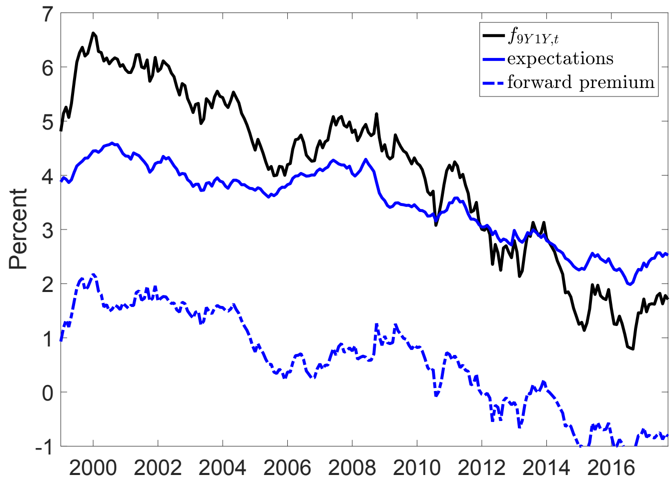


Note: Panel (a) plots the model-implied dynamics of the expected and most likely path of the short rate together with the forward rate for a fixed horizon in March 2019 based on the $SRTSM_B$ model. Panel (b) plots the timing of the first DFR hike by +10 bp based on the short rate distribution and the modal path of the short rate. End-of-month values for January 1999 to October 2017.

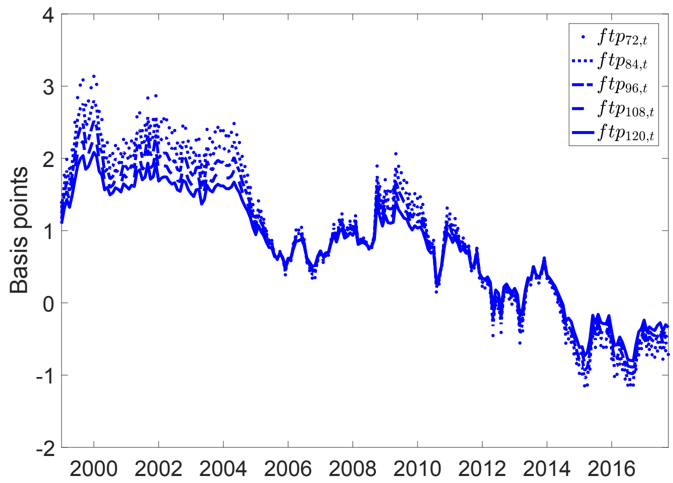
variation increases to roughly 60%. In terms of variation in the change in the forward rate, 73% can be attributed to the change in forward premia, highlighting their prominent role at longer tenures. At the same time, these numbers imply that the variation of long-term

Figure 5: **Long-term forward rate decomposition**

(a) 9Y1Y forward rate



(b) (Normalized) long-term forward premia



Note: Panel (a) plots the time series of the decomposition of the 9Y1Y forward rate. Panel (b) plots the time series of normalized 1-month forward premia at the $6, 8, 8, 9$ and 10-year horizons. Forward premia are normalized by maturity in months. End-of-month values for January 1999 to October 2017.

forward rates in terms of level and change is explained by the expectations component, too. Importantly, this also holds true in the run-up to the decisions of the Eurosystem to implement large-scale asset purchases that had been increasingly anticipated since summer 2014. Indeed, our model suggests that roughly one half of the observed decline of the 10Y-OIS rate from September 2014 to March 2015 can be explained by changes in the average path of the expected short rate over the 10-year horizon. This stands in contrast to the findings of Lemke and Werner (2017), who find that almost all of the long-term yield decline during this period was due to the decline in the term premium within the portfolio rebalancing channel.

In order to pass judgment on the economic plausibility of the level and the variability of the expected short-term interest rates in intermediate and long-term forward rates (and therefore also on the forward premia), we compare the expectations component with an estimated equilibrium nominal short-term interest rate derived from a macroeconomic model. Interest rate expectations contained in financial market prices at the long end of the term structure should position themselves at this level if it is assumed that the term structure reflects macroeconomic information, particularly with regard to long-term inflation expectations and the equilibrium real interest rate. The latter is determined by estimating a natural rate of interest which is consistent with a permanently closed output gap and a stable inflation rate in the medium to longer term, after the economy recovers from all cyclical fluctuations.[14]

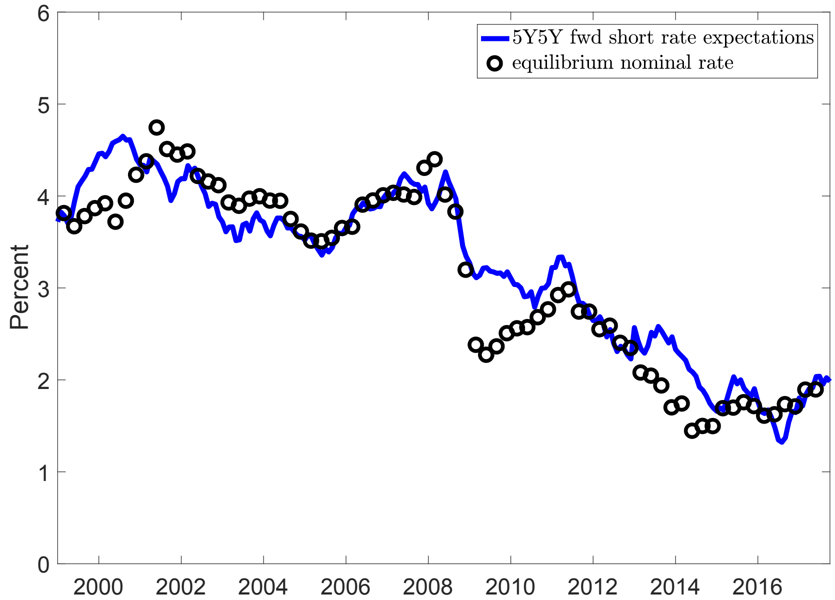
Indeed, 5Y5Y interest rate expectations derived from our benchmark model capture the level and path of the nominal natural interest rate quite well. In this period, the latter is primarily driven by the real natural interest rate path while simultaneously longer-term inflation expectations are rather stable. This observation is interesting as the two models do not share any information in the estimations. While $SRTSM_B$ solely contains term structure information, the macroeconomic model only takes the inflation rate, the level of GDP and the ex ante short-term real interest rate into consideration. Long-term forward rates thus appear to reflect trends in key macroeconomic variables in both real and nominal terms, which play an important role in the formation of far-distant rate expectations (see also Bauer and Rudebusch, 2017; Crump et al., 2017; Cieslak and Povala, 2015; Dijk, Koopman, Wel, and Wright, 2014) on this assessment).

We also compare our intermediate and far-distant forward rate decomposition (5Y5Y fwd) to US estimates based on Kim and Wright (2005), who also incorporate survey information into their term structure model. As shown in Figure A.2, until the beginning of 2013 the expectations component in US and euro area 5Y5Y forward rates is similar in terms of both level and variation. The high co-movement in US and euro area forward rates during this period of time is also related to a significant extent to US and euro area forward premia.[15] From summer 2013 onwards however, initiated by the US taper tantrum and followed by a deteriorating economic and inflation outlook as well as increasing expectations of large-scale asset purchases in the euro area, US and euro area far-distant short rate expectations decoupled significantly with the latter falling. The

[14]We exemplarily choose the real natural rate estimate based on Holston et al. (2017) and add medium- to long-term inflation expectations based on Consensus forecasts to present the rate in nominal terms. The maturity perspective of the derived natural rate of interest in this model estimation is not explicitly defined, but refers to a longer-term perspective due to the modeling strategy and the definition of the latent variable and shock processes: "Our definition takes a 'longer-run' perspective, in that it refers to the level of real interest rates expected to prevail, say, five to ten years in the future, after the economy has emerged from any cyclical fluctuations and is expanding at its trend rate." (Laubach and Williams, 2016).

[15]Indeed correlation coefficients during this period are 0.9 and 0.8 for the expectations component and the forward premium.

Figure 6: **5Y5Y short rate expectations and longer-run equilibrium nominal rate**



Note: This figure plots the time series of the $SRTSM_B$ model-implied average short rate expectations in 5 to 10 years together with an estimate of the longer-run nominal equilibrium rate based on Holston et al. (2017). The equilibrium nominal rate is derived by adjusting the estimated longer-run real equilibrium rate and adding longer-run inflation expectations based on Consensus forecasts.

same holds for the dynamics of the euro area forward premium, which was much more depressed than its US counterpart in the run-up to the APP decision in January 2015.[16]

Finally, we check to what extent the asymmetry of the short rate distribution also matters for long-term interest rates. By comparing interest rates and shadow interest rates under both the $\mathbb{Q}$- and $\mathbb{P}$-measure, it is possible to compute a measure of the degree the time-varying ELB exerts influence at the long end of the term structure of interest rates. Indeed, our findings suggest that it does so, in particular since the beginning of 2014 (Figure A.3). The ELB wedge widened not only under the $\mathbb{Q}$-measure but also under the $\mathbb{P}$-measure, though not to the same quantitative extent. A somewhat more nuanced picture can be observed for far-distant forward rate (Figure A.4). While under the Q-measure the ELB wedge widened from 2014, the mean and the mode of the short rate under the $\mathbb{P}$-measure at the $10Y1M$-horizon is essentially identical.

[16]Correlation coefficients declined to 0.4 and 0.6 for the expectations component and the forward premium.

4.4 Assessing the impact of monetary policy

To provide evidence on how monetary policy influences the various components of the term structure, we investigate how forward rates, short rate expectations and forward premia respond to monetary policy shocks within our model. As these shocks are not directly observable, a viable workaround is to assume that changes of selected interest rates around monetary policy announcement dates are reliable observable proxies for monetary policy shocks which can then be used to study the response of interest rates (Kuttner, 2001; Cochrane and Piazzesi, 2002; Gurkaynak et al., 2005; Piazzesi and Swanson, 2008; Nakamura and Steinsson, 2018, among others). Recent applications to estimated term structure models are Abrahams et al. (2016); Crump et al. (2017).

However, this identification strategy may run the risk of capturing only part of the underlying monetary policy shock, and they may be measured with error. Therefore, tight windows around monetary policy announcements are typically required in order to reduce endogeneity and noise concerns (Gurkaynak et al., 2005; Nakamura and Steinsson, 2018). Moreover, the literature implicitly assumes that the reaction of interest rates to monetary policy (and other) shocks is constant over time by applying linear regression techniques. Our benchmark model challenges this assumption, as it convincingly shows that interest rates are actually non-linear functions of the pricing factors and the reaction of interest rates to innovations in the pricing factors crucially depends on how large the ELB wedge is at a given point in time (see Sections 4.2 and 4.3 above).

To alleviate these concerns, we treat changes in interest rates around monetary policy announcements as instrument variables and not as directly observable monetary policy shocks. This approach has been applied in the macroeconomic proxy SVAR literature that aims to identify the dynamic causal effects of various macroeconomic shocks (Stock and Watson, 2012; Mertens and Ravn, 2012; Gertler and Karadi, 2015).

Following standard terminology, we assume that the L reduced-form innovations u_t of the transition equation 11 are L linear combinations of structural shocks ϵ_t. Therefore, it holds that

$$u_t = H\epsilon_t = [H_1, \dots, H_L]\,(\epsilon_{1,t}, \dots, \epsilon_{L,t})' \tag{13}$$

where H_1 is the first column of H and $\epsilon_{1,t}$ is the first structural shock. With $\Omega_u = \Sigma\Sigma'$, it also holds that $\Omega_u = H\Omega_\epsilon H'$. Given invertibility of the system, structural shocks can be expressed as linear combinations of reduced-form innovations

$$\epsilon_t = H^{-1}u_t. \tag{14}$$

As discussed in Stock and Watson (2012, 2018), structural shocks and hence H can be recovered by a predictive regression of the relevant instrument z_t on the innovations u_t up to scale and sign. The scale and sign of the structural shock, say $\epsilon_{1,t}$ and H_1, are determined by normalizing the shock to have a unit current impact on a specific pricing factor. Most importantly, while the link between the instrument and the innovations remains linear, the instrument approach allows us to model the reaction of yields and forward rates in a non-linear way in line with Equation 7. Thus, monetary policy shocks may exhibit a different impact on the yield and forward curve at a given point in time depending on the size of the ELB wedge.

In the following we identify conventional (CMP) and unconventional monetary policy (UMP) shocks based on the instrument data set of Mandler and Scharnagl (2018). The data set consists of daily changes of various financial market variables used as instruments for monetary policy related shocks during days of press conferences following meetings of the ECB's Governing Council, press releases concering non-standard monetary policy measures, speeches and interviews by both the President and the Vice-President of the ECB and events related to allotment days of non-standard refinancing operations. The daily changes of these instruments at defined events are then aggregated to monthly frequency. We use the first principal component of the daily change of five variables, the 1Y Bund yield, the 1st EURIBOR as well as the 1st, 2nd and 3rd EONIA future contract as instrument for a conventional monetary policy shock. As instrument for an unconventional monetary policy shock we take the first principal component of the daily change in the $10Y$ Bund, French and Italian yield. We separate CMP from UMP periods by estimating the CMP shocks based on the sample period January 1999 to June 2014 and UMP shocks based on the sample period July 2014 to October 2017.

Note that our instruments do not inform why they changed during monetary policy related events. They may change due to a monetary policy target shock, they may change due to monetary policy communication and forward guidance or they reveal changes of the central bank's stand on the future path of output or inflation via information effects Nakamura and Steinsson (2018). In so far, in identifying monetary policy shocks, we measure the total impact of monetary policy news and do no isolate the various channels through which monetary policy actions may impact the yield curve.

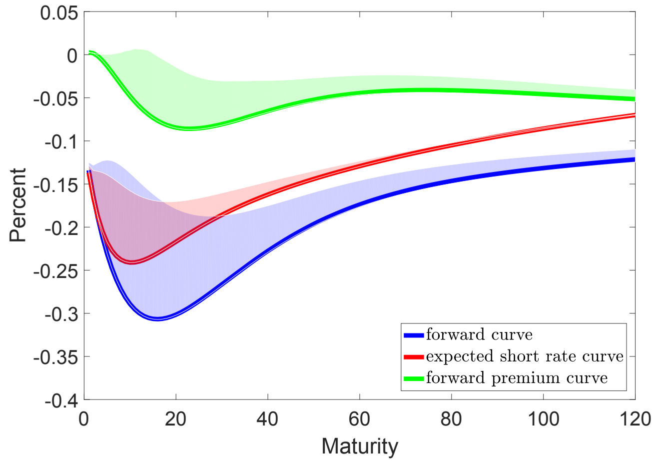
In order to compute economically interpretable impulse response functions based on the identified monetary policy shocks, we rotate our benchmark model $SRTSM_B$ as described in Section 3. In particular, we transform the three latent factors in a way that they resemble the 1-months, 2-year and 10-year (shadow) rate. We then normalize the CMP shock in sign and size so that a 10 basis point change in this shock implies an equally large change in the (shadow) short rate. A UMP shock is normalized so that on (median) impact this shock triggers a change in the 10-year yield by 10 basis points.

Results for the instantaneous response of the components of the forward curve to an expansionary conventional monetary policy shock during the period January 1999 to June 2014 are depicted in panel (a) of Figure 7. Note, however, that the figure does not show uncertainty around the impulse responses. It merely shows the distribution of impulse responses to monetary policy shocks at different points in time and highlights the asymmetry of responses depending on the strength of the binding character of the ELB. The nominal forward curve exhibits the largest response at the 1- to 2-year maturity horizon with a negative reaction even at very long-term maturities. Hence, our model implies a very high persistence of conventional monetary policy shocks along the forward curve. Interestingly, at maturities up to 2 years, the decline in the forward curve is due to both, changes in the expected short rate and forward premia, with the former dominating the overall effect. Also at longer maturities, the effect on the forward curve is dominated by the expectations component.[17] The U-shaped response of the forward curve also highlights the communication / forward guidance component of CMP shocks. While our identification strategy does not allow to separate pure target from communication shocks, we can still identify pure target shocks in our rotated model representation as

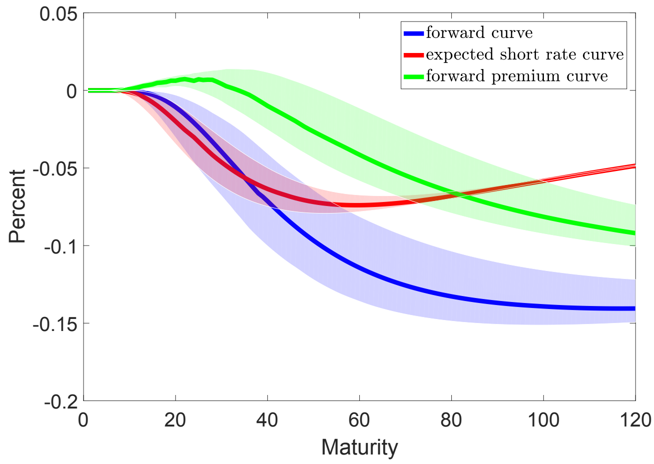
[17]See Nakamura and Steinsson (2018) for a similar result based on US data.

Figure 7: **Instantaneous response to monetary policy shocks**

(a) Conventional MP shock (01/99-06/14)



(b) Unconventional MP shock (07/14-10/17)



Note: Panel (a) plots the median instantaneous response of the forward curve and its components with [15%−85%] quantiles to a conventional monetary policy shock (CMP) for the sample period January 1999 to June 2015. Panel (b) plots the median instantaneous response of the forward curve and its components with [15% − 85%] quantiles to an unconventional monetary policy shock (UMP) for the sample period July 2014 to October 2017.

a shock to the first pricing factor is a shock to the short rate prior to the ELB period. Indeed, a comparison of the forward curve reaction in response to the model-derived target shock and the estimated CMP shock indicates that much of the response based on our identification comes from monetary policy announcements that lead to changing beliefs about the future path of monetary policy rates explaining the U-shaped pattern.[18]

[18] For a similar result see Leombroni, Vedoli, Venter, and Whelan (2017) who decompose ECB monetary

Finally, panel (a) of Figure 7 also illustrates the increasingly binding character of the ELB between mid-2012 and mid-2014 which is expressed by the muted response of the forward rate components at the 85% percentile.

Panel (b) of Figure 7 depicts the corresponding instantaneous response of the forward curve together with the expected short rate and forward premium curve between July 2014 and October 2017 to UMP shocks. The median reaction at the long end is negative and spills over to medium-term maturities. Up to the 2-year horizon, however, there is essentially no reaction as rates are stuck at the ELB. The largest impact on the forward curve stems from the forward premium at the 10-year maturity horizon, emphasizing the transmission of non-standard measures through duration extraction. At medium-term maturities our model attributes a more prominent role to the expectations component. However, even at very long-term maturities, the expected short rate falls in reaction to an unconventional monetary policy shock. Therefore, our model also highlights the signaling channel of non-standard monetary policy measures.[19]

In Table 2, we perform a historical decomposition of the 10-year OIS rate for various sample periods in order to assess the contribution of UMP shocks to the change of this rate. Between June 2014 and the start of asset purchases in March 2015, the rate dropped by 0.77%, which is attributed almost entirely to UMP shocks according to our model estimates. Both the term premium and the expectations component contributed to this decline. Between March 2015 and September 2016, one third of the observed change in the 10-year OIS rate stems from non-identified shocks affecting mainly the term premium component while UMP shocks continue to exert downward pressure on the yield via the expectations and term premium component . From September 2016 onwards, UMP and others shocks again contribute to the rise of the 10-year OIS rate by 0.6%.

Finally, we take a closer look at the shadow short rate and analyze to what extent its dynamics are related to UMP shocks (Figure A.6). It turns out that although these shocks increasingly affected the shadow short rate throughout 2015 and at the end of 2016, given the high persistence of UMP shocks, much of the variation stems from other, non-identified shocks. Therefore, its move deep into negative territory should not be interpreted as a pure reflection of a sequence of UMP shocks.

4.5 Specification analysis and robustness of model-implied rate expectations

4.5.1 In-sample fit

In this Section, we compare the results of our benchmark model to those of alternative modeling specifications. We run estimations of further DTSMs including GATSMs and SRTSMs that do or do not account for a time-varying ELB or survey information. In

policy surprises into target and communication shocks. They also find a humped- (U-) shaped pattern in reaction to communication shocks while the effects of target shocks are small and cancel out quickly.

[19] Swanson (2017) uses high-frequency regressions around FOMC announcements to estimate effects of LSAP and forward guidance shocks on asset prices based on additional identification restrictions. He finds that both forward guidance as well as LSAPs were about equally effective for medium-term Treasury yields, stocks, and exchange rates. Forward guidance had larger effects on short-term Treasury yields while LSAPs had larger effects on long-term Treasury yields, corporate bond yields, and interest rate uncertainty.

Table 2: **Contribution of unconventional monetary policy shocks to change in interest rates**

10Y-OIS rate		total	expectations	term premium
07/14 – 03/15:	total	-77	-37	-40
	UMP shock	-89	-56	-32
	other	12	19	-7
03/15 – 09/16:	total	-34	-41	6
	UMP shock	-65	-39	-26
	other	30	-1	32
09/16 – 10/17:	total	62	56	6
	UMP shock	37	13	23
	other	26	43	-17

Note: This table shows the contribution of unconventional monetary policy shocks to the change in the 10Y-OIS rate for selected sample periods based on the $SRTSM_B$ model and unconventional monetary policy (UMP) shocks identified with external instruments.

particular, we estimate two additional SRTSM specifications, one in which the ELB equals the DFR ($SRTSM_{DFR}$) and one in which we implement the same ELB set-up as in our benchmark model, but in which we exclude survey information ($SRTSM_{woS}$). In addition, we estimate three GATSM model variants ($GATSM_{OLS}$, $GATSM_S$, $GATSM_{BC}$) based on Joslin et al. (2011) which differ with respect to the use of surveys and with respect to the application of bias correction to the parameters under the $\mathbb{P}$-measure in line with (Bauer et al., 2012).

We start by comparing the overall in-sample model fit. As shown in Table A.4, all models generate a similar average model fit, ranging between 2 and 3 basis points based on the mean absolute error. As a result, there is no model specification that performs significantly better in terms of average model fit. However, the comparison of model-implied yield curves with observed yields at selected dates reveals noticeable differences across models (see Figure 1).[20] The following observations stand out: Prior to the ELB period, all inspected models generate a similar fit of the yield curve. However, this changes with the beginning of the ELB period. Both $SRTSM_B$ and $GATSM_{OLS}$ fit the observed data during this period slightly better than $SRTSM_{DFR}$.[21] We show this exemplarily for February 2016. At this time, market participants were broadly expecting a further DFR cut at the next meeting of the ECB's Governing Council. Given their downward flexibility, both models are able to fit the negative slope of the yield curve. While in

[20] For readability, we do not show the model variants $GATSM_S$, $GATSM_{BC}$ and $SRTSM_{woS}$ in Figure 1.

[21] This is in line with findings by (Kortela, 2016; Wu and Xia, 2017)

$GATSM_{OLS}$ this flexibility is ensured by the absence of a lower bound, in $SRTSM_B$ accounting for expected ELB shifts is crucial to generate a satisfying yield curve fit. In contrast, a specification that does not account for expected DFR shifts as in $SRTSM_{DFR}$ fails to reproduce a downward sloping forward curve which trades below the current DFR. This shortcoming has important implications for the distribution of short rates and yield curve decompositions, a finding we will discuss later in Subsection 4.5.2. While a look at the yield curve in February 2016 shows that $GATSM_{OLS}$ is best capable of fitting the downward sloping yield curve at the lower bound, $SRTSM_B$ plays out its strengths vis-a-vis $GATSM$ whenever the short end of the yield curve is flat over an extended period of time (see October 2012).

4.5.2 Short rate summary statistics and rate expectations

Comparing the implications of different model specifications for short rate summary statistics, the most notable difference is related to the model-implied unconditional mean of the short rate (see Table 3). While the estimated models without surveys ($SRTMS_{woS}$, $GATSM_{OLS}$, $GATSM_{BC}$) generate an unconditional mean between 0.79 and 1.78, the models with surveys ($SRTSM_B, SRTSM_{DFR}$ and $GATSM_S$) imply values between 3.67 and 4.38 for the short rate. Clearly, the inclusion of surveys leads to markedly higher levels of far-distant short rate expectations. To partly overcome the shortcoming of a very low unconditional mean in a data sample that is characterized by a prolonged period of low interest rates such as the one considered in this paper, the pricing factors could also be de-meaned as in Adrian et al. (2013). Alternatively, it could be specified that the unconditional mean of the pricing factors $E^{\mathbb{P}}[X_t]$ must equal their sample mean (Bauer et al., 2012). Both approaches ensure that the unconditional mean of the short rate $E^{\mathbb{P}}[i_{1,t}]$ matches its sample mean, thereby partly alleviating the small sample problem with respect to the level of far-distant expected short rates (see the result for $GATMS_{OLS}$ in brackets as well as $GATMS_{BC}$). Still, based on the short rate summary statistics, far-distant short rate expectations are lower compared to survey-based estimations. Including an ELB specification, in contrast, does not result in a clear difference with respect to the unconditional mean. While $SRTSM_B$ produces the highest unconditional mean, the second highest level can be found in $GATSM_S$ followed by $SRTSM_{DFR}$ with the DFR as ELB specification.

Turning to the mean reversion characteristics of the pricing factors with its implications for the persistence of the short rate process, interestingly, all estimated models produce a rather slow mean reversion, so that far-distant short rate expectations react to shocks to the pricing factors to a significant extent. The maximum eigenvalue of the matrix $\rho^{\mathbb{P}}$ in all model variants is larger or equal 0.99. $SRTSM_{DFR}$ implies the lowest half-life of the most persistent factor process with around 5.5 years. In contrast to the US findings of Kim and Priebsch (2013), our estimated $GATSM$s exhibit an even higher persistence of the short rate process. The half-life of a shock to the most persistent pricing factor for the the non-bias corrected $GATSM$ variants is between 7.3 and 11.6 years, although the models are estimated over the entire ELB period. Also, the inclusion of short- and long-term interest rate survey information as in $GATSM_S$ does not change this result. Our findings indicate that with respect to the considered euro area yield curve sample, estimated DTSMs always produce a very high persistence of the short rate process

Table 3: **(Shadow) short rate summary statistics – $\mathbb{P}$-estimates**

model	$SRTSM_B$	$SRTSM_{DFR}$	$SRTSM_{woS}$
unconditional mean $E^{\mathbb{P}}i_1$:	4.546	4.130	0.743
eigenvalues under $\mathbb{P}$-measure:	0.990	0.989	0.990
	0.908	0.919	0.895
	0.837	0.861	0.895
half-life in years:	5.75	5.50	6.33
model	$GATSM_{OLS}$	$GATSM_S$	$GATSM_{BC}$
unconditional mean $E^{\mathbb{P}}i_1$:	−0.789	4.647	1.778
	(1.778)		
eigenvalues under $\mathbb{P}$-measure:	0.996	0.992	0.999
	0.917	0.938	0.918
	0.917	0.812	0.918
half-life in years:	11.58	7.33	99.50
sample mean (i_1): 1.78			

under the $\mathbb{P}$-measure. Therefore, the estimated difference in the persistence of the pricing factors between non-biased and biased-corrected estimates up to the 10-year horizon are not substantially large, which stands in contrast to US evidence (Bauer, Rudebusch, and Wu, 2014; Wright, 2014).

We now turn to the derivation of model-implied near- and far-distant short rate expectations. We start with short-term horizons and check whether the inclusion of an ELB specification has an important impact on the behavior of the short rate path at short-term horizons. Assuming our ELB specification in $SRTSM_B$ to be a reasonable approximation of the true ELB, we first check the number of ELB violations by counting the number of months in which the expected short rate path falls below the (expected) ELB, l_{t+h}, for the various model variants (Table A.5). While ELB violations are excluded by construction in $SRTSM_B$ and $SRTSM_{woS}$, in $SRTSM_{DFR}$ few violations occur in periods in which the DFR is a binding restriction for the short rate while being below the ELB (mainly as there exists a positive spread between the DFR and the short rate). Obviously, all $GATSM$s fail to respect the ELB restrictions observed in the data during the ELB period. The violations in these models amount to between 22 and 52 months.

The importance of specifying a DTSM for the euro areas as a $SRTSM$ with an ELB specification can also be highlighted when assessing near-term monetary policy rate expectations. In Figure A.7, we simulate the median lift-off distribution of a +10 BP DFR hike for the various model variants.[22] Clearly, $GATSMs$ produce a wide spectrum of

[22]The lift-off distribution is calculated by simulating a large number of short rate paths under the $\mathbb{P}$-measure and then saving the future horizon at which each single path rises above a certain threshold. We define the threshold for a +10 bp DFR hike as our benchmark ELB specification plus 10 bp. For

results. On the one hand, the lift-off measure based on $GATSM_{BC}$ turns out to be highly volatile with month-to-month changes amounting to several years, which seems rather unreliable. On the other hand, $GATSM_S$ produces almost no variation in the lift-off measure at all. $GATSM_{OLS}$ comes out between those two extreme results, still offering a rather high amount of variation, reacting strongly to movements in interest rates.

Compared to $GATSM_{BC}$, but also to $GATSM_{OLS}$, the models $SRTSM_B$, $SRTSM_{DFR}$ and $SRTSM_{woS}$ all produce less volatile lift-off series which are very similar in terms of dynamics but reveal larger differences in terms of level. The results suggest that survey information on the one hand reduces the degree of stickiness of the short rate at the lower bound in times when forward rates as well as DFR expectations are tilted to the downside. On the other hand, this additional information also dampens the reaction of short rate expectations to large swings in interest rates as observed during the Bund tantrum at the beginning of 2015 or in the wake of the global hike in rates in fall 2016. With respect to the ELB specification and associated fitting errors of the model-implied short rate, both features have a pronounced impact on the median distribution of the most likely short rate path (see the simulation results for $SRTSM_{DFR}$).

Regarding long-term rate expectations, Figure A.8 depicts the 10Y1M expected short rate of our benchmark model (modal path) together with estimated confidence interval bands based on parameter estimation and current state filter uncertainty.[23] All survey-based models lie within the confidence interval bands of $SRTSM_B$, so that we conclude that the results for long-term rate expectation are robust to model specification and economically plausible as long as survey information is included. In contrast, $SRTSM_{woS}$, $GATSM_{OLS}$ and $GATSM_{BC}$ generate a significantly lower level of short rate expectations at far-distant horizons. Interestingly, up to the ELB period, far-distant short rate expectations in $GATSM_{BC}$ do not exhibit implausibly large time variation compared to $GATSM_{OLS}$ as partly documented for bias-corrected estimates based on US data (Wright, 2014).

4.5.3 Monte Carlo exercise

As a robustness check, we conduct a Monte Carlo simulation study for which we simulate interest rates with $J = 1, 3, 6, 12, 24, 36, 60, 84, 120$ months of maturities based on an SRTSM with a fixed ELB at 0%. In light of the high persistence of interest rates observed

example, if currently the short rate were trading at a 5 BP spread above the DFR, the threshold for an expected +10 bp DFR hike would be −25 bp. Thus, the simulated lift-off horizon partly depends on the observed spread. Alternatively, one could assume a constant spread across all times. However, this would not affect results signficantly.

[23]The Monte Carlo integration approach to simulate parameter and current state filter uncertainty relies on Hamilton (1994, 898) but we exclude forecasting uncertainty with respect to the risk factors. At first hand, what seems surprising is that estimation uncertainty with respect to the expected short rate in 10 years falls significantly during the ELB period. However, this finding originates from the fact that the shadow short rate which embeds both filter and parameter uncertainty is way below the ELB in negative territory during the ELB period. The conditional short rate distribution is censored below the ELB (which is itself deterministic), with a point mass of $Prob(i_{1,t+h} \leq l_{t+h})$ at l_{t+h}. This implies that a significant proportion of estimation uncertainty is likewise censored below the ELB and thus is not reflected in long-term expected short rates. Moreover, due to the incorporation of long-term survey information, the unconditional mean of the short rate under the $\mathbb{P}$-measure is estimated very precisely with a standard deviation of roughly 0.3% based on parameter uncertainty.

in the euro area sample and given the high computational costs associated with non-linear estimations, in the Monte Carlo exercise we simulate a sample length of $T = 720$ months (compared to $T = 226$ in the euro area sample) in order to check whether our specification analysis can also be confirmed in a much longer data sample. Notice that we only consider those samples that comprise at least 12 and not more than 60 months in which the short rate is stuck at the lower bound. A total number of 50 samples is then used during this exercise.[24] In line with Kim and Singleton (2012), we also simulate survey data by generating model-implied expectations and adding measurement errors similar in size of those estimated in our benchmark model. We add those surveys at quarterly frequency for 3 months rate expectations in 12 and 24 months, and at bi-annual frequency for 3 months rate expectations in 6 to 10 years. For each sample we run estimations based on our $SRTSM$s and $GATSM$s specifications.

The results of this exercise confirm our finding that survey information is essential to pin down the data generating process (DGP) in an environment of very persistent interest rates and prolonged ELB periods. This result holds despite using long samples comprising 60 years of monthly observations (see Table 4). Indeed, only the models that include survey information ($SRTSM_B$,$GATMS_S$) are able to pin down the unconditional mean of the DGP fairly closely while producing high persistence in model-implied interest rates. $GATSM_{OLS}$ and $GATSM_{BC}$, on the other hand, underestimate both the unconditional mean and the persistence of the true DGP. While their estimate for the unconditional mean matches the sample mean of simulated yields, the latter itself is an insufficient proxy for the unconditional mean of the short rate because the ELB period biases the sample mean downward.

Table 4: **Simulation results (median) – long samples**

model	DGP	$SRTSM_B$	$SRTSM_{woS}$	$GATSM_{OLS}$
unconditional mean $E^{\mathbb{P}}(i_{1,t})$:	3.693	3.565	3.371	2.862
sample mean:	2.888			
max eigenvalues under $\mathbb{P}$:	0.992	0.986	0.979	0.977
model	DGP	$GATSM_S$	$GATSM_{BC}$	
median unconditional mean $E^{\mathbb{P}}(i_{1,t})$:	3.693	3.530	2.880	
median sample mean:	2.888			
median max eigenvalues under $\mathbb{P}$:	0.992	0.987	0.984	

[24]In our simulations approximately 2 out of 100 samples were classified as lower bound sample.

5 Concluding remarks

We propose a shadow rate term structure model for the euro area OIS yield curve that preforms well when evaluated against two criteria (i) good model fit and (ii) the derivation of plausible short-and long-term rate expectations which can be used for policy analysis. Our model explicitly accounts for the specific features of the euro area yield curve sample which can be regarded as very small and characterized by highly persistent interest rate dynamics near or at the time-varying effective lower bound for a prolonged period of time. To do so, our model features such a lower bound that is forward-looking in the sense that anticipated changes in the DFR are taken into account before their realization and it considers the spread between the policy rate, i.e. the deposit facility rate in times of negative interest rate policies, and the short rate of the OIS yield curve. To better pin down short- and especially long-term expectations embedded in yield curve data, we also inform the model with survey-based interest rate forecasts.

We use our model to assess monetary policy expectations derived from the short end of the yield curve by accounting for the asymmetry of the distribution of short rates during the effective lower bound period. The forward curve itself gives an upward biased picture with respect to future monetary policy rate decisions given negative forward premia even at 1-year horizons. Similarly, mean estimates of future monetary policy rates are upward biased given the truncated distribution of future short rates. Correct inference with respect to monetary policy expectations can only be drawn from the modal, i.e. most likely, path of future short rates.

At far-distant horizons our model delivers short rate expectations that are highly correlated with an estimated nominal equilibrium short rate derived from a macroeconomic modeling set-up, even though the considered models do not share any information during the estimations. According to our model results, long-term forward rates thus appear to reflect trends in key macroeconomic variables in both real and nominal terms, which play an important role in the formation of far-distant rate expectations. Moreover, non-standard monetary policy measures together with interest rate forward guidance not only depressed forward premia but also the expectations component embedded in intermediate and long-term forward rate maturities, thereby highlighting the signaling channel of asset purchases.

We confirm this narrative by assessing the impact of conventional and unconventional monetary policy shocks based on high frequency identification external instrument approach. Our model produces a U-shaped response of the forward curve in response to a conventional monetary policy shock which emphasizes its communication / forward guidance character. The median reaction to an unconventional monetary policy shock at the long end is negative and spills over to medium-term maturities. In the run-up to the start of asset purchases in March 2015 unconventional monetary policy shocks considerably contributed to the drop in long-term interest rates according to our model. Term premia as well as short rate expectations fell in response to these monetary policy shocks thereby also highlighting the signaling channel of non-standard monetary policy measures.

We test alternative modeling specifications including shadow short rate models with different effective lower bound definitions. We also exclude survey information from our preferred model and we estimate various Gaussian affine term structure variants. Overall, we find that these alternative models either exhibit an unsatisfying model fit and / or produce implausible short- and long-term rate expectations from an economic perspective in addition to less convincing outcomes when assessing short-term monetary policy rate expectations. We finally confirm our findings by a Monte Carlo analysis comprising simulated yield curve samples including prolonged periods at the effective lower bound. We find that when facing such samples, including survey information is important to recover the true data generating process.

Going forward, there are important issues which could be explored further. For instance, it would be interesting to see how our model estimates the effects of monetary policy shocks on the term structure if we isolate the various channels (pure target shocks, forward guidance, information effects) through which high-frequency changes of financial market variables transmit to the yield curve at monetary policy announcement dates. To do so, it would be worthwhile to filter our model on a daily basis. Moreover, the presented model is specified to provide a good performance for the OIS curve from a statistical as well as economic perspective. Augmenting our model to jointly estimate the euro area OIS yield curve together with a sovereign yield curve would be very fruitful. With such a joint model, we could disentangle the drivers of the spread between OIS and sovereign yields and we could include additional long-term survey forecasts which are available for a much longer time span for sovereign bonds. In particular, it would be interesting to analyze how the interplay between the ELB of the OIS curve as well as possible scarcity factors in sovereign bond markets drive the spread between the two curves. This is up for future research.

References

Abrahams, M., T. Adrian, R. K. Crump, E. Moench, and R. Yu (2016). Decomposing real and nominal yield curves. Journal of Monetary Economics 84(C), 182–200.

Adrian, T., R. K. Crump, and E. Moench (2013). Pricing the term structure with linear regressions. Journal of Financial Economics 110(1), 110–138.

Andreasen, M. M. and A. Meldrum (2015). Market beliefs about the UK monetary policy life-off horizon: a no-arbitrage shadow rate term structure model approach. Bank of England working papers 541, Bank of England.

Bauer, M. D. and G. D. Rudebusch (2014). The signalling channel for Federal Reserve bond purchases. International Journal of Central Banking 10(3), 233–289.

Bauer, M. D. and G. D. Rudebusch (2016). Monetary policy expectations at the zero lower bound. Journal of Money, Credit and Banking 48(7), 1439–1465.

Bauer, M. D. and G. D. Rudebusch (2017). Interest rates under falling stars. Working Paper Series 2017–16, Federal Reserve Bank of San Francisco.

Bauer, M. D., G. D. Rudebusch, and C. J. Wu (2012). Correcting estimation bias in dynamic term structure models. Journal of Business and Economic Statistics 30(3), 454–467.

Bauer, M. D., G. D. Rudebusch, and J. C. Wu (2014). Term premia and inflation uncertainty: Empirical evidence from an international panel dataset: Comment. American Economic Review 104(1), 323–37.

Chernov, M. and P. Mueller (2012). The term structure of inflation expectations. Journal of Financial Economics 106(2), 367–394.

Christensen, J. H. E., F. X. Diebold, and G. D. Rudebusch (2011). The affine arbitrage-free class of Nelson-Siegel term structure models. Journal of Econometrics 164(1), 4–20.

Christensen, J. H. E. and G. D. Rudebusch (2015). Estimating shadow-rate term structure models with near-zero yields. Journal of Financial Econometrics 13(2), 226–259.

Cieslak, A. and P. Povala (2015). Expected returns in treasury bonds. Review of Financial Studies 28(10), 2859–2901.

Cochrane, J. H. and M. Piazzesi (2002). The Fed and interest rates – a high-frequency identification. American Economic Review 92(2), 90–95.

Cochrane, J. H. and M. Piazzesi (2008). Decomposing the yield curve. mimeo.

Crump, R. K., S. Eusepi, and E. Moench (2017). The term structure of expectations and bond yields. Staff Reports 775, Federal Reserve Bank of New York.

Deutsche Bundesbank (2014). Excess liquidity and short-term money market rates. Deutsche Bundesbank Monthly Report, November 2014.

Dijk, D., S. J. Koopman, M. Wel, and J. H. Wright (2014). Forecasting interest rates with shifting endpoints. Journal of Applied Econometrics 29(5), 693–712.

Duffee, G. R. (2011). Information in (and not in) the term structure. Review of Financial Studies 24(9), 2895–2934.

Duffee, G. R. and R. H. Stanton (2012). Estimation of dynamic term structure models. Quarterly Journal of Finance 2(02), 1–51.

Gertler, M. and P. Karadi (2015). Monetary policy surprises, credit costs, and economic activity. American Economic Journal: Macroeconomics 7(1), 44–76.

Gurkaynak, R. S., B. Sack, and E. Swanson (2005). Do actions speak louder than words? the response of asset prices to monetary policy actions and statements. International Journal of Central Banking 1(1).

Hamilton, J. (1994). Time series analysis. Princeton, NJ: Princeton Univ. Press.

Hamilton, J. D. and J. C. Wu (2012). Identification and estimation of gaussian affine term structure models. Journal of Econometrics 168(2), 315–331.

Holston, K., T. Laubach, and J. Williams (2017). Measuring the natural rate of interest: International trends and determinants. Journal of International Economics 108(1), 59–75.

Ichiue, H. and Y. Ueno (2013, May). Estimating term premia at the zero bound: An analysis of Japanese, US, and UK Yields. Bank of Japan Working Paper Series 13-E-8, Bank of Japan.

Joslin, S., K. J. Singleton, and H. Zhu (2011). A new perspective on gaussian dynamic term structure models. Review of Financial Studies 24(3), 926–970.

Kim, D. H. (2008). Challenges for macro-finance modeling. BIS Working Paper 240.

Kim, D. H. and A. Orphanides (2012). Term structure estimation with survey data on interest rate forecasts. Journal of Financial and Quantitative Analysis 47(1), 241–272.

Kim, D. H. and M. Priebsch (2013). Estimation of multi-factor shadow rate term structure models. Preliminary draft.

Kim, D. H. and K. J. Singleton (2012). Term structure models and the zero bound: an empirical investigation of Japanese yields. Journal of Econometrics 170(1), 32–49.

Kim, D. H. and J. H. Wright (2005). An arbitrage-free three-factor term structure model and the recent behavior of long-term yields and distant-horizon forward rates. Finance and Economic Disucssion Series, Board of Governors of the Federal Reserve System 2005–33.

Kortela, T. (2016). A shadow rate model with time-varying lower bound of interest rates. Bank of Finland Research Discussion Paper 19.

Krippner, L. (2015a, December). A comment on Wu and Xia (2015), and the case for two-factor shadow short rates. CAMA Working Papers 2015–48, Centre for Applied Macroeconomic Analysis, Crawford School of Public Policy, The Australian National University.

Krippner, L. (2015b). A theoretical foundation for the Nelson-Siegel class of yield curve models. Journal of Applied Econometrics 30(1), 97–118.

Krippner, L. (2015c). Zero Lower Bound Term Structure Modeling. New York: Palgrave Macmillan US.

Kuttner, K. N. (2001). Monetary policy surprises and interest rates: Evidence from the Fed funds futures market. Journal of Monetary Economics 47(3), 523–544.

Laubach, T. and J. Williams (2016). Measuring the natural rate of interest redux. Business Economics 41, 57–67.

Lemke, W. and A. Vladu (2016). Below the zero lower bound: A shadow-rate term structure model for the euro area. Deutsche Bundesbank Discussion Paper 39.

Lemke, W. and T. Werner (2017). Dissecting long-term bund yields in the run-up to the ecb's public sector purchase programme. ECB Working Paper 2106.

Leombroni, M., A. Vedoli, G. Venter, and O. Whelan (2017). Central bank communication and the yield curve. mimeo, Finance Meeting EUROFIDAI - AFFI.

Mandler, M. and M. Scharnagl (2018). Estimating the effects of the Euroystem's asset purchase programme at the country level using an external instruments identification. mimeo.

Mertens, K. and M. O. Ravn (2012). Empirical evidence on the aggregate effects of anticipated and unanticipated US tax policy shocks. American Economic Journal: Economic Policy 4(2), 145–181.

Motto, R., C. Altavilla, and G. Carboni (2015). Asset purchase programmes and financial markets: lessons from the euro area. Working Paper Series 1864, European Central Bank.

Nakamura, E. and J. Steinsson (2018). High-frequency identification of monetary non-neutrality: The information effect. The Quarterly Journal of Economics, forthcoming.

Piazzesi, M. and E. T. Swanson (2008). Futures prices as risk-adjusted forecasts of monetary policy. Journal of Monetary Economics 55(4), 677–691.

Priebsch, M. A. (2013). Computing arbitrage-free yields in multi-factor gaussian shadow-rate term structure models. Finance and Economic Disucssion Series, Board of Governors of the Federal Reserve System 2013–63.

Priebsch, M. A. (2017). A shadow rate model of intermediate-term policy rate expectations. FED Notes October 04 2017.

Stock, J. H. and M. W. Watson (2012). Disentangling the channels of the 2007-2009 recession. Brookings Papers on Economic Activity 2012(1), 81–135.

Stock, J. H. and M. W. Watson (2018). Identification and estimation of dynamic causal effects in macroeconomics using external instruments. The Economic Journal 128(610), 917–948.

Swanson, E. T. (2017). Measuring the effects of Federal Reserve forward guidance and asset purchases on financial markets. NBER Working Papers 23311, National Bureau of Economic Research, Inc.

Swanson, E. T. and J. C. Williams (2014). Measuring the effect of the zero lower bound on medium- and longer-term interest rates. American Economic Review 104(10), 3154–85.

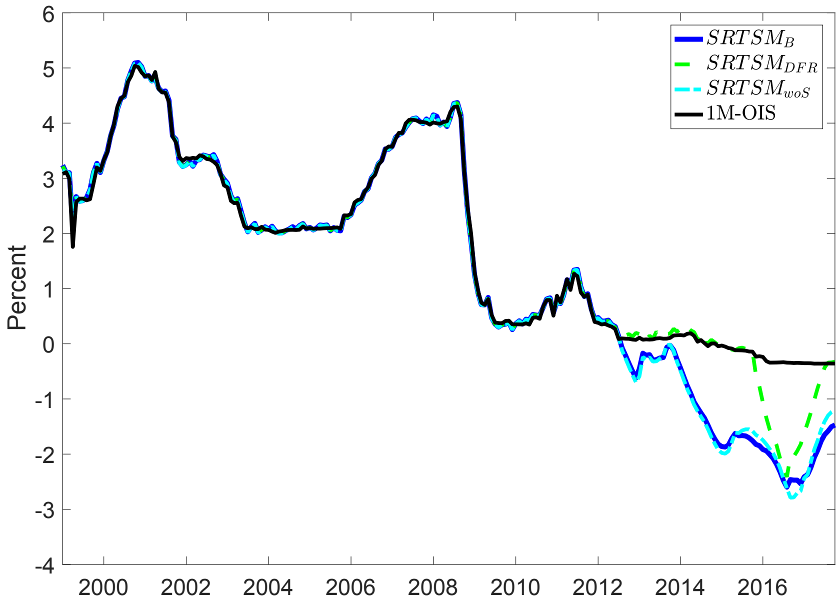
Wright, J. H. (2014). Term premia and inflation uncertainty: Empirical evidence from an international panel dataset: Reply. American Economic Review 104(1), 338–41.

Wu, C. J. and F. D. N. Xia (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. Journal of Money, Credit and Banking 48(2-3), 253–291.

Wu, C. J. and F. D. N. Xia (2017). Negative interest rate policy and yield curve. Chicago Booth Research Paper 17–34.

A Appendix

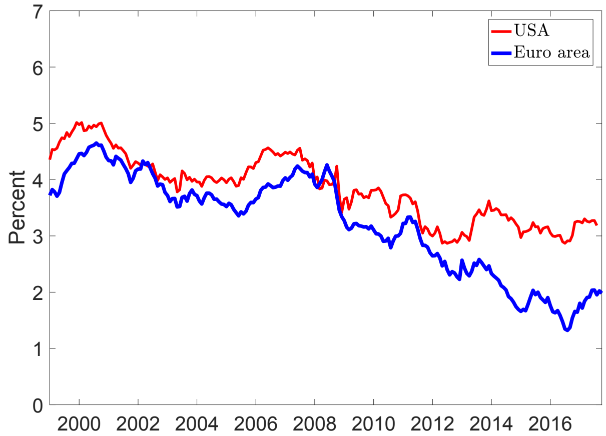
Figure A.1: **Shadow short rates**



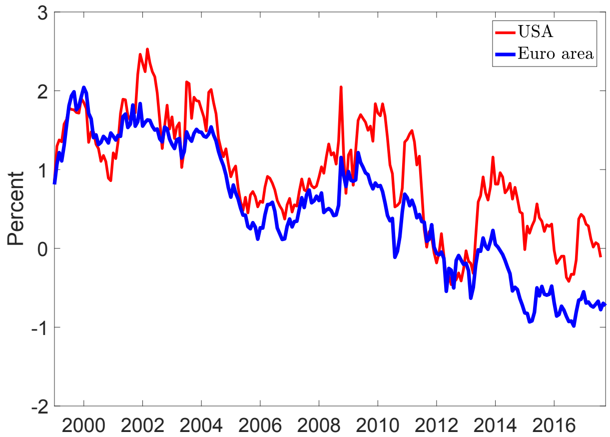
Note: This figure plots the model-implied shadow short rate based on various term structure model specifications including $SRTSM_B$,$SRTSM_{DFR}$ and $SRTSM_{woS}$. End-of-month values for January 1999 to October 2017.

Figure A.2: **5Y5Y forward rate decomposition US vs. euro area**

(a) Expectations



(b) Forward premium



Note: Panel (a) plots the expectations component of the time series of the decomposition of the 5Y5Y forward rate. Panel (b) plots the corresponding forward premium component. Based on $SRTMS_B$ for the euro area and Kim and Wright (2005) for the US. End-of-month values for January 1999 to October 2017.

Table A.1: **Parameter estimates for** $SRTSM_B$

	X-factor representation				P-factor representation		
$\mu^{\mathbb{P}}$	0.0617	-0.2226	0.2208	$\mu_P^{\mathbb{P}}$	0.4834	-0.1907	0.1350
	(0.0518)	(0.5135)	(0.5008)		(0.3311)	(0.4328)	(0.1207)
$\rho^{\mathbb{P}}$	0.9921	0.0356	0.0351	$\rho_P^{\mathbb{P}}$	0.9917	-0.1018	-0.7059
	(0.0202)	(0.1295)	(0.1361)		(0.0075)	(0.1151)	(0.4258)
	0.0176	0.9402	0.0730		-0.0036	1.0287	0.5770
	(0.0809)	(0.2683)	(0.2861)		(0.0120)	(0.1916)	(0.3848)
	-0.0267	-0.0464	0.8031		0.0006	-0.0407	0.7151
	(0.1077)	(0.1206)	(0.1436)		(0.0053)	(0.0512)	(0.1101)
$\mu^{\mathbb{Q}}$	0.0278	0	0	$\mu_P^{\mathbb{Q}}$	0.2927	-0.1897	0.0873
	(0.0019)				(0.1977)	(1.6098)	(0.6824)
$\rho^{\mathbb{Q}}$	0.9970	0	0	$\rho_P^{\mathbb{Q}}$	1.0051	-0.0402	-0.6685
	(0.0004)				(0.0060)	(2.5336)	(10.9948)
	0	0.9398	0		-0.0045	1.0484	0.5011
		(0.0050)	0		(0.0002)	(0.0006)	(0.0019)
	0	0	0.9238		0.0010	-0.0291	0.8071
			(0.0045)		(0.0000)	(-0.0000)	(0.0003)
Σ	0.3050	0	0	Σ_P	0.4601	0	0
	(0.0250)				(0.0335)		
	-0.8456	2.3844	0		0.0575	0.2725	0
	(0.4430)	(1.3180)	0		(0.0542)	(0.0313)	0
	0.5422	-2.3823	0.1779		-0.0241	-0.0586	0.0719
	(0.4347)	(1.3208)	(0.0249)		(0.0134)	(0.0108)	(0.0105)
δ_0	0			$\delta_{0,P}$	-0.0690		
δ_1	1	1	1	$\delta_{1,P}$	0.3177	-0.3778	0.5159
σ^i	0.0416						
σ_{12M}^{survey}	0.1898	σ_{24M}^{survey}	0.3079				
$\sigma_{6Y->10Y}^{survey}$	0.2243						

Note: Parameter estimates of the $SRTSM_B$ based on the X-factor as well as rotated P-factor representation. Asymptotic quasi-maximum likelihood standard errors in parentheses. σ^i denotes the standard deviation of measurement errors of the considered yields which is the same across considered maturities. σ^{survey} is the standard deviation of measurement errors of 3M interest rate survey expectations for the respective forecast horizons.

Table A.2: **1Y1Y forward rate variance decomposition**

model		$SRTSM_B$	$SRTSM_{DFR}$	$SRTSM_{woS}$
Level				
total sample:				
	expectations	0.88	0.87	0.75
	forward premium	0.12	0.13	0.25
pre-ELB sample:				
	expectations	0.85	0.86	0.75
	forward premium	0.15	0.14	0.25
ELB sample:				
	expectations	1.11	1.14	0.94
	forward premium	−0.11	−0.14	0.06
Difference				
total sample:				
	expectations	0.74	0.73	0.95
	forward premium	0.26	−0.27	−0.05
pre-ELB sample:				
	expectations	0.73	0.72	0.95
	forward premium	0.27	0.28	0.05
ELB sample:				
	expectations	0.96	0.94	1.05
	forward premium	0.04	0.06	−0.05

model		$GATSM_{OLS}$	$GATSM_S$	$GATSM_{BC}$
Level				
total sample:				
	expectations	0.82	0.87	0.87
	forward premium	0.18	0.13	0.13
pre-ELB sample:				
	expectations	0.84	0.88	0.89
	forward premium	0.16	0.12	0.11
ELB sample:				
	expectations	0.69	0.87	0.73
	forward premium	0.31	0.13	0.27
Difference				
total sample:				
	expectations	1.03	0.75	1.09
	forward premium	−0.03	0.25	−0.09
pre-ELB sample:				
	expectations	1.04	0.75	1.10
	forward premium	−0.04	0.25	−0.10
ELB sample:				
	expectations	0.92	0.74	0.98
	forward premium	0.08	0.26	0.02

Table A.3: **9Y1Y forward rate variance decomposition**

model		$SRTSM_B$	$SRTSM_{DFR}$	$SRTSM_{woS}$
Level				
total sample:				
	expectations	0.44	0.41	0.29
	forward premium	0.56	0.59	0.71
pre-ELB sample:				
	expectations	0.38	0.39	0.26
	forward premium	0.62	0.61	0.74
ELB sample:				
	expectations	0.40	0.40	0.32
	forward premium	0.60	0.60	0.68
Difference				
total sample:				
	expectations	0.27	0.31	0.23
	forward premium	0.73	0.69	0.77
pre-ELB sample:				
	expectations	0.24	0.28	0.22
	forward premium	0.76	0.62	0.78
ELB sample:				
	expectations	0.32	0.37	0.26
	forward premium	0.68	0.68	0.74
model		$GATSM_{OLS}$	$GATSM_S$	$GATSM_{BC}$
Level				
total sample:				
	expectations	0.55	0.48	0.86
	forward premium	0.45	0.52	0.14
pre-ELB sample:				
	expectations	0.57	0.50	0.88
	forward premium	0.43	0.50	0.12
ELB sample:				
	expectations	0.36	0.35	0.56
	forward premium	0.64	0.65	0.44
Difference				
total sample:				
	expectations	0.41	0.64	0.41
	forward premium	0.59	0.36	0.59
pre-ELB sample:				
	expectations	0.44	0.69	0.43
	forward premium	0.56	0.31	0.57
ELB sample:				
	expectations	0.32	0.51	0.36
	forward premium	0.68	0.49	0.64

Table A.4: **In-sample model fit across models**

model	$SRTSM_B$	$SRTSM_{DFR}$	$SRTSM_{woS}$
total sample:	3	3	3
pre-ELB sample:	3	3	3
ELB sample:	2	3	2
model	$GATSM_{OLS}$	$GATSM_S$	$GATSM_{BC}$
total sample:	2	3	2
pre-ELB sample:	3	3	3
ELB sample:	2	2	2

Note: This table shows the mean absolute error of model-implied yields to observed yields for different sample periods. The total sample covers the period 1999M1-2017M10, while the pre-ELB sample covers the period 1999M1-2012M6 and the ELB sample the period 2012M7-2017M10.

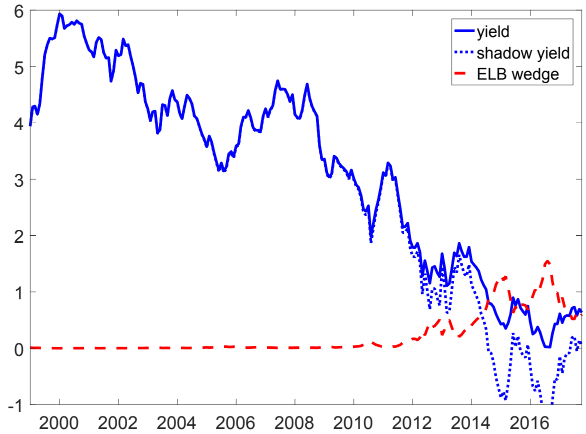
Table A.5: **Lower bound violations of expected short rate paths**

number of months for which $E_t^{\mathbb{P}}[i_{1,t+n}] < l_{t+h}$
for $n = 1, 2, \dots, 120$ and $t = 1, 2, \dots, 226$

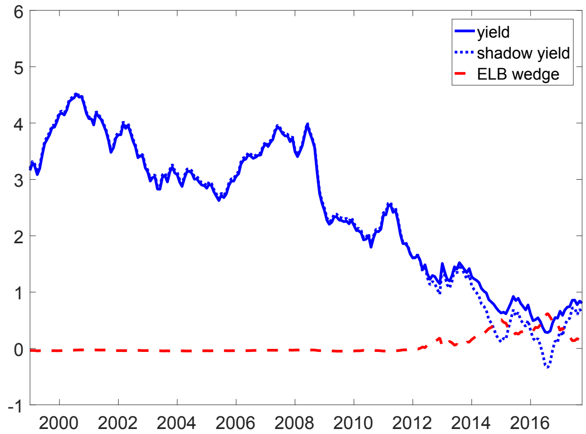
model	$SRTSM_B$	$SRTSM_{DFR}$	$SRTSM_{woS}$
	0	15	0
model	$GATSM_{JSZ}$	$GATSM_S$	$GATSM_{BC}$
	22	40	52

Figure A.3: **10-year yield and 10-year shadow yield**

(a) $\mathbb{Q}$-measure



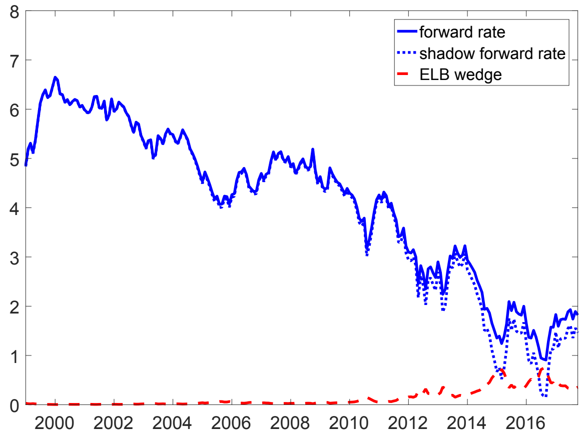
(b) $\mathbb{P}$-measure



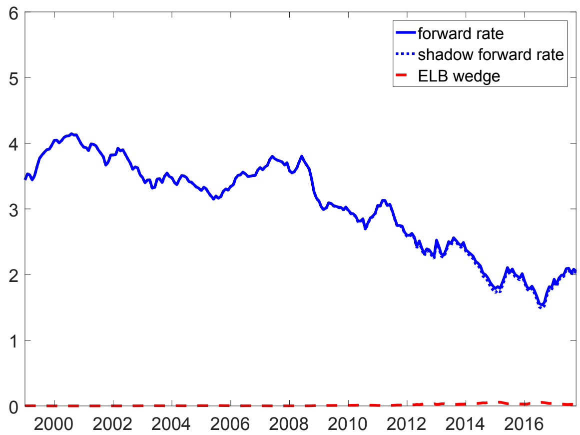
Note: Panel (a) plots the 10-year yield and shadow yield under the $\mathbb{Q}$-measure and panel (b) under the $\mathbb{P}$-measure based on $SRTMS_B$. End-of-month values for January 1999 to October 2017.

Figure A.4: **10Y1M forward rate and 10Y1M shadow forward rate**

(a) $\mathbb{Q}$-measure



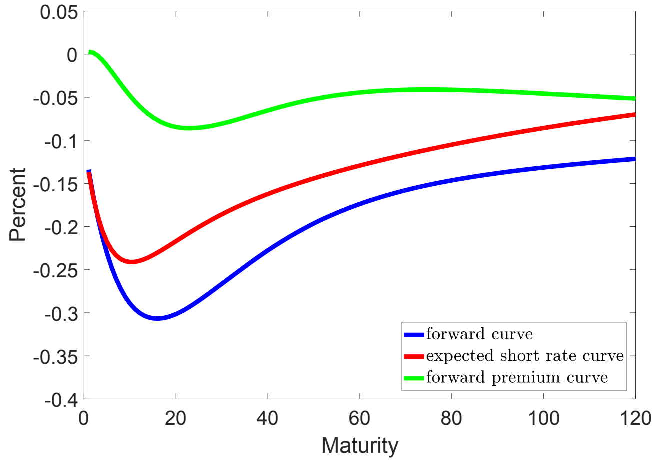
(b) $\mathbb{P}$-measure



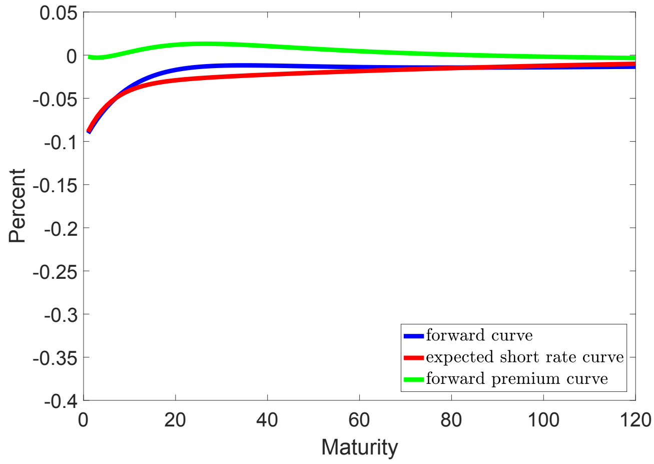
Note: Panel (a) plots the 10Y1M forward rate and shadow forward rate under the $\mathbb{Q}$-measure and panel (b) under the $\mathbb{P}$-measure based on $SRTMS_B$. End-of-month values for January 1999 to October 2017.

Figure A.5: **Instantaneous response to monetary policy shocks**

(a) CMP shock



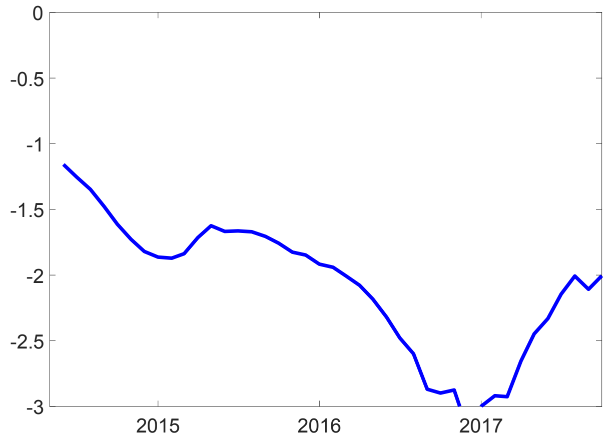
(b) Target shock



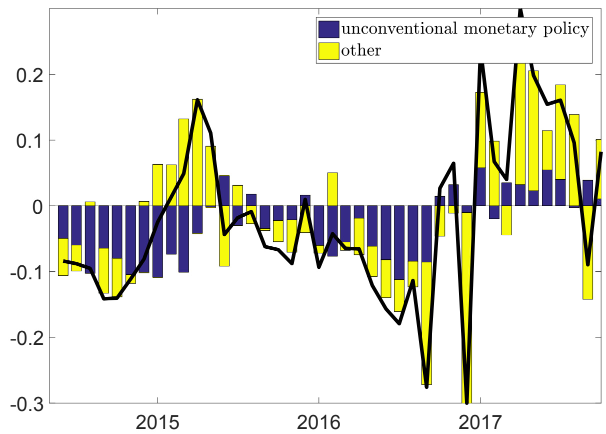
Note: Panel (a) plots the median instantaneous forward curve response and its components based on $SRTSM_B$ and a high frequency identification approach for the sample period January 1999 to June 2014. Panel (b) plots the median instantaneous forward curve response and its components based on $SRTSM_B$ and a shock to the short rate.

Figure A.6: **Historical decomposition of the shadow short rate**

(a) level of the shadow short rate

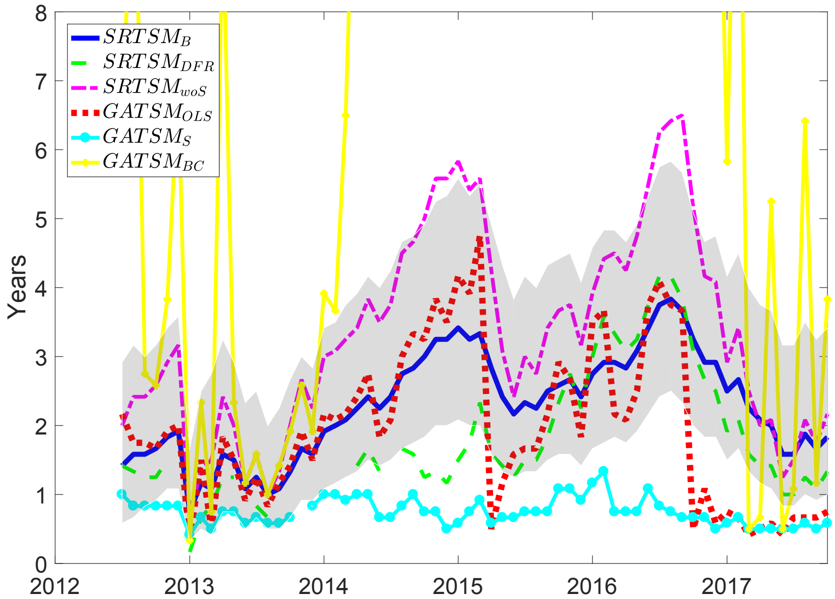


(b) change and contribution of shocks



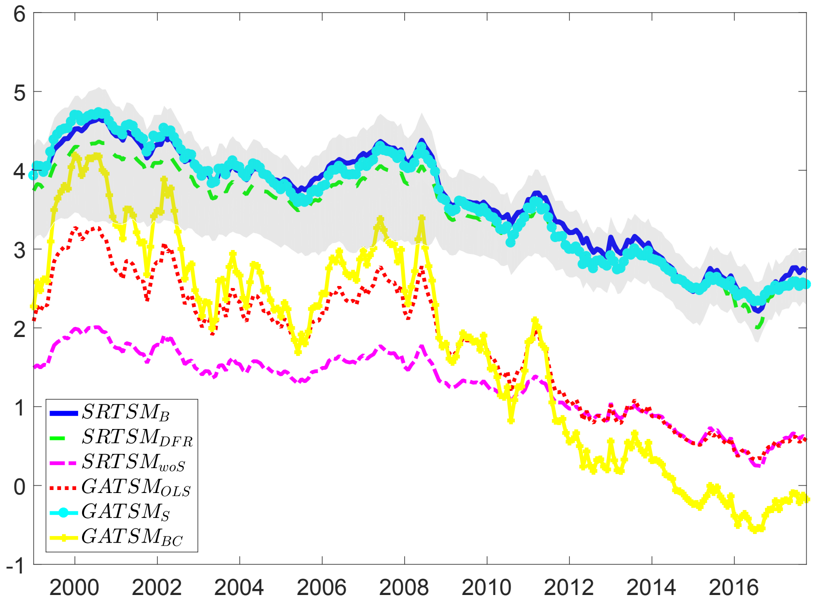
Note: Panel (a) plots the shadow short rate from June 2014 to October 2017 based on $SRTSM_B$. Panel (b) plots the corresponding historical decomposition with a focus on unconventional monetary policy shocks.

Figure A.7: **+10 BP DFR hike (median distribution)**



Note: This figure plots the number of months of the median distribution of a +10 BP DFR hike based on various model specifications. End-of-month values January 2012 to October 2017. The shaded area lies between the 15% and 85% quantile of our benchmark median distribution.

Figure A.8: **10Y1M short rate expectations**



Note: This figure plots model-implied expected short rates based on various term structure model specifications together with 15% and 85%- quantile confidence intervals based on our preferred $SRTSM_B$ model. Confidence intervals refer to parameter estimation and current state filter uncertainty. End-of-month values for January 1999 to October 2017.