# Studies in Monetary Economics

**Fabian Schupp***

Inaugural-Dissertation
zur Erlangung des Doktorgrades
der Justus-Liebig-Universität Gießen
Fachbereich Wirtschaftswissenschaften

Betreuer:
Prof. Dr. Peter Tillmann
Justus-Liebig-Universität Gießen
Prof. Dr. Andreas Walter
Justus-Liebig-Universität Gießen

*Deutsche Bundesbank
Wilhelm-Epstein-Straße 14
60431 Frankfurt
Email: fabian.schupp@bundesbank.de

# Acknowledgements

Diese Arbeit hat über die Jahre ihrer Entstehung von der Unterstützung einer Vielzahl von Menschen profitiert, die mich stets begleitet und ermutigt haben und denen nicht zuletzt deswegen größter Dank gebührt.

Zuallererst möchte ich mich bei Prof. Dr. Tillmann bedanken, der sich bereit erklärt hat, mir als Doktorvater beiseite zu stehen und mir so ermöglicht hat, mich dieser Aufgabe zu stellen. Ebenso gilt mein Dank Herrn Prof. Dr. Andreas Walter, der sich als Zweitgutachter zur Verfügung gestellt hat.

Obwohl ich seit Beginn dieser Arbeit fest in meinem Job bei der Bundesbank eingebunden war, hatte ich das Glück, von wunderbaren Mitdoktoranden zu profitieren, die aus der Ferne einerseits hervorragende Leidensgenossen waren, aber auch stets in Wort und Tat unterstützend zur Seite standen. Dazu gehörten mein langer Wegbegleiter und ehemaliger WG-Genosse Jörg Schmidt, Lucas Hafemann, Paul Rudel und David Finck.

Diese Arbeit wäre in dieser Form außerdem nicht ohne die Unterstützung meiner Kollegen bei der Bundesbank möglich gewesen, wo ich die meiste Zeit meiner Promotion in der Abteilung für Geldpolitik und monetäre Analyse verbracht habe. Vor allem möchte ich mich bei Dr. Jan Scheithauer bedanken, der sich zu Beginn sehr dafür eingesetzt hat, es mir zu ermöglichen, meine Dissertation in Verbindung mit meiner Stelle bei der Bundesbank in Angriff zu nehmen. Somit hat er ebenfalls wesentlich dazu beigetragen, dass dieses Vorhaben überhaupt erst möglich wurde. Dies gilt ebenso für Dr. Andreas Worms, der als mein Abteilungsleiter zunächst meiner Einstellung zugestimmt hat und auch stets eine große Unterstützung war.

Ein wesentlicher Anteil dieser Arbeit ist nicht nur parallel zu meinem Job bei der Bundesbank entstanden, sondern gerade auch im Zuge dieser. So entstand das dritte Kapitel meiner Promotion im Rahmen einer Praxisphase im Zentralbereich Finanzstabilität in Zusammenarbeit mit Leonid Silbermann, dem ich sehr dankbar dafür bin, mich bei meinen ersten Forschungsschritten begleitet zu haben. Ebenso danke ich Alexander Schulz, der uns als damaliger Hauptgruppenleiter ermutigt hat, unser Projekt als Forschungsarbeit zu veröffentlichen.

Der Großteil dieser Promotion beschäftigt sich mit der Modellierung der Zinsstrukturkurve, die heute auch den Fokus meiner Arbeit bei der Bundesbank und der Europäischen Zentralbank darstellt. Dass ich mich diesem Thema annehmen konnte und in der Lage war, es zu begreifen, verdanke ich einzig und alleine meinem Freund und Ko-Autor Dr. Felix Geiger. Mit seiner Begeisterung und Begabung hat er mich nicht nur davon überzeugt, mich diesem Thema anzunehmen, sondern er stand auch stets als Lehrer, Mentor und Ratgeber an meiner Seite. Auf unsere zukünftigen Diskussionen und Projekte bei Wein und Pasta bei Da Franco freue ich mich jetzt schon.

Im politischen und manchmal hektischen Betrieb der Bundesbank ist Forschung nur möglich, wenn alle an einem Strang ziehen. Daher gilt mein Dank auch Florian Anders, mit dem ich jahrelang eine Schreibtischinsel geteilt habe, womit er nicht nur die guten, sondern auch die frustrierenden Zeiten hautnah miterleben musste.

Neben meiner Arbeit bei der Bundesbank hat mich das Thema Zinsstrukturmodellierung im Jahr 2018 auch zur Europäischen Zentralbank in die Abteilung Capital Markets and Financial Structure verschlagen. Dort habe ich enorm von der Unterstützung meiner Kollegin Dr. Andreea Vladu und meines Kollegen Dr. Wolfgang Lemke profitiert, die mit ihrer Expertise und Leidenschaft für die Zinsstrukturmodellierung Ratgeber und Quelle der Inspiration waren. Beiden schulde ich großen Dank. Ebenso gebührt dieser aber auch Dr. Thomas Werner, der zusammen mit Wolfgang und auch Fleming Würz die Entscheidung getroffen hat, mir diese Chance bei der Europäischen Zentralbank zu geben.

Wie bereits zuvor bezüglich der Bundesbank erwähnt, gilt auch bei der Europäischen Zentralbank, dass Forschungsarbeit nur mit Unterstützung der KollegInnen möglich ist. Insbesondere möchte ich mich bei Dr. Benjamin Böninghausen, Dr. Daniel Kapp und Gregory Kidd bedanken, die einerseits mit vielen guten Diskussionen, aber auch mit konkreten Kommentaren zu Teilen dieser Arbeit wesentlich beigetragen haben.

Jedes der Kapitel dieser Arbeit profitierte von hilfreichen Kommentaren und Beiträgen etlicher Personen, denen ich an dieser Stelle danken möchte. Dazu gehören Dr. Bruno De Backer, Prof. Dr. Ansgar Belke, Prof. Dr. Jörg Breitung, Prof. Dr. Falko Fecht, Dr. Cornelia Kerl, Dr. Wolfgang Lemke, Dr. Marcel Priebsch, Dr. Martin Mandler, Dr. Christoph Memmel, Prof. Dr. Emanuel Moench, Dr. Frieder Mokinski, Jan Paulick, Prof. Dr. Guillaume Rousselet, Dr. Michael Scharnagel, Carmen Schell, Dr. Christian Speck, Dr. Alexander Schmidt, Luzie Thiel, Dr. Johannes Tischer, Dr. Benjamin Weigert und Dr. Dora Xia.

Zuletzt geht der größte Dank an diejenigen, die nicht nur während dieser Promotion, sondern weit darüber hinaus stets die größte Unterstützung waren. Dazu gehört insbesondere meine Familie, Markus, Heinz und Karin Schupp, die mich bereits mein ganzes Leben uneingeschränkt und bedingungslos unterstützen. Das ist nicht für jedermann selbstverständlich und dafür bin ich sehr dankbar. Außerdem bin ich auch meiner Frau, Laura

Schupp, zu großem Dank verpflichtet, welche die gesamte Zeit meiner Promotion stets an meiner Seite war und meinen Kopf des Öfteren aus dem Sand gezogen hat, wenn die Dinge nicht gut liefen.

*Fabian Schupp*

Frankfurt, den 21. März 2020

# Contents

# List of Figures

# List of Tables

# Introduction

Since the outbreak of the great financial crisis (GFC) in 2008 and later also in response to the consequences of the sovereign debt crisis, central banks around the globe have not only reacted by rapidly cutting the key policy rates to zero or even negative levels, but have also adopted a series of unconventional monetary policy measures.

In the euro area, many of these measures, in particular those in immediate response to the GFC and the sovereign debt crisis were primarily aimed at repairing an impaired monetary policy transmission process. While the ECB was successful in this regard, a persistently subdued inflation outlook over the medium term and rising deflationary pressures led the ECB to deploy a set of unconventional policy measures to increase the accommodative stance of monetary policy. These comprised targeted longer-term refinancing operations and purchases of sovereign bonds, alongside private sector assets, such as asset-backed securities, covered bonds and corporate bonds.

Naturally, the increased breadth of the monetary policy tool kit also led to an increasing complexity of monetary policy analysis. However, central banks depend on reliable information about the effectiveness of their measures in order to take appropriate decisions about its future monetary policy course. In this regard, given the importance of interest rates in the monetary transmission process and the evaluation of the monetary stance, the analysis of the term structure of risk free interest rates plays a key role, and had to evolve significantly over the last years.

For the analysis of the term structure of interest rates, term structure models have long been an established and widely used tool among central bankers. Yet, with interest rates close to their effective lower bound (ELB) and central banks no longer targeting only the very short end of the yield curve, the demands on these models have increased substantially. This is especially true for the euro area, where analysis is impeded by a relatively short sample of interest rates in light of their high persistence, and a lower bound that kept changing over the course of the past years. Against this backdrop, Chapters 1 and 2 of this thesis propose modelling advances that allow to deepen the understanding of the yield curve and its drivers and improve upon existing approaches of modelling the term structure of interest rates.

In particular, Chapter 1 – "With a little help from my friends: survey-based derivation of euro area short rate expectations at the effective lower bound", joint work with Felix Geiger – discusses the particularities of the euro area yield curve and how these can best be addressed within a shadow rate term structure model (SRTSM) framework. The Chapter introduces a SRTSM for the euro area OIS yield curve which explicitly accounts for the relatively short euro area sample and the high persistence in interest rates, fulfilling two important 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, incorporating survey forecasts on short- and long-term interest rate expectations, improves the model's capability to pin down the future path of short rates, which is particularly important when decomposing longer-term yields and forward rates.

Furthermore, the proposed 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 as implied by its forward guidance. As this forward guidance links the possible lift-off of policy rates 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 results are in line with this hypothesis and highlight the announcement of asset purchases as a commitment device for future short rates.

In addition, 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. This allows us to identify both conventional and unconventional monetary policy shocks. In consequence, 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. In contrast, the median reaction to an unconventional monetary policy shock is negative at the long end and spills over to medium-term maturities. The largest impact of an unconventional monetary policy shock on the forward curve stems from the forward premium and takes place at the 10-year maturity horizon pointing to the transmission of non-standard measures via duration extraction. At medium-term maturities our model attributes a more prominent role to the expectations component.

Finally, 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.

While Chapter 1 focuses on the nominal term structure of euro area OIS yields, one needs to bare in mind that by definition, any move in nominal rates is driven by either the inflation component or a change in real rates. While central banks aim to steer the level and expectations of nominal rates, it is essential for monetary authorities to effectively influence real rates in the intended manner, as according to economic theory it is the level of real rates that matters for consumption and investment and thus ultimately drives inflation.

Therefore, Chapter 2 – "The (ir)relevance of the nominal lower bound for real yield curve analysis" – presents a joint model for euro area nominal rates and inflation-linked swap (ILS) rates, which allows isolating real and inflation components of nominal interest rates. Different from earlier models focusing on the euro area (see Hördahl and Tristani (2014); García and Werner (2012)), the model in this thesis comprises the ELB of nominal interest rates as a new and unique feature for this class of models. As has been argued before, failing to do so may otherwise lead to implausible estimates for rate expectations and premia and consequently also to a non-reliable inference of the dynamics of inflation expectations and real rates embedded in observed nominal rates (Carriero, Mouabbi and Vangelista, 2018).

Indeed, results suggest that modelling the ELB is of relevance for two reasons. First, an analysis of responses by yield components to shocks to the inflation factor shows that the magnitude and sign of these responses are conditional on the degree to which the ELB is binding. For nominal yields, we observe a decreasing impact of inflation shocks across all maturities, the closer rates are to the ELB. The response of real rates is non-linear. While nominal rates are distant from the ELB, real rates show a positive response to a positive inflation shock; they react negatively when nominal rates are close to or at the ELB. Overall, these results suggest that the ELB introduces non-linearities with a meaningful impact on structural relationships in the economy. The finding of non-linear or time-varying impulse responses relates to findings of Mertens and Williams (2018) who, in a small structural model, find that the lower bound alters the distributions of both interest rates and inflation by restricting the central bank's scope for action. The findings further relate to work by King (2019) and Geiger and Schupp (2018) who likewise attest a decreasing effectiveness of conventional monetary policy at the ELB due to a receding reactiveness of interest rates, in particular, at shorter maturities.

Second, isolated changes in the ELB impact, in particular, nominal and real forward rates mainly through their expectations component. In our analysis, a 10-bp cut in the

ELB yields an average impact of -5 (-3) bps on 24-month (120-month) nominal forward rates. These impacts are almost entirely transmitted through real rate expectations and only to a very small extent through real or inflation risk premia. Thus, these results imply that the central bank can lower real rate expectations by solely changing the effective lower bound of interest rates. These results build upon work of Lemke and Vladu (2016) who have shown that the perceived lower bound by itself can be considered a monetary policy tool to lower yields across all horizons.

As much as the GFC and the following sovereign debt crisis led to a permanent change in the Eurosystem's monetary framework, it was followed by an equally large change in financial regulation. Among the main causes of the financial crisis had been liquidity shortages in the global financial sector as banks failed to prepare themselves for short-term liquidity stress. In response, the Basel Committee on Banking Supervision introduced the Liquidity Coverage Ratio (LCR), which obliges banks to ensure a sufficient amount of unencumbered highly liquid assets to withstand a 30 day liquidity stress scenario. In addition, the newly introduced Net Stable Funding Ration (NSFR) demands that banks procure sufficient stable funding over a time horizon of one year.

While a full assessment of the effectiveness of the newly introduced regulations is challenging at this stage, Chapter 3 – "The role of structural funding for stability in the German Banking Sector", joint work with Leonid Silbermann – presents an empirical evaluation of the relevance of stable funding for the probability of banks experiencing financial distress. The objective of this analysis is to provide an empirical assessment of the effectiveness of funding regulation introduced in response to the GFC as to this end financial theory has not been conclusive on this question.

On the one hand, wholesale funding, especially owing to its short-term maturity structure, is often thought to have a disciplining effect on banks as it prompts them to rollover their debt frequently. Given their high expertise, wholesale investors would also be expected to provide better and closer monitoring of banks than depositors would, while also opening up more investment opportunities for banks (Brunnermeier (2009), Calomiris and Kahn (1991), Huang and Ratnovski (2011)).

On the other hand, a sufficiently high degree of wholesale funders' seniority might force otherwise financially sound banks into inefficient liquidation given publicly available but imprecise information like market prices and credit ratings. Using a noisy negative public signal on banks' project quality, wholesale investors have the incentive to reduce their monitoring and withdraw their funds if their seniority governing the division of banks' liquidation value is sufficiently high. This holds true especially for large and publicly traded banks, while traditional banks holding opaque and non-tradable loans should still profit from wholesale funding and its disciplining character. A higher share of deposit funding (along with a higher precision of the public signal) might even fortify this mechanism, given that more deposits incentivize early withdrawals by wholesale creditors, as they raise the liquidation value (Huang and Ratnovski (2011)).

Another potential source of instability of wholesale funding are the so called liquidity spirals (Brunnermeier and Pedersen (2009)). The reason is that a major part of wholesale funding is obtained by borrowing against assets subject to haircuts. Operating at the edge of being equity constrained, these haircuts determine a bank's maximum leverage, so that rising haircuts force banks to either raise more equity or deleverage by selling off assets in order to hold their leverage constant. If there is a general increase in haircuts due to rising volatility in the market, the banking system might experience extreme funding stress.

Against this background, Chapter 3 presents empirical evidence based on supervisory data on critical events of financial institutions spanning a time period of 19 years, which is combined with balance sheet data as well as other supervisory data in order to estimate the effect of stable funding on banks' probabilities of financial distress. Due to the fact that the NSFR cannot be calculated exactly for the time period prior to its implementation, we use the loan-to-deposit ratio and the loan-to-interbank-liabilities ratio as proxies for stable funding. Indeed, our results suggest that stable funding makes critical events significantly less likely for savings banks and credit cooperatives, suggesting a stabilizing effect of the net stable funding ratio.

# Bibliography


Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007-08, Journal of Economic Prespectives **23**(1): 77–100.

Brunnermeier, M. K. and Pedersen, L. H. (2009). Market liquidity and funding liquidity, Review of Financial Studies **22**(6): 2201–2238.

Calomiris, C. W. and Kahn, C. M. (1991). The role of demandable debt in structuring optimal banking arrangements, American Economic Review **81**(3): 497–513.

Carriero, A., Mouabbi, S. and Vangelista, E. (2018). UK term structure decompositions at the zero lower bound, Journal of Applied Econometrics **33**: 643–661.

García, J. A. and Werner, T. (2012). Inflation risks and inflation risk premia, ECB Working Paper Series 1162.

Geiger, F. and Schupp, F. (2018). With a little help from my friends: Survey-based derivation of euro area short rate expectations at the effective lower bound, Deutsche Bundesbank Discussion Paper 27.

Hördahl, P. and Tristani, O. (2014). Inflation risk premia in the euro area and the United States, International Journal of Central Banking **10**: 1–47.

Huang, R. and Ratnovski, L. (2011). The dark side of bank wholesale funding, Journal of Financial Intermediation **20**(2): 248–263.

King, T. B. (2019). Expectation and duration at the effective lower bound, Journal of Financial Economics **in press**.

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

Mertens, T. M. and Williams, J. C. (2018). What to expect from the lower bound on interest rates: Evidence from derivatives prices, Federal Reserve Bank of San Francisco Working Paper 2018-13.

# Chapter 1

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

*Joint with Felix Geiger*

## 1.1 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 shadow rate term structure model (SRTSM) 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. Gaussian affine term structure model (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 include Motto, Altavilla and Carboni (2015); Lemke and Werner (2017).

The paper is structured as follows: Section 2.2 introduces our preferred benchmark model with a focus on modeling the time-varying ELB. Section 2.3 discusses our estimation strategy. In Section 2.4 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 2.5 concludes.

## 1.2 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

$$X_t = \mu^{\mathbb{Q}} + \rho^{\mathbb{Q}} X_{t-1} + \Sigma u_t, \qquad u_t \sim N(0, I) \tag{1.1}$$

$$X_t = \mu^{\mathbb{P}} + \rho^{\mathbb{P}} X_{t-1} + \Sigma u_t, \qquad u_t \sim N(0, I). \tag{1.2}$$

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

$$si_{1,t} = \delta_0 + \delta_1' X_t. \tag{1.3}$$

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

$$i_{1,t} = \max(si_{1,t}, l_t). \tag{1.4}$$

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

$$P_{n,t} = E_t^{\mathbb{Q}}\left[\exp\left(-\sum_{i=0}^{n-1} i_{1,t+i}\right)\right] \tag{1.5}$$

and continuously compounded spot rates thus as

$$i_{n,t} = -n^{-1}\ln P_{n,t}. \tag{1.6}$$

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

$$f_{h,t} \approx \int \left(l_{t+h} + \sigma_h^{\mathbb{Q}} g\left(\frac{sf_{h,t} - l_{t+h}}{\sigma_h^{\mathbb{Q}}}\right)\right) P_t^{\mathbb{Q}}(l_{t+h})\,\mathrm{d}x \tag{1.7}$$

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

[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).

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:

$$l_{t+h} = \begin{cases} 0 & \text{if prior to ELB period and } \forall h = 0, 1, 2, \dots \\ \gamma_t i_t^{DFR} + (1-\gamma_t) i_{t+1}^{DFR} + sp_t & \text{if ELB period and } h = 0 \\ \min(l_t, \bar{f}_t) & \text{if ELB period and } \forall h = 1, 2, \dots \end{cases} \tag{1.8}$$

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 $\gamma_t$ 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 2.4 in this repsect). With this deterministic lower bound specification we follow Wu and Xia (2016) and Equation 2.17 can then be approximated analytically as

$$f_{h,t} \approx l_{t+h} + \sigma_h^{\mathbb{Q}} g\left(\frac{sf_{h,t} - l_{t+h}}{\sigma_h^{\mathbb{Q}}}\right). \tag{1.9}$$

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 additionally inform the model with survey forecasts on short rate expectations. We treat survey forecasts as the survey participant's believe over the most likely future realization of short rates. This notion is important as it implies that at or near the effective lower bound, i.e. when the distribution of interest rates is truncated and asymmetric, it should

[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.

be the mode of future interest rate distributions and not the mean that should be fitted to these survey information. 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

$$i_{n,t+j}^{survey} = max(E_t^{\mathbb{P}}\left[si_{n,t+j}\right], l_{t+h}) + e_{n,t}^{survey} \tag{1.10}$$

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

## 1.3 Estimation

For estimation purposes, we cast our benchmark model $SRTSM_B$ in state space form with the transition equation given by Equation 2.2

$$X_t = \mu^{\mathbb{P}} + \rho^{\mathbb{P}} X_{t-1} + \Sigma u_t, \qquad u_t \sim N(0, I). \tag{1.11}$$

The measurement equation takes the form of

$$\hat{Y}_t = Y_t + e_t \tag{1.12}$$

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 $\sigma^i$ for yields[5] and $\sigma_n^{survey}$ 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.

[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.

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

[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, $\mu^{\mathbb{Q}} = [k_\infty^{\mathbb{Q}}, 0, 0]'$, $\Sigma$ 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 $\mu_P, \rho_P, \Sigma_P$ 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 2.18 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

[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).

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 parameter $\gamma_t$. 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.

## 1.4 Results

### 1.4.1 Goodness of fit

Overall, our benchmark model ($SRTSM_B$) performs well in terms of model fit (see Table 1.1, parameter estimates are reported in Table 2.A7). 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 1.1). 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. At other dates, it shows, that it is essential to account for expected DFR cuts in form of future changes of the effective lower bound. In February 2016, when market participants were broadly expecting a further DFR cut, our model is able to replicate a downward

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

**Table 1.1: 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 | | | | | | | |

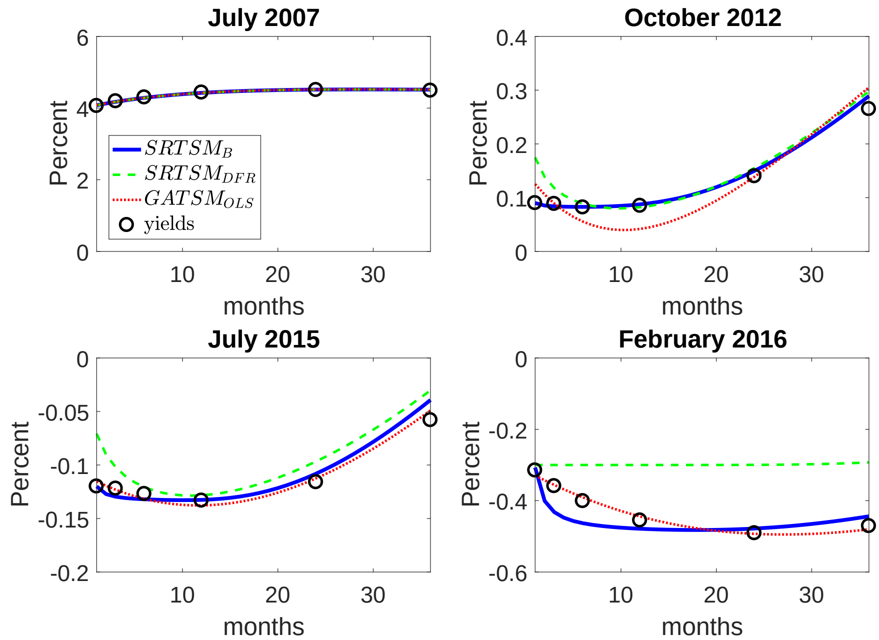
Note: This table shows the mean absolute errors (MAE) of model-implied yields and short rate expectations compared to observed yields and survey forecasts for selected sample periods in basis points. The total sample covers the period January 1999 to October 2017 while the pre-ELB sample covers the period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

sloping yield curve. A model assuming a constant ELB at the DFR for all horizons $t+h$ ($SRTSM_{DFR}$ instead ignores the downward sloping forward curve and instead produces a flat path at the current DFR).

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 1.2). 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 rate first moves below the ELB insensitive to other modeling specifications which may affect the dynamics of the pricing factors (see Figure 1.A1).[10]

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

**Figure 1.1: Yield curve model fit at selected dates**



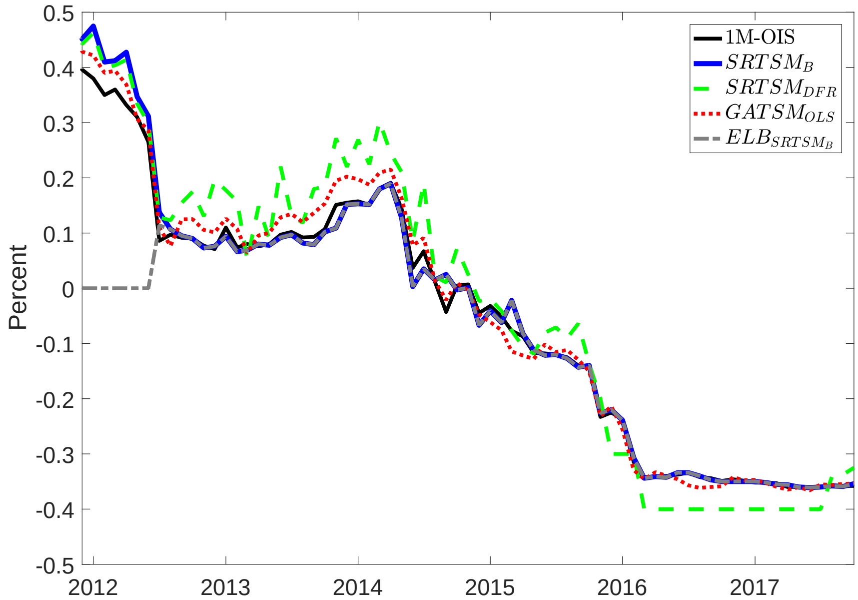

**Note: This figure plots the model-implied yield curve based on various term structure model specifications including $SRTSM_B$, $SRTSM_{DFR}$ and $GATSM$ up to 3 years based on selected dates.**

### 1.4.2 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 1.3) 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 1.A2, 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 1.3). For comparability, forward premia are scaled to unit per month and reported in basis points. The figure shows that after

**Figure 1.2: 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.**

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

[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."

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 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).

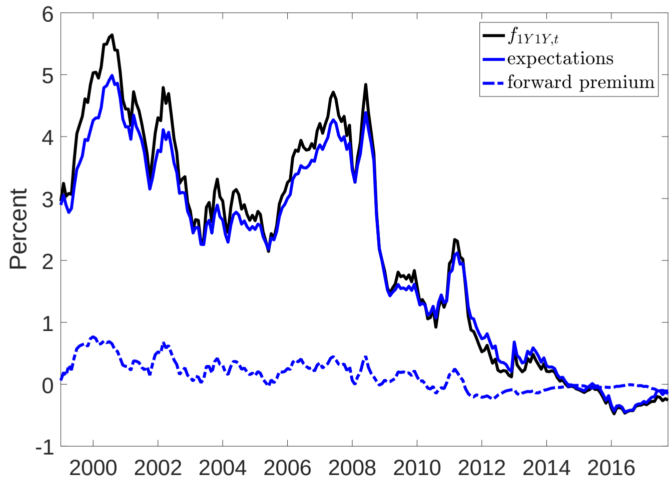
Given the asymmetry of the distribution of future short rates during the ELB period, our model also accounts for the wedge between the *mean* and the *mode*, i.e. the most likely future short rate path which is eminent at short- and medium-term horizons where the ELB implies a truncated distribution. 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 1.4). 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 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 1.4 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

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

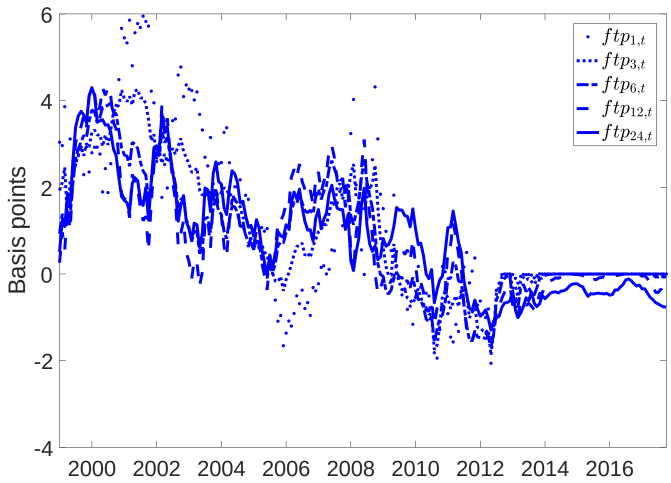
[13] The lift-off distribution is calculated by simulating a large number of short rate paths under the $\mathbb{P}$-measure and then saving the future horizon at which each single path rises above a certain threshold. While determining these future horizons, the fact can be accounted for that some paths 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 1.3: Short-term forward rate decomposition

(a) 1Y1Y forward rate




(b) (Normalized) short-term forward premia

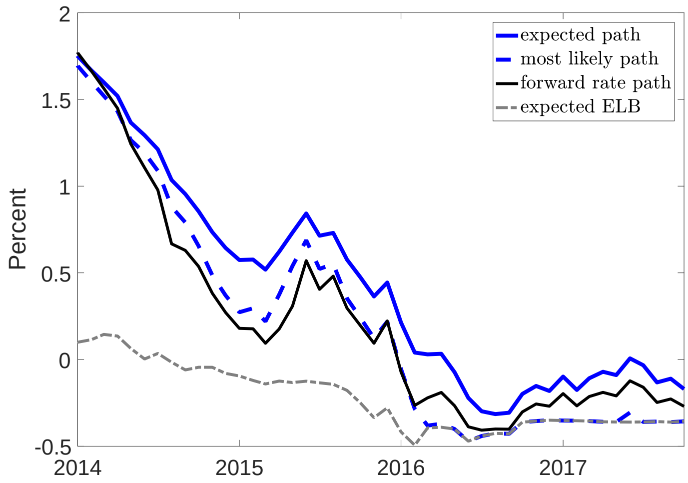



Note: Panel (a) plots the time series of the decomposition of the 1Y1Y forward rate. Panel (b) plots the time series of normalized 1-month forward premia at the $1, 3, 6, 12$ and 24-months horizons. Forward premia are normalized by maturity in months. End-of-month values for January 1999 to October 2017.

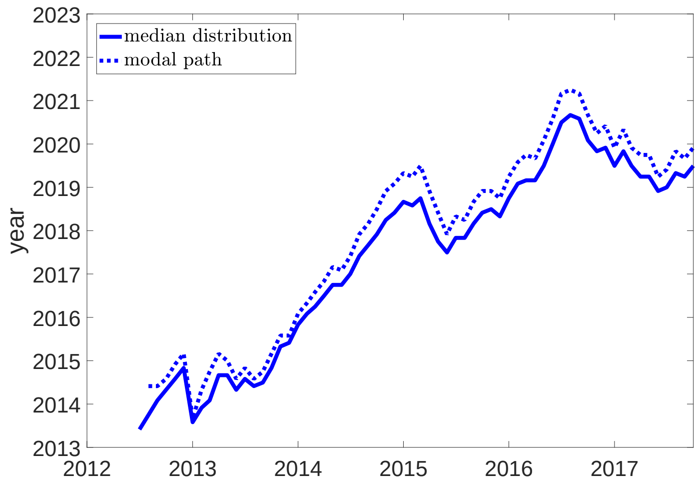
as most likely. For the end of the sample in October 2017, this assessment implies a first DFR hike in the summer of 2019.

Figure 1.4: 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.

### 1.4.3 Model-implied longer-term rate expectations

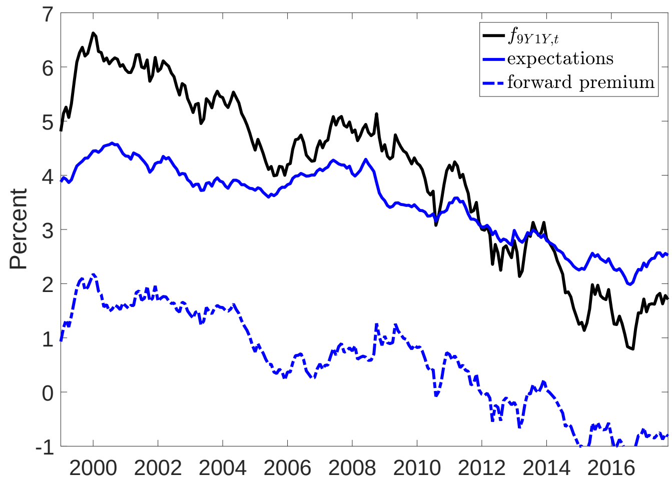
In this Section, we turn to the implications of model-implied intermediate and long-term expectations as well as term premia based on our benchmark model. To start with, in Table 2.1 we report summary statistics for the (shadow) short rate based on the $\mathbb{P}$-measure. The model is estimated with 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 1.5. 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 1.5). Note that at these intermediate to long-term maturities, forward premia co-move more linearly than at shorter maturities (see panel (b) of Figure 1.3). 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.

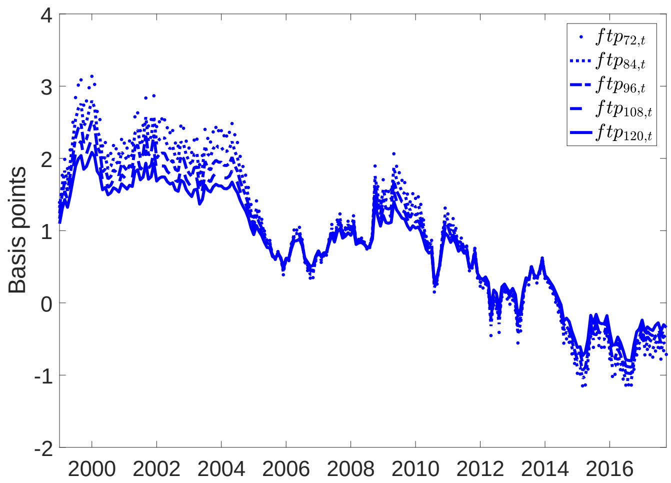
A variance decomposition for the 9Y1Y forward rate confirms that over the total sample roughly 56% of the variation in the level of the $9Y1Y$ rate is due to the forward premium component (see Table 1.A3). In the ELB period, the share of the forward premium variation increases to roughly 60%. In terms 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 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

Figure 1.5: 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.

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]

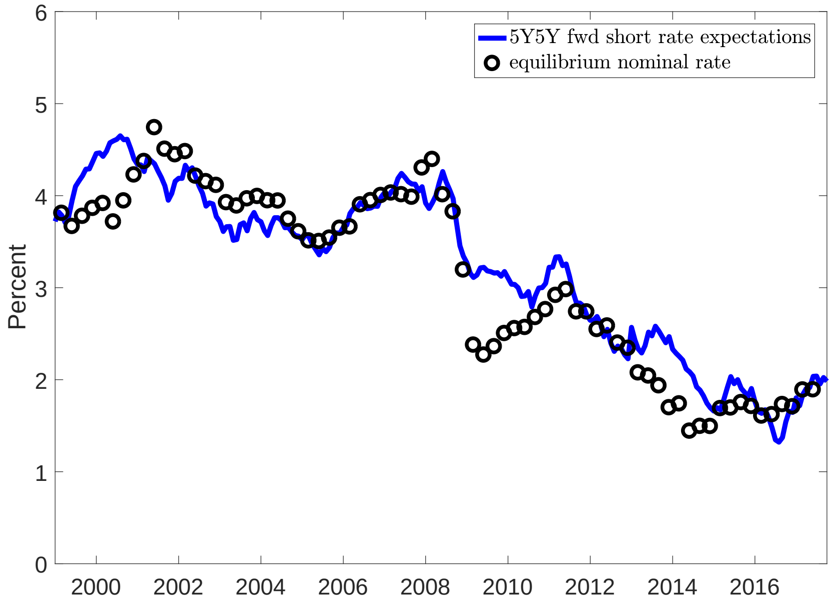
Indeed, 5Y5Y interest rate expectations derived from our benchmark model capture the level and path of the nominal natural interest rate quite well. In this period, the latter is primarily driven by the real natural interest rate path while simultaneously longer-term inflation expectations are rather 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 1.A2, 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

[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 1.6: 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.

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 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 1.A3). 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 1.A4). While under

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

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.

### 1.4.4 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 1.4.2 and 1.4.3 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 2.20 are $L$ linear combinations of structural shocks $\epsilon_t$. Therefore, it holds that

$$u_t = H\epsilon_t = [H_1, \ldots, H_L]\,(\epsilon_{1,t}, \ldots, \epsilon_{L,t})' \tag{1.13}$$

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

$$\epsilon_t = H^{-1} u_t. \tag{1.14}$$

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 2.17. 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.

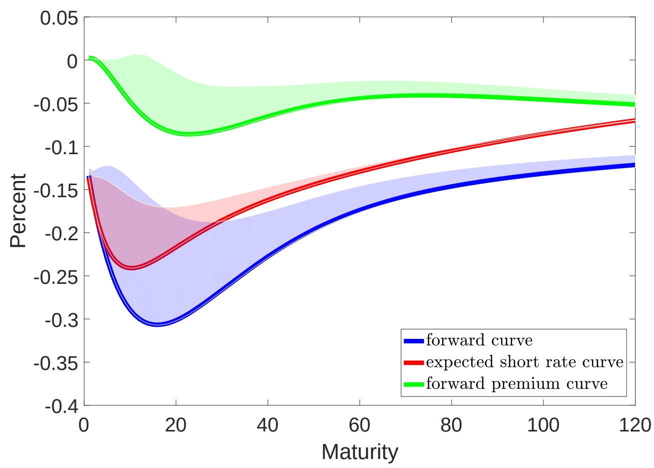
In the following we identify conventional (CMP) and unconventional monetary policy (UMP) shocks based on the instrument data set of Mandler and Scharnagl (2018). The data set consists of daily changes of various financial market variables used as instruments for monetary policy related shocks during 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.

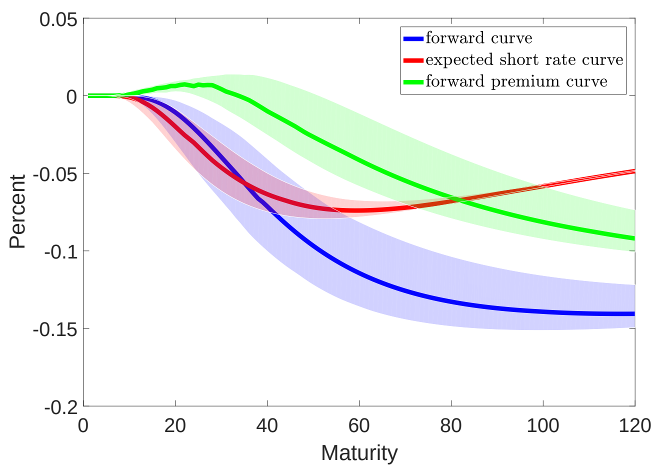
In order to compute economically interpretable impulse response functions based on the identified monetary policy shocks, we rotate our benchmark model $SRTSM_B$ as described in Section 2.3. In particular, we transform the three latent factors in a way that they resemble the 1-months, 2-year and 10-year (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.

Figure 1.7: 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 2014. 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.

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 1.7. 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 a shock to the first pricing factor prior to the ELB period is equivalent to a short rate shock. 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] Finally, panel (a) of Figure 1.7 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 1.7 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

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

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

channel of non-standard monetary policy measures.[19]

In Table 1.2, 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%.

**Table 1.2: 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.

Finally, we take a closer look at the shadow short rate and analyze to what extent its dynamics are related to UMP shocks (Figure 1.A6). It turns out that although these shocks increasingly affected the shadow short rate throughout 2015 and at the end of

[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.

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.

### 1.4.5 Specification analysis and robustness of model-implied rate expectations

#### 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 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 1.A4, 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 1.1).[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 $GATSM_{OLS}$ 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.

[20] For readability, we do not show the model variants $GATSM_S$, $GATSM_{BC}$ and $SRTSM_{woS}$ in Figure 1.1.

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

This shortcoming has important implications for the distribution of short rates and yield curve decompositions, a finding we will discuss later in Subsection 1.4.5. 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).

**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 2.1). 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 than or equal to 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

**Table 1.3: (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 |
| 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 | | | |

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 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 1.A5). 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 1.A7, 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 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 1.A8 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

[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 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.

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).

**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 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 1.4). 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.

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

**Table 1.4: 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 | |

## 1.5 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.

An important caveat of our work that could be addressed in future work is the deterministic specification of the lower bound. While our specification has important advantages for modelling near-term short-rate expectations, allowing the lower bound to follow a stochastic process could deliver more insights on the market's perception of where the lower bound truly lies. Further, our model in its current specification is not capable of capturing certain effects of the Eurosystem's asset purchases like the liquidity-induced widening of the spread between Bund and OIS yields at the very short-end. 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.

# Bibliography

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

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

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

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

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

Bauer, M. D. and Rudebusch, G. D. (2017). Interest rates under falling stars, Working Paper Series 2017–16.

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

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

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

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

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

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

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

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

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

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

Dijk, D., Koopman, S. J., Wel, M. and Wright, J. H. (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 Stanton, R. H. (2012). Estimation of dynamic term structure models, Quarterly Journal of Finance **2**(02): 1–51.

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

Gurkaynak, R. S., Sack, B. and Swanson, E. (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 Univ. Press, Princeton, NJ.

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

Holston, K., Laubach, T. and Williams, J. (2017). Measuring the natural rate of interest: International trends and determinants, Journal of International Economics pp. S59–S75.

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

Joslin, S., Singleton, K. J. and Zhu, H. (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 Orphanides, A. (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 Priebsch, M. (2013). Estimation of multi-factor shadow rate term structure models, Preliminary draft.

Kim, D. H. and Singleton, K. J. (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 Wright, J. H. (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). A comment on Wu and Xia (2015), and the case for two-factor shadow short rates, CAMA Working Papers 2015–48.

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, Palgrave Macmillan US, New York.

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

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

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

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

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

Mertens, K. and Ravn, M. O. (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., Altavilla, C. and Carboni, G. (2015). Asset purchase programmes and financial markets: lessons from the euro area, Working Paper Series 1864.

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

Piazzesi, M. and Swanson, E. T. (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 Discussion 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, FEDS Notes October 04, 2017.

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

Stock, J. H. and Watson, M. W. (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.

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

# 1.A Appendix

## 1.A.1 Parameter estimates

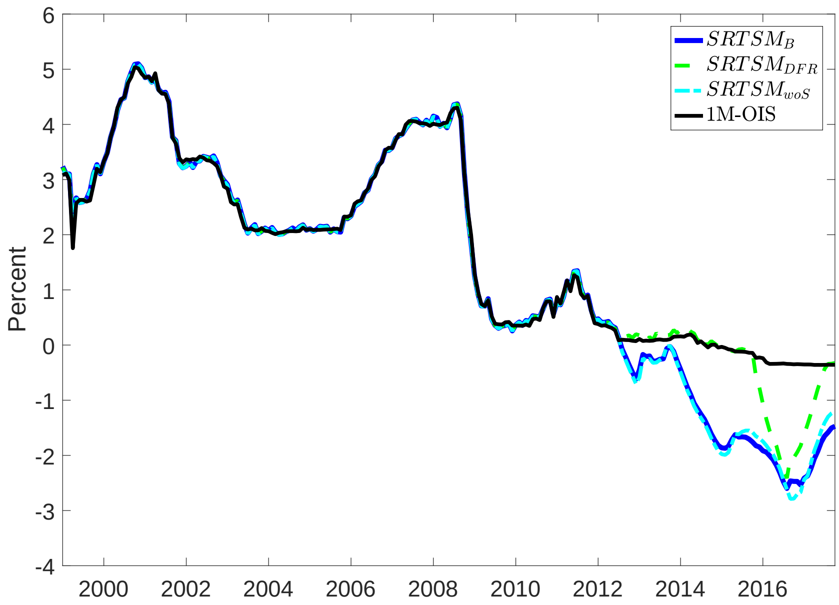
**Table 1.A1: Parameter estimates for $SRTSM_B$**

| | $X$-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) |
| $\Sigma$ | 0.3050 | 0 | 0 | $\Sigma_P$ | 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) |
| $\delta_0$ | 0 | | | $\delta_{0,P}$ | -0.0690 | | |
| $\delta_1$ | 1 | 1 | 1 | $\delta_{1,P}$ | 0.3177 | -0.3778 | 0.5159 |
| $\sigma^i$ | 0.0416 | | | | | | |
| $\sigma_{12M}^{survey}$ | 0.1898 | $\sigma_{24M}^{survey}$ | 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. $\sigma^i$ denotes the standard deviation of measurement errors of the considered yields which is the same across considered maturities. $\sigma^{survey}$ is the standard deviation of measurement errors of 3M interest rate survey expectations for the respective forecast horizons.

### 1.A.2 Shadow short rate estimates

**Figure 1.A1: 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.**

### 1.A.3 Variance decompositions

**Table 1.A2: 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 1.A3: 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 |

### 1.A.4 In-sample model fit across models

**Table 1.A4: 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.

### 1.A.5 Lower bound violations

**Table 1.A5: Lower bound violations of expected short rate paths**

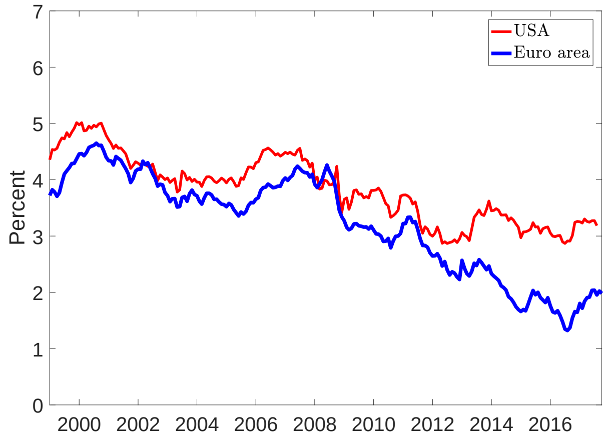
number of months for which $E_t^{\mathbb{P}}[i_{1,t+n}] < l_{t+h}$
for $n = 1, 2, \ldots, 120$ and $t = 1, 2, \ldots, 226$

| model | $SRTSM_B$ | $SRTSM_{DFR}$ | $SRTSM_{woS}$ |
|---|---|---|---|
| | 0 | 15 | 0 |
| **model** | $GATSM_{OLS}$ | $GATSM_S$ | $GATSM_{BC}$ |
| | 22 | 40 | 52 |

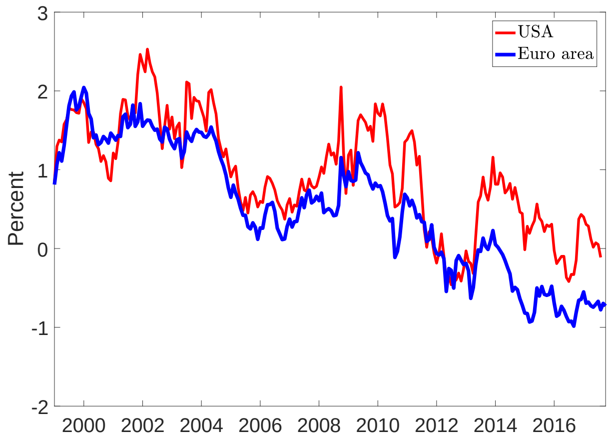
### 1.A.6 US vs euroa area decompositions

Figure 1.A2: 5Y5Y forward rate decomposition US vs. euro area

(a) Expectations




(b) Forward premium

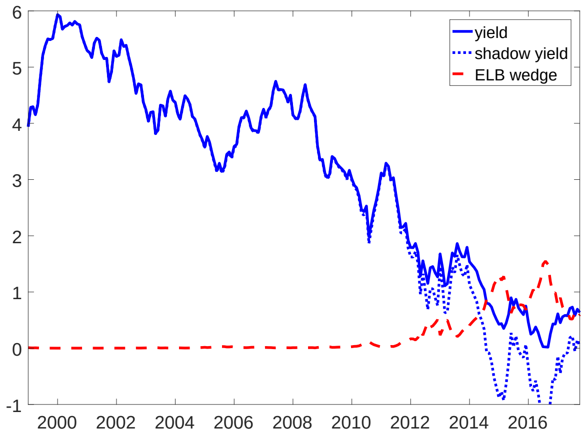



Note: Panel (a) plots the expectations component of the time series of the decomposition of the 5Y5Y forward rate. Panel (b) plots the corresponding forward premium component. Based on $SRTMS_B$ for the euro area and Kim and Wright (2005) for the US. End-of-month values for January 1999 to October 2017.

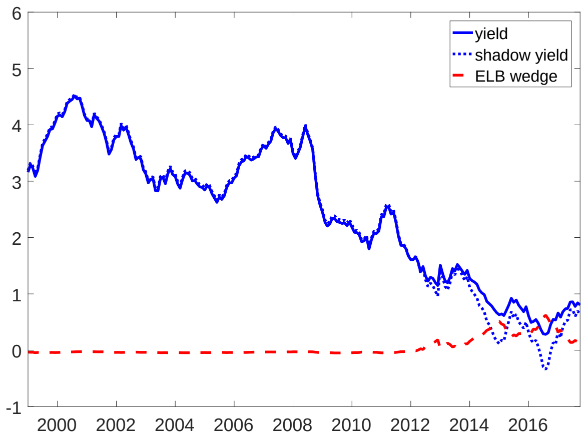
### 1.A.7 The ELB wedge

Figure 1.A3: 10-year yield and 10-year shadow yield

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



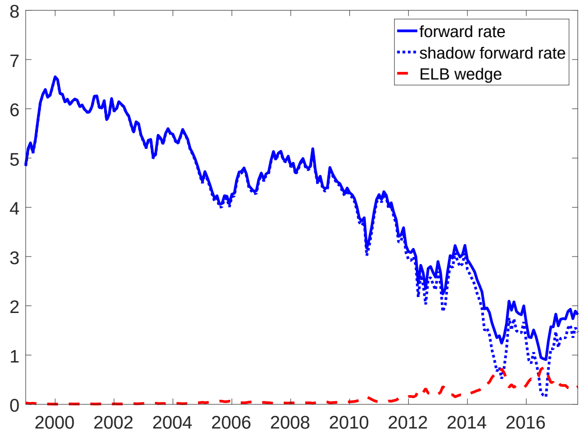

(b) $\mathbb{P}$-measure



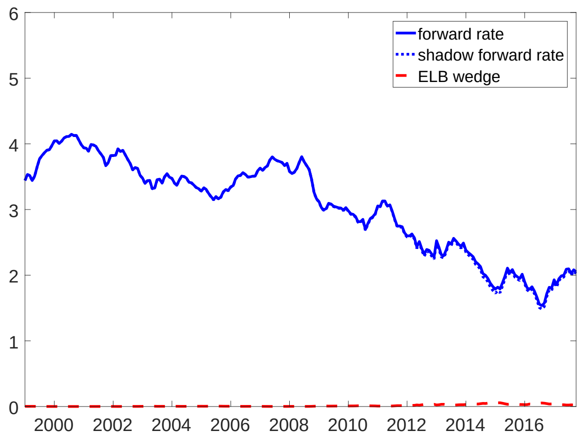

Note: Panel (a) plots the 10-year yield and shadow yield under the $\mathbb{Q}$-measure and panel (b) under the $\mathbb{P}$-measure based on $SRTMS_B$. End-of-month values for January 1999 to October 2017.

Figure 1.A4: 10Y1M forward rate and 10Y1M shadow forward rate

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




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

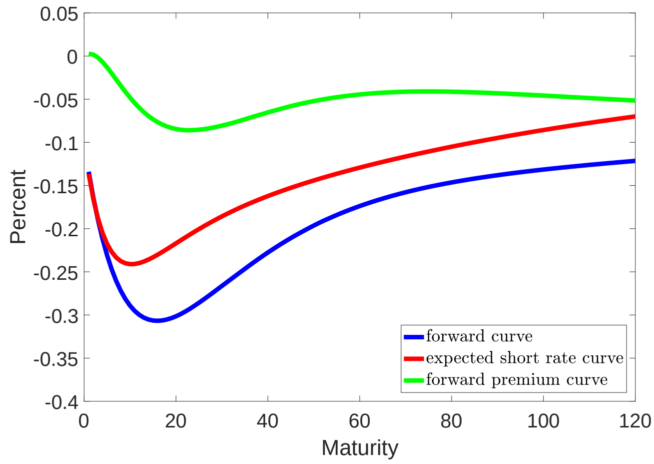



Note: Panel (a) plots the 10Y1M forward rate and shadow forward rate under the $\mathbb{Q}$-measure and panel (b) under the $\mathbb{P}$-measure based on $SRTMS_B$. End-of-month values for January 1999 to October 2017.

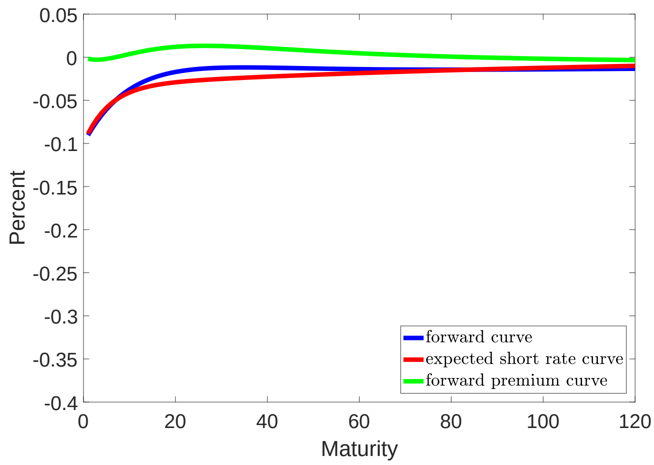
## 1.A.8 Further shock analyses

Figure 1.A5: Instantaneous response to monetary policy shocks

(a) CMP shock



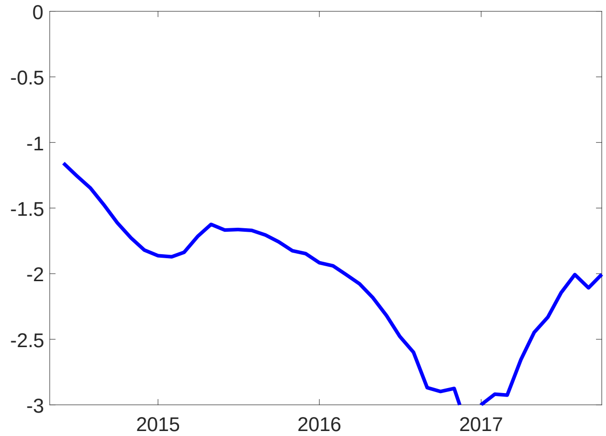

(b) Target shock



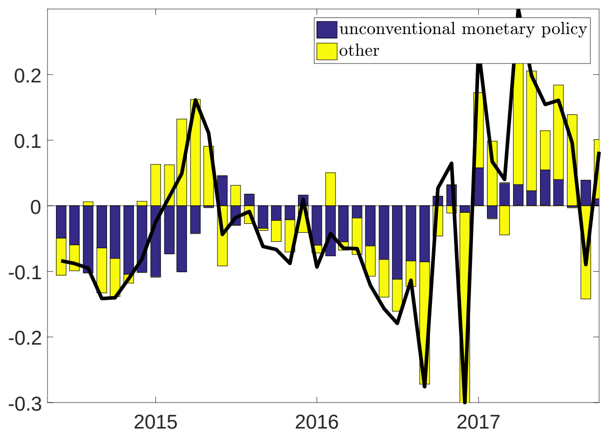

Note: Panel (a) plots the median instantaneous forward curve response and its components based on $SRTSM_B$ and a high frequency identification approach for the sample period January 1999 to June 2014. Panel (b) plots the median instantaneous forward curve response and its components based on $SRTSM_B$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

Figure 1.A6: Historical decomposition of the shadow short rate

(a) level of the shadow short rate



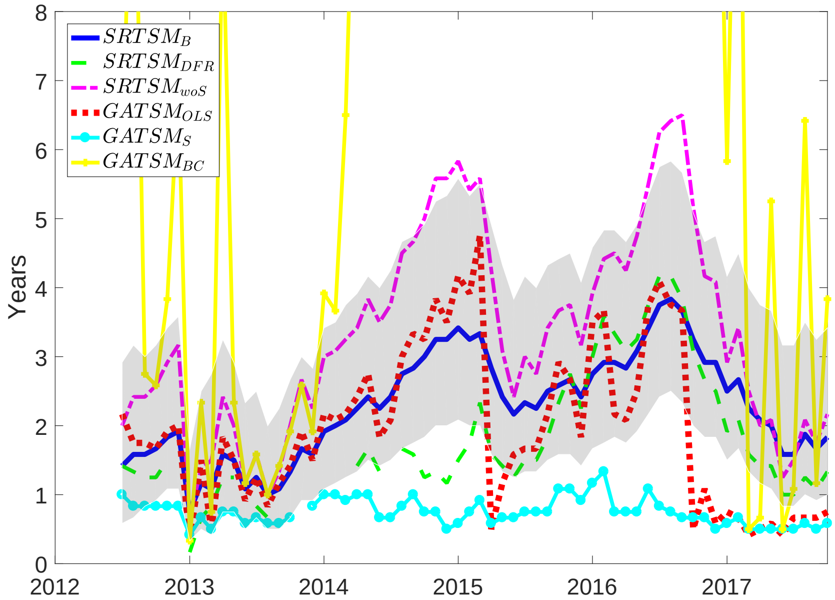

(b) change and contribution of shocks




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.

### 1.A.9 Time to lift-off across models

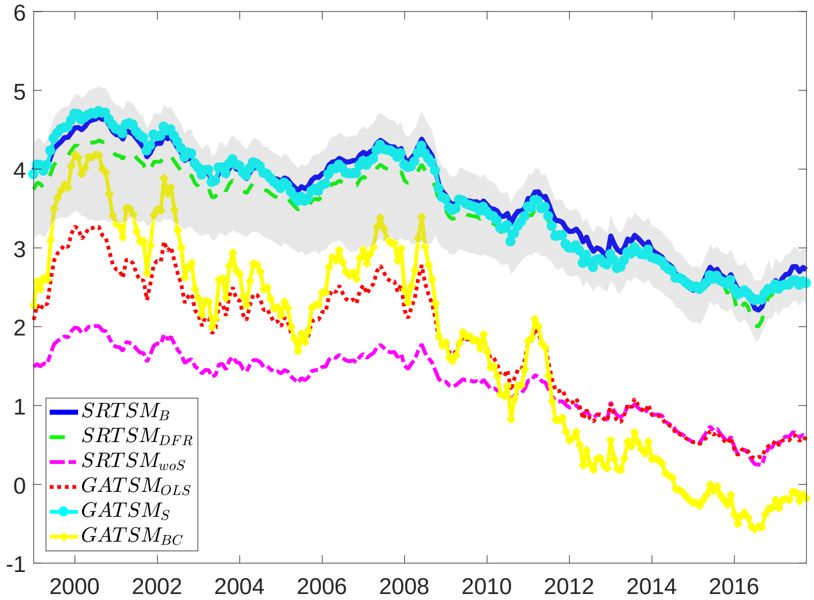
**Figure 1.A7: +10 BP DFR hike (median distribution)**




**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.**

## 1.A.10 Long-term short rate expectations across models

**Figure 1.A8: 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.**

# Chapter 2

# The (ir)relevance of the nominal lower bound for real yield curve analysis

## 2.1 Introduction

The analysis of the term structure of interest rates is a central focus of the assessment of the transmission and effectiveness of monetary policy. By definition, any move in nominal rates is driven by either the inflation component or the real rate component. While central banks aim to steer the level and expectations of nominal rates, it is essential for monetary authorities that they manage to effectively influence real rates in the intended manner, as according to economic theory, it is the level of real rates that matters for consumption and investment and thus ultimately drives inflation.

A standard tool for the analysis of yields are dynamic term structure models (DTSMs). Most commonly, they are used to decompose the yield curve into genuine expectations about future short rates and the term premium, which compensates the investor for the uncertainty about future short rate realizations. However, beyond the decomposition of nominal yields, they can also be applied for a further decomposition of these expectations and premia into their real and inflation components. While earlier models generally assumed that yields are linear functions of a small set of pricing factors, the literature has moved towards more complicated models – so-called shadow rate term structure models (SRTSMs) – since yields have been considered close to or at their effective lower bound (ELB). As it is assumed that yields cannot fall below their ELB, this implies that they follow a non-linear distribution.

The literature has argued that failing to take this non-linearity into account may otherwise lead to implausible estimates for rate expectations and premia (see e.g. Krippner (2015a), Priebsch (2013), Lemke and Vladu (2016), Wu and Xia (2016), Geiger and Schupp (2018)) and consequently also to a non-reliable inference of the dynamics of inflation expectations and real rates embedded in observed nominal rates (Carriero, Mouabbi and Vangelista (2018)). Against this backdrop, I propose a joint model for euro area nominal rates and inflation-linked swap (ILS) rates, which allows the aforementioned components to be isolated. Unlike earlier models focusing on the euro area (see Hördahl and Tristani (2014), García and Werner (2012)), the model in this paper explicitly takes into account the ELB of nominal interest rates, which for the euro area is considered to be time-varying (Lemke and Vladu (2016), Wu and Xia (2017)). This implies a non-linear interest rate distribution close to or at the ELB, as substantially lower interest rates are considered to be unlikely if not ruled out.

Indeed, results suggest that modelling the ELB is of relevance for two reasons. First, an analysis of responses by yield components to shocks to the inflation factor shows that the magnitude and sign of these responses are conditional on the degree to which the ELB is binding. For nominal yields, we observe a decreasing impact of inflation shocks across all maturities, the closer rates are to the ELB. The response of real rates is non-linear. While nominal rates are distant from the ELB, real rates show a positive response to a positive inflation shock; they react negatively when nominal rates are close to or at the ELB. Overall, these results suggest that the ELB introduces non-linearities with a meaningful impact on structural relationships in the economy. The finding of non-linear or time-varying impulse responses relates to findings of Mertens and Williams (2018) who, in a small structural model, find that the lower bound alters the distributions of both interest rates and inflation by restricting the central bank's scope for action. The findings further relate to work by King (2019) and Geiger and Schupp (2018) who likewise attest a decreasing effectiveness of conventional monetary policy at the ELB due to a receding reactiveness of interest rates, in particular, at shorter maturities.

Second, isolated changes in the ELB impact, in particular, nominal and real forward rates mainly through their expectations component. In our analysis, a 10-bp cut in the ELB yields an average impact of -5 (-3) bps on 24-month (120-month) nominal forward rates. These impacts are almost entirely transmitted through real rate expectations and only to a very small extent through real or inflation risk premia. Thus, these results imply that the central bank can lower real rate expectations by solely changing the effective lower bound of interest rates. These results build upon work of Lemke and Vladu (2016) who have shown that the perceived lower bound by itself can be considered a monetary policy tool to lower yields across all horizons.

While the above results stress the importance of incorporating the ELB, another finding of this paper is that similar yield decompositions are obtained from the model whether or not it incorporates a lower bound, conditional of the inclusion of survey information on expected rates and inflation. In fact, the model in both cases achieves a similar fit of these surveys, the expectations components do not differ markedly, even though both models do yield somewhat different results in terms of persistence and the unconditional means of the nominal short rate, real short rate and inflation.

The proposed model is further applied to a decomposition of the change in nominal long-term rates between mid-2014 and mid-2016. This decline is often considered to have been initiated in anticipation of the Eurosystem's unconventional monetary policy measures, in particular, its large-scale asset purchases. Commonly, such programmes are considered to affect yields mainly through two channels: 1) the duration extraction or portfolio rebalancing channel affecting risk premia (see Vayanos and Vila (2009)), and 2) the rate signalling channel affecting rate expectations (see Bauer and Rudebusch (2014)). Indeed, the results show that both, nominal rate expectations and premia contributed to the decline which is principally in line with both these transmission channels mentioned above. At the same time, however, the reduction to a large extent also reflected declines in inflation expectations and inflation risk premia, which may be an expression of market's anticipating an increased probability of low inflation or even deflation scenarios (see also Camba-Mendez and Werner (2017), García and Werner (2012)). Overall, this lays the ground for the supposition that monetary policy may have had adverse effects through negative information effects (see Christensen and Spiegel, 2019).

The paper is also closely related to the vast body of literature on joint real-nominal yield curve modelling. For work that focuses on the US, see Ang, Bekart and Wei (2008), Adrian and Wu (2009), Campbell, Sunderam and Viceira (2016), Christensen, Lopez and Rudebusch (2010), D'Amico, Kim and Wei (2018), Chen, Liu and Cheng (2010). Hördahl and Tristani (2014) jointly model the real and nominal term structure of interest rates for the euro area. Other related work with a focus on the euro area, which, however, does not jointly model real and nominal yields, but focuses on the term structure of inflation and the inflation risk premium based on data for euro area inflation-linked swap rates, can be found in García and Werner (2012) and Camba-Mendez and Werner (2017). For an analysis for the UK, see Barr and Campbell (1997) and Carriero et al. (2018), while Christensen and Spiegel (2019) cover the topic with a focus on Japan. Among all related work, Carriero et al. (2018) are, to the best of my knowledge, the only ones who also incorporate a lower bound for nominal rates. Unlike the model presented in this paper, the latter, however, do not model a time-varying lower bound, nor do they incorporate surveys. The model presented here is further distinct in its identification scheme and in incorporating an observed measure of inflation, while the model of Carriero et al. (2018) builds on latent factors only.

My paper is further related to the literature on yield curve modelling in lower bound environments. For the US, see Krippner (2015a), Christensen and Rudebusch (2015), Bauer and Rudebusch (2014), Wu and Xia (2016), Priebsch (2013). Applications for Japan and the UK comprise Ichiue and Ueno (2013) and Andreasen and Meldrum (2015). Other papers estimating shadow rate term structure models (SRTSMs) on euro area data are, e.g., Lemke and Vladu (2016), Kortela (2016), Wu and Xia (2017), Geiger and Schupp (2018).

## 2.2 Model

The model assumes that the term structure of interest rates is explained by $N = 4$ factors $X_t^j$, with $j = 1, 2, 3, \Pi$.[1] The factors are defined such that the first three factors may be interpreted as three latent real yield curve factors, while observed monthly inflation constitutes the fourth factor. Factor dynamics follow a first-order Gaussian vector autoregressive process both under the risk-neutral ($\mathbb{Q}$) and the historical ($\mathbb{P}$) probability measure.

$$X_t = \mu^{\mathbb{Q}} + \rho^{\mathbb{Q}} X_{t-1} + \Sigma u_t, \qquad u_t \sim N(0, I) \tag{2.1}$$

$$X_t = \mu^{\mathbb{P}} + \rho^{\mathbb{P}} X_{t-1} + \Sigma u_t, \qquad u_t \sim N(0, I). \tag{2.2}$$

### 2.2.1 Real and Nominal Shadow Short Rates

Following the standard literature on SRTSMs it is assumed that the actual nominal short rate is constrained by a (time-varying) ELB $l_t$, which serves as hard floor. Thus, by assumption, the short rate corresponds to the shadow short rate as long as the latter is above the ELB and equals the ELB otherwise. This specification also allows for forward rates and the expected path of the short rate to remain at this ELB for an extended period of time, as has been observed in the euro area since interest rates have reached the ELB. Specifically, it holds that

$$i_{1,t} = \max(si_{1,t}, l_t), \tag{2.3}$$

where $si_{1,t}$ is the shadow short rate. From an economic perspective, the nominal shadow rate can be interpreted as the short rate which would prevail in the absence of

[1] This specification follows Ajello, Benzoni and Chyruk (2012).

the ELB, and thus describes the hypothetical value of the option to hold cash (see Black, 1995). Essentially, the existence of the nominal shadow rate also implies the existence of a real shadow short rate $si^*_{t,1}$ which Black (1995) describes as the difference between the nominal shadow rate $si_t$ and inflation:[2]

$$si^*_{t,1} = si_{t,1} - E^{\mathbb{Q}}_t(\Pi_{t+1}). \tag{2.4}$$

Another central assumption of the model proposed here is that $si^*_{t,1}$ is linear in the pricing factors:

$$si^*_{1,t} = \delta_0 + \delta_1^{'} X_t, \tag{2.5}$$

where $\delta_1 = [1; 1; 1; \delta_\Pi]$.[3]

### 2.2.2 Nominal Bond Prices

Central to any term structure model is the assumption of no arbitrage, which implies the existence of a unique stochastic discount factor (SDF) $m$ which prices all bonds of any maturity $n$. For the price of a nominal zero-coupon bond of maturity $n$, it then holds that

$$P_{n,t} = E^{\mathbb{P}}_t[m_{t+1} P_{n-1,t+1}] \tag{2.6}$$

In general, the SDF can be defined in real and nominal terms depending on which kind of bond is to be priced. For real bonds, the real pricing kernel in the following is defined as proposed by Ang et al. (2008):

[2]The real shadow short rate will differ from the actual real rate to the extent that the nominal shadow short rate differs from the actual nominal short rate. Further note that while actual real rates are technically not constrained by a lower bound, the nominal lower bound implies that the space of feasible real rate realizations is still constrained to the extent that they emerge as the difference of ex-ante expected inflation and constrained nominal rates. Thus, at the ELB the lowest feasible real rate realizations decisively depend on the upper tail of the inflation distribution.

[3]The choice of $\delta_\Pi$ does have theoretical implications. As Ang et al. (2008) argue, a zero loading of the real short rate on expected inflation implies money neutrality. A possible Mundell-Tobin effect would call for a negative correlation, and an activist Taylor rule, on the other hand, would predict a positive correlation. We decide to leave this parameter unrestricted.

$$m^*_{t+1} = exp(-i^*_{1,t} - \frac{1}{2}\lambda'_t\lambda_t - \lambda'_t\epsilon_{t+1}) \tag{2.7}$$

with $i^*_t$ representing the real short rate. Subsequently the nominal pricing kernel is

$$\begin{aligned} m_{t+1} =& m^*_{t+1}\frac{Q_t}{Q_{t+1}} = m^*_{t+1}exp(-\pi_{t+1}) \\ =& exp(-i^*_{1,t} - \pi_{t+1} - \frac{1}{2}\lambda'_t\lambda_t - \lambda'_t\epsilon_{t+1}). \end{aligned} \tag{2.8}$$

Note, that $\lambda_t$ constitute the prices of risk investors demand in the market. Following Dai and Singleton (2002), these are themselves linear functions of the factors $X_t$ and thus time-varying. Their function takes the form

$$\lambda_t = \lambda_0 + \lambda'_1 X_t. \tag{2.9}$$

Following Wu and Xia (2017), shadow real yields are also assumed to be linear functions of the pricing factors:

$$si^*_{n,t} = a_n + b'_n X_t, \tag{2.10}$$

with $a_n = -A_n/n$ and $b_n = -B_n/n$.
Subsequently, expressions for $a_n$ and $b_n$ are obtained via recursive solutions[4]:

$$A_{n+1} = -\delta_0 + A_n + B_n(\rho_0^{\mathbb{P}} - \Sigma\lambda_0) - \rho_0^{\pi,\mathbb{P}} + \frac{1}{2}B_n\Sigma\Sigma' B_n + \frac{1}{2}\Sigma^\pi\Sigma^{\pi'} \tag{2.11}$$

$$B_{n+1} = -\delta_1 - \rho_1^{\pi,\mathbb{P}} + B_n^{*'}(\rho_1^{\mathbb{P}} - \Sigma\lambda_1) + \Sigma^\pi\lambda_1 \tag{2.12}$$

Note that $\rho_0^{\mathbb{Q}} = \rho_0^{\mathbb{P}} - \Sigma\lambda_0$ and $\rho_1^{\mathbb{Q}} = \rho_1^{\mathbb{P}} - \Sigma\lambda_1$.

$$A_1 = -\delta_0 - \rho_0^{\pi,\mathbb{P}} + \Sigma^\pi\lambda_0 + \frac{1}{2}\Sigma^\pi\Sigma^{\pi'} \tag{2.13}$$

$$B'_1 = -\delta'_1 - \rho_1^{\pi,\mathbb{P}} + \Sigma^\pi\lambda_1 \tag{2.14}$$

so that here the nominal shadow short rate is defined as

[4]For details see Appendix 2.A.1.

$$si_{t,1} = \delta_0 + \rho^{\pi,\mathbb{P}} - \Sigma^{\pi}\lambda_0 - \frac{1}{2}\Sigma^{\pi}\Sigma^{\pi'} + (\delta_1' + \rho_1^{\pi,\mathbb{P}} - \Sigma^{\pi}\lambda_1)X_t \tag{2.15}$$

Finally, it then follows for shadow forward rates:

$$sf_{n,t} = (A_{n+1} - A_n) + (B_{n+1}' - B_n')X_t. \tag{2.16}$$

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. However, Wu and Xia (2017) show that generally implied one-period forward rates $n$ periods ahead, $f_{n,t}$, can be expressed as

$$f_{n,t} \approx \int \left( l_{t+n} + \sigma_n^{\mathbb{Q}} g\left( \frac{sf_{n,t} - l_{t+n}}{\sigma_n^{\mathbb{Q}}} \right) \right) P_t^{\mathbb{Q}}(l_{t+n})\, \mathrm{d}x \tag{2.17}$$

where $g(x) = x\Phi(x) + \phi(x)$ with $\Phi(x)$ the standard normal cdf, $\phi(x)$ the standard normal pdf, and $\sigma_n^{\mathbb{Q}}$ the conditional variance of future shadow short rates. Note that in this general form, the forward rate is calculated as the average of future short rates with $l_{t+n}$ weighted by the risk-neutral probability of $l_{t+n}$.

In euro area term structure literature, the lower bound is typically regarded as time-varying (see i.a. Lemke and Vladu (2016), Kortela (2016), Wu and Xia (2017), Geiger and Schupp (2018)). Allowing the ELB to change over time acknowledges that before interest rates were actually lowered to negative levels, it was reasonable to assume that zero would have constituted the ELB for interest rates. Indeed, Lemke and Vladu (2016) present survey evidence that the first cut to negative levels in the euro area was widely unanticipated at that point in time. Later, even after interest rates were lowered into negative territory, it was not clear that the ECB would lower rates even further as statements by ECB President Mario Draghi attest. After the cut to -10 bps as well as after the move to -20 bps, he declared that the technical lower bound of interest rates had been reached.[5] Thus, allowing for discrete changes of $l_t$ accommodates the notion that the market adapted perceptions of where the ELB with each subsequent cut in the course

[5]E.g. after the ECB Governing Council lowered the DFR to -10 bps on 5 June 2014, President Draghi at the press conference emphasized that "[...] for all the practical purposes, we have reached the lower bound". While saying that this would not exclude some "little technical adjustments, which could lead to some lower interest rates", he then repeated that "from all practical purposes, I would consider having reached the lower bound today". Then, after the DFR was cut to -20 bps after all in September 2014, President Draghi again said that the lower bound had now been finally reached. He announced this cut as a technical adjustment, now even ruling out further adjustments. After the consecutive cuts to -30 and -40 bps, the President avoided any statements on the lower bound of interest rates.

of 2014-2016.[6]

The literature offers a number of alternatives to mirror this ELB dynamic in a otherwise standard SRTSM. The simplest calibration would hardwire the ELB to equal the level of the Deposit Facility Rate (DFR) during the lower bound period beginning in summer 2012 (see e.g. Kortela, 2016)). However, this omits that downward sloping forward rate constellations, in particular, during the years 2014 to 2016 indeed signalled that the market did not necessarily consider the current DFR to be the actual ELB. While it then still would be plausible to assume that the DFR is the lower bound for the short rate, this does not necessarily hold for all future expected short rates. This was first addressed by Wu and Xia (2016), who at each point in time allow for expected changes in the lower bound, which is modelled to follow a Markov-chain process. Here, we follow Geiger and Schupp (2018), who assume that for all future dates $t+n$ the perceived lower bound equals the minimum forward rate, while the current short rate remains bound by the DFR. This allows the model to fit a downward sloping yield curve also at the current ELB.[7]

More precisely, the ELB is the specified in the following way:

$$l_{t+n} = \begin{cases} 0 & \text{if prior to ELB period and } \forall n = 0, 1, 2, \ldots \\ \gamma_t i_t^{DFR} + (1-\gamma_t) i_{t+1}^{DFR} + sp_t & \text{if ELB period and } n = 0 \\ \min(l_t, \bar{f}_t) & \text{if ELB period and } \forall n = 1, 2, \ldots \end{cases} \tag{2.18}$$

with $\bar{f}_t = \min(f_{t,n})$ for $n = [1, 2, \ldots, N]$. In the period before reaching the ELB, the current and expected ELB is set to zero. Following Wu and Xia (2016) this leads to the following analytical approximation of Equation 2.19:

$$f_{h,t} \approx l_{t+n} + \sigma_n^{\mathbb{Q}} g\left(\frac{sf_{n,t} - l_{t+n}}{\sigma_n^{\mathbb{Q}}}\right). \tag{2.19}$$

[6] OIS rates are in general considered to be bound by the Eurosystem's DFR as 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.

[7] The lower bound specification of Geiger and Schupp (2018) also accounts for calender effects by setting the current ELB, $l_t$, equal to the weighted average of the DFR in period $t$ and the expected DFR in period $t+1$, which in their specification is treated as being known in period $t$, where $\gamma_t$ is the fraction of days between the end of the month and the next Governing Council meeting in the following month. Moreover, expectations of future changes in the lower bound are accounted for by separately defining a lower bound for all future periods $t+h$ as the minimum of the current lower bound $l_t$ and the observed 1-month forward rates over the next 24 months.

## 2.3 Estimation

For the estimation, the model is cast into state space form with the transition equation given by Equation 2.2:

$$X_t = \mu^{\mathbb{P}} + \rho^{\mathbb{P}} X_{t-1} + \Sigma u_t, \qquad u_t \sim N(0, I). \tag{2.20}$$

The measurement equation takes the form of

$$\hat{Z}_t = Z_t + e_t \tag{2.21}$$

where $Z_t$ contains observed yields, ILS rates, observed 1-month Inflation $\Pi^o$ and the survey information on short-rate and inflation expectations as explained above with model-implied yields $Y_t = g(X_t, \rho_0^{\mathbb{Q}}, \rho_1^{\mathbb{Q}}, \Sigma, \delta_0, \delta_1, \lambda_0, \lambda_1)$.

Without further restrictions, the latent state is not uniquely determined. In general, identifying the model and preventing the latent factors from shifting, rotating or scaling, only a small number of restrictions are needed. Here, the identification follows Joslin, Singleton and Zhu (2011) who develop a maximally-flexible model in which all identifying restrictions are imposed on the cross-section of yields, while time series dynamics of yields are described by an unrestricted VAR(1) process.[8]

An additional measurement equation is formulated for ILS rates, which we interpret as the observed break-even inflation rate ($BEIR^o$). The model-implied $BEIR$ itself is defined as

$$BEIR_{t,n} = i_{n,t+j} - i^*_{n,t+j} \tag{2.22}$$

As our model does not directly observe the actual real rate $i^*_{n,t+j}$, we re-formulate the above as

[8]Specifically, it is imposed that $\rho^{\mathbb{Q}} = diag(\rho_1^{1,\mathbb{Q}}, \rho_1^{2,\mathbb{Q}}, \rho_1^{3,\mathbb{Q}}, \rho_1^{\Pi,\mathbb{Q}})$ and is in Jordan form, $\rho_0^{\mathbb{Q}} = [\kappa_\infty^{\mathbb{Q}}, 0, 0, \rho_0^{\Pi}]$, $\delta_0 = 0$ and $\delta_1 = [1, 1, 1, \Pi]$. Deviating from Joslin et al. (2011), $\Sigma$ is restricted to be diagonal, so that shocks $u_t$ are orthogonal to each other. On the one hand, this implies that shocks to inflation do not directly impact real factors, which seems to be a plausible assumption to make. On the other hand, the diagonality assumption on the latent block follows Christensen, Diebold and Rudebusch (2011) who suggest that this assumption improves upon the forecast performance of the model. In addition, it has been shown that allowing for correlation among the shocks significantly reduced the model's ability to fit survey-based inflation expectations.

$$BEIR_{t,n} = i^*_{n,t+j} + E^{\mathbb{P}}_t(\Pi_{t,n}) + IRP_{t,n} - i^*_{n,t+j} \tag{2.23}$$

$$BEIR_{t,n} = E^{\mathbb{P}}_t(\Pi_{t,n}) + IRP_{t,n} \tag{2.24}$$

where $E^{\mathbb{P}}_t(\Pi_{t,n})$ and $IRP_{t,n}$ are genuine inflation expectations and the inflation risk premium. To properly account for convexity effects, which in our model partly depend on the inflation risk prices $\lambda_{0/1,\Pi}$, we determine the $IRP$ as

$$IRP_{n,t} = i_{n,t} - i^{w/oIRP}_{n,t} \tag{2.25}$$

where the latter term is determined by computing nominal yields while setting all $\lambda_{0/1,\Pi}$ to zero.

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 distant short-rate expectations. To 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 as advocated by Kim and Orphanides (2012).[9] When including survey information, it is crucial to allow for measurement errors when aligning model-implied expectations with corresponding survey forecasts as there is little evidence that these surveys perfectly reflect actual expectations embedded in the yield curve. 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:

$$i^{survey}_{n,t+j} = E^{\mathbb{P}}_t\left[i_{n,t+j}\right] + e^{i_{survey}}_{n,t} \tag{2.26}$$

where $e^{i_{survey}}_{n,t}$ is the survey expectation measurement error with standard deviation $\sigma^{\Pi_{survey}}$.

The model further incorporates survey information on inflation expectations, which enter the model via the following measurement equation:

$$\Pi^{survey}_{n,t+j} = E^{\mathbb{P}}_t\left[i_{n,t+j}\right] + e^{\Pi_{survey}}_{n,t} \tag{2.27}$$

and $e^{\Pi_{survey}}_{n,t}$ is the survey expectation measurement error with standard deviation $\sigma^{\Pi_{survey}}$.[10]

[9] Further applications of term structure models including surveys are, e.g., Priebsch (2017), Guimarães (2014), Chernov and Mueller (2012) and Geiger and Schupp (2018).

[10] We allow the standard deviation of measurement errors of surveys to differ between the short- and long-term interest rate and inflation surveys.

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.[11]

As regards the data, we use monthly overnight index swap (OIS) rates based on EONIA and euro area inflation-linked swap (ILS) rates spanning a sample from June 2005 to December 2019. The length of the sample is determined by the availability of reliable euro area ILS rates. OIS rates are included for maturities of 1,3, and 6 months as well as 1,2,3,5,7 and 10 years, while the ILS maturities included are 1,2,3,4,5,7,9 and 10 years. Hence, our sample consists of $T = 175$ months for $J_i = 9$ and $J_\Pi = 8$ maturities. In addition to OIS and ILS rates, we further included survey information on interest rate and inflation expectations provided by Consensus Economics and the ECB's Survey of Professional Forecasters (SPF). In particular, we include Consensus economics 3-month interest rate forecasts for 1 to 7 quarters as well as 6 to 10 years ahead. As regards inflation expectations, SPF average forecasts of year-on-year inflation 1, 2 and 5 years ahead are included.

## 2.4 Results

### 2.4.1 Goodness of Fit

Overall, the model delivers a satisfying fit of yields across all maturities, with an average mean absolute error (MAE) of 4 bps over the entire sample. ILS rates are fitted with MAE of 2 bps and short-term interest rate and inflation surveys with 16 and 30 bps, respectively (see Figure 2.1 and Tables 2.A1 and 2.A4).

As has already been observed for nominal yields in Geiger and Schupp (2018), the fit improves notably after the ELB is reached, especially at the very short end. For nominal yields this result seems straightforward, as the chosen lower bound specification almost guarantees a very good fit of the short rate, ensuring that the ELB is binding at least for the short rate.

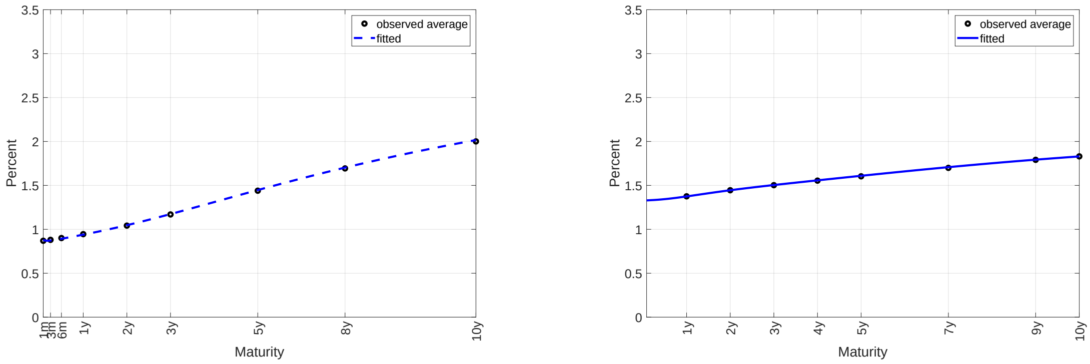
The larger fitting errors with respect to surveys are in line with other results from the literature (see e.g. Priebsch (2017) and Geiger and Schupp (2018)). This mainly reflects that the model incorporates considerably less information in terms of the number of observations on interest rate expectations compared to observed yields. However, to some extent, this may also signal that expectations embedded in market prices deviate from those expressed by survey participants.[12] In this regard, it is interesting that fitting

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

[12] Potential sources of such deviations are numerous, and many have been discussed in the literature

Figure 2.1: Average model fit

(a) OIS yields (b) ILS rates




Note: Panel (a) depicts the average fit of OIS yields for the maturities included in the model. Panel (b) depicts the average fit of ILS rates for the maturities included in the model.

errors for surveys decrease to a similar extent once entering the ELB period in mid-2012. Since then, the installment of forward guidance by the ECB's Governing Council in 2013 (see Hattori, Schrimpf and Sushko, 2016) and also the strong deterioration in the inflation outlook since mid-2014 may have further increased certainty about the rate outlook.[13] In light of these events, the forward curve as well as the path of survey expectations for the 3-months rate up to 7 quarters ahead flattened considerably. This seems likely to have contributed to some convergence in expectations by market and survey participants which in turn may partly explain these lower fitting errors.

### 2.4.2 The Real-Nominal Decomposition of Interest Rates and the Nominal Effective Lower Bound

The following section will explore in more detail the ways in which the ELB is affecting the decomposition of the nominal yield curve in its real and inflation components. To begin

before. 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 survey participants compared to the overall number of market participants. Further, there is a potential discrepancy between the information sets available to survey and market participants, given that surveys are collected over a particular reporting period, rather than at the point in time at which we observe the end-of-month interest rate. Therefore, it can well be assumed that the subjective expectations of survey participants deviate from the objective statistical $\mathbb{P}$-measure expectation. Also, survey participants are potentially not interested in revealing their true expectations, leaving surveys biased themselves, making them an inaccurate measure of participants' true expectations (Cochrane and Piazzesi, 2008; Chernov and Mueller, 2012)

[13]This increase in certainty, for example, manifests in an observed lower realized yield volatility (see Figure).

with, this analysis is based on a comparison of the yield decomposition implied by the proposed lower bound model ($RTSM_{LB}$) and an affine version of this model ($RTSM_{woLB}$). Table 2.1 summarizes estimates of the unconditional means of the nominal and real short rate as well of inflation. In addition, it also depicts information about the estimated persistence of factor dynamics. In both models, the unconditional mean of the inflation is estimated to be around 1.9%, in line with the what would be expected according the Eurosystem's inflation aim of close to, but below, 2% over the medium term. At the same time, the models disagree on the unconditional mean of nominal and real rates. The lower bound model estimates imply them to be 3% and 1.6%, while they are estimated to be somewhat higher in the affine model, at 3.7% and 3.2%. This mainly reflects differences in the persistencies of the state dynamics under the $\mathbb{P}$-measure.

**Table 2.1: (Shadow) short rate summary statistics – $\mathbb{P}$-estimates**

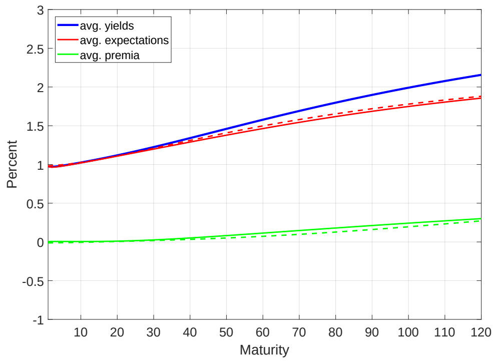
| Model | $RTSM_{LB}$ | $RTSM_{woLB}$ |
|---|---|---|
| Unconditional mean $E^{\mathbb{P}} i_1$: | 2.994 | 3.710 |
| Unconditional mean $E^{\mathbb{P}} i_1^*$: | 1.090 | 1.896 |
| Unconditional mean $E^{\mathbb{P}} \Pi_1$: | 1.903 | 1.814 |
| Eigenvalues under $\mathbb{P}$-measure: | 0.985 | 0.987 |
| | 0.967 | 0.987 |
| | 0.889 | 0.931 |
| | 0.889 | 0.931 |
| Model | $RTSM_{LB}^{noIRSurveys}$ | $RTSM_{woLB}^{noIRSurveys}$ |
| Unconditional mean $E^{\mathbb{P}} i_1$: | 1.587 | 3.240 |
| Unconditional mean $E^{\mathbb{P}} i_1^*$: | −0.353 | 1.366 |
| Unconditional mean $E^{\mathbb{P}} \Pi_1$: | 1.940 | 1.873 |
| Eigenvalues under $\mathbb{P}$-measure: | 0.985 | 0.982 |
| | 0.967 | 0.982 |
| | 0.878 | 0.916 |
| | 0.878 | 0.916 |
| Sample mean ($i_1$): 0.870 | | |

Nevertheless, and despite the differences in the estimated dynamics under the $\mathbb{P}$-measure, average decompositions of the nominal yield curve hardly differ across the lower bound and affine version of the model. Likewise, average decompositions of the nominal and real components do not differ by much (see Figure 2.2).[14] Somewhat larger but still

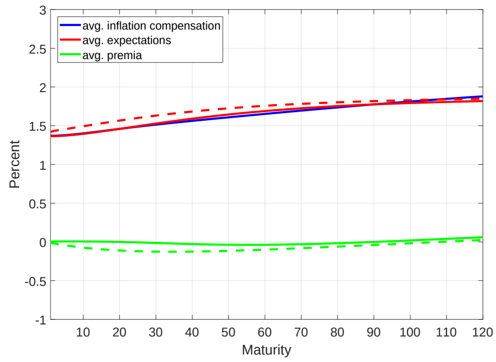
[14]In both model versions, average premia of around zero at shorter maturities emerge from an implied

Figure 2.2: Average decomposition yield components

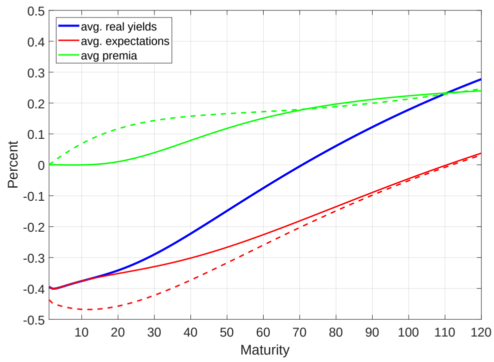
(a) Nominal yields




(b) Inflation-linked swap rates




(c) Real yields




Note: Panel (a) depicts the average model-implied decomposition of the term structure of nominal yields. Panel (b) depicts the average model-implied decomposition of the term structure of inflation-linked swap rates. Panel (c) depicts the average model-implied decomposition of the term structure of real yields. In the panels, solid lines are based on the lower bound model, while dashed lines depict results from the affine model.

contained differences emerge in both decompositions of the inflation component and real yields, in particular, at the short to medium maturities (see Panel (b) and Panel (c) of Figure 2.2). On average, inflation expectations are around 10 bps lower across maturities shorter than 5 years, while differences are less pronounced at longer horizons. Naturally, the opposite is true for the inflation risk premium, which is higher on average in the lower bound model. Mirroring observations for the decomposition of the inflation component, Panel (c) of Figure 2.2 shows that the real rate expectations in the lower bound model

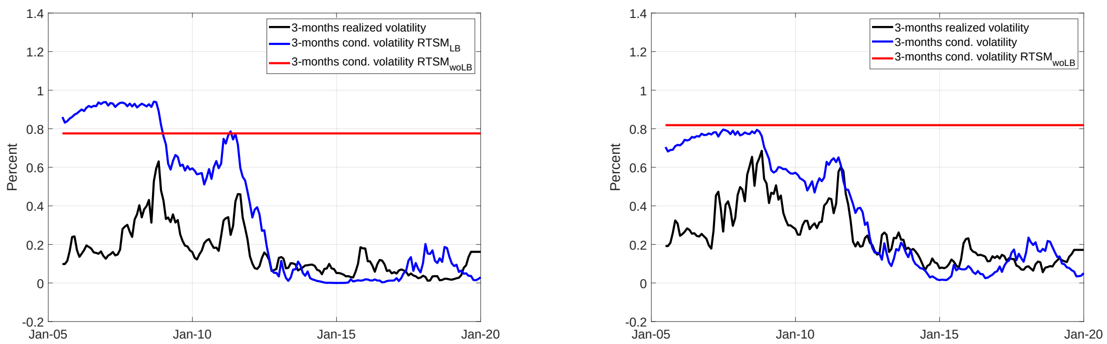
convergence of all premium components towards zero at horizons of up to 1 year since around 2013, potentially driven by the ECB's forward guidance. These results are in line with Geiger and Schupp (2018) and Priebsch (2017), who finds similar results for the US.

tend to be somewhat higher across the term structure, with both average decompositions converging at longer horizons.

While rate volatility will by definition be constant in the affine model, one important feature of lower bound models is that they can retrace the dynamics of realized interest rate volatility. At the ELB this reduced interest rate volatility is also an expression of the fact that interest rates were not expected to go much lower, while on the other hand monetary policy amid persistently low inflation was not signalling any rate hikes in the near future. This, the affine model fails to reproduce. In fact, its constant volatility assumption to the contrary implies that even at the ELB there is equal chance of even lower rates as there is of an increase in rates, as the implied distribution is strictly symmetric. Thus, with respect to these considerations, modelling the ELB is essential despite the fact that both model-implied yield decompositions are very similar (see Figure 2.3).[15]

Figure 2.3: Three-months conditional volatilities of yields

(a) 1-year yield (b) 3-year yield




Note: The chart depicts realized 3-months conditional volatilities as well as model-implied conditional volatilities based on the $RTSM_{LB}$ and $RTSM_{woLB}$ of the 1-year and 3-year yield.

At first sight, the observed differences in yield decompositions seem quite surprising as they challenge the view in the literature that shadow rate models are essential for plausible yield decompositions at or close to the ELB.[16] One common observation is that

[15]Realized volatility has been computed by considering all daily changes over a 3-months window: $RealizedVol_{t,3m}(y_t^n) = \sqrt{\sum(\Delta y_{t+n}^n)^2}$. For the affine model the 3-months conditional volatility can be expressed in closed-form: $Vol_t^{RTSM_{woLB}}(y_{t+n}^n) = \sqrt{Var_t(y_{t+n}^n)} = \sqrt{B_n' Var_t(X_{t+n}) B_n}$. No closed-form expression exists in for the lower bound model. Therefore, we follow Lemke and Vladu (2016) and at each point in time conduct a Monte Carlo simulation computing 5,000 draws of $X_{t+n}$ based on their $\mathbb{P}$-parameters. For each draw, we compute the corresponding yields and subsequently compute the standard deviation of these 5,000 draws of yields.

[16]This point will appear in most works that apply a shadow rate model, but the first to raise it include, e.g., Krippner (2015a), Wu and Xia (2016) and Lemke and Vladu (2016).

affine models fail to produce stickiness in short-term short rate expectations, which tend to rise from the ELB rather quickly, mean-reverting over the long-run. Hence, these models usually produce relatively large negative term premia at the very short end. This is not the case in the models considered here. On reflection, though, they seem less surprising, as in fact, both models considered here share, as an input, a considerable amount of survey information about nominal rate expectations for shorter and longer horizons. As both models fit these surveys almost equally well (see Table 2.A1 and Table 2.A3), this information allows both models to produce very similar paths of the expected short rate, which at times remains flat for a considerable time period.

In both the lower bound and in the affine model, the exclusion of this survey information impacts, in particular, on estimates of the unconditional mean and the presistence of the factor dynamics mirroring the difficulties in identifying the $\mathbb{P}$-measure in a small sample. Figure 2.A1 documents differences in the models in terms of their average decompositions of nominal and real yields and the inflation component. Along this dimension, it seems as if results from the lower bound models remain close to those from the survey-informed models. In particular, the lower bound model without surveys still implies stickiness of rate expectations at the effective lower bound. The main difference is that these expectations are then lower on average than in the models including interest rate surveys, implying somewhat higher term premia on average. The opposite is true for the affine models without interest rate surveys. Without this information the model is no longer able to produce paths of the expected short rate which remain at the ELB for an extended period of time. This is reflected in the average expected short rate path which immediately starts mean-reverting. After all, this leads to premia which are substantially lower and highly negative across all maturities.

Among models that include surveys, differences in forecast performance are again small (see Table 2.A5). Overall, including surveys leads to lower forecast errors in terms of root mean squared errors (RMSEs), in particular, for shorter maturities and at shorter forecast horizons. Both models including survey information about interest rate expectations outperform their counterparts not including this information in terms of forecasting errors. While differences are minor for the shadow rate model, RMSEs in the affine model without survey information exceed those of the other models more than two-fold. Thus, in line with the results of Kim and Orphanides (2012), it shows that surveys can help to produce more plausible in-sample forecasts in affine models.

For longer maturities, results are more mixed as surveys do not necessarily seem to improve forecast performance even for shorter forecast horizons. However, this is not a surprising result given the high uncertainty surrounding such long-term forecasts. Also, as documented by Crump, Eusepi and Moench (2017), it shows that long-term surveys systematically overshoot long-term rate realizations. However, despite the poor performance of these surveys, we still see good reason to include them, considering this as a trade-off between a better forecasting performance and producing model-implied rate expectations close to what market participants actually believed at a certain point in time.

Marked differences in forecast performance become evident in almost all models when samples before and after reaching the ELB are compared.[17] For both lower bound models and the affine model including surveys, the forecast errors become very small for the short maturities of 6-months and 1-year, ranging between 8 and 29 bps at the 6- and 1-year forecast horizon. While the lower bound model without surveys also fares quite well in this sample, it is still outperformed by both models including surveys, even though none of these can beat the random walk, which performs equally well.[18]

Overall, the similarity of both model-implied yield decompositions means, that for plain decompositions of the yield curve, affine models may be appropriate, which for policy analysis would be a particularly useful outcome for at least two reasons: 1) these models are much easier to estimate given that observable pricing factors can be used. 2) The use of observable factors allows them to be computed at a daily frequency, thus facilitating more timely analysis. However, it is also important to note that similar decompositions of the affine and non-affine model should not hide the fact that the affine model still regards rate realisations well below the ELB as likely outcomes. Further, it also still fails to replicate the stylized fact of reduced interest rate volatility at the ELB.

### 2.4.3 Lower Bound Implied Non-linearities and Inflation Shocks

The following subsection discusses ELB-implied structural changes in yield curve responses to shocks. While real and nominal decompositions do not necessarily have to differ by much in non-linear lower bound and affine models (see Section 2.4.2), the lower bound may still be of importance for how external shocks transmit along the yield curve. Given that inflation enters as observable factors, while at the same time the factor error standard deviation $\Sigma$ is assumed to be diagonal (see Footnote 8), the model allows analysis of the response of yield components to inflation shocks. Thus, inflation shocks are easily fed into the model. Although, factor dynamics are linear, yields are non-linear functions of those states. Ultimately, this is done by computing the difference between expected model-implied yields, expectations and premia conditional on state $X_t$ and $X_t^{shock}$. Thus, e.g., for yields it follows for the impulse response ($IR$) in all future periods $t + h$

[17] Here, the lower bound period is defined as the sub-sample starting in June 2012.

[18] Note that for inflation forecasts, the sample period plays less of a role, with forecast performances across models being roughly the same over the full and both sub-samples (see Table 2.A6).

conditional on $t$ that

$$IR_{t+h} = E_t^{\mathbb{P}}(y_{t+h}|X_t^{shock}) - E_t^{\mathbb{P}}(y_{t+h}|X_t) \tag{2.28}$$

In the following, we consider a 10-bp shock to $X_t^{\Pi}$.[19]

Figure 2.4 and Figure 2.5 show the impulse responses to such a shock at the 2- and 10-year maturity over the entire sample. To mark periods near to or far away from the ELB, impulse responses for June 2007 and January 2015 are plotted together with the median impulse response and the one for mid-2018, when the ECB was still approaching an exit from its unconventional measures.

At the 2-year maturity, the inflation shock turns out to be quite persistent, fading after around 3 years, and it transmits mainly through expected inflation, while the reaction of the inflation risk premium is very muted (see Panels (d) to (f) in Figure 2.4). As implied by the linear state dynamics, the response of inflation expectations is the same over the sample. In line, with the observation of inflation risk premia converging towards zero at the lower bound, Panel (f) in Figure 2.4 suggests that in cases where interest rates were expected to remain at the ELB for long (e.g. in January 2015; see red line in Figure 2.4) the inflation risk premium at the 2-year horizon no longer reacts.

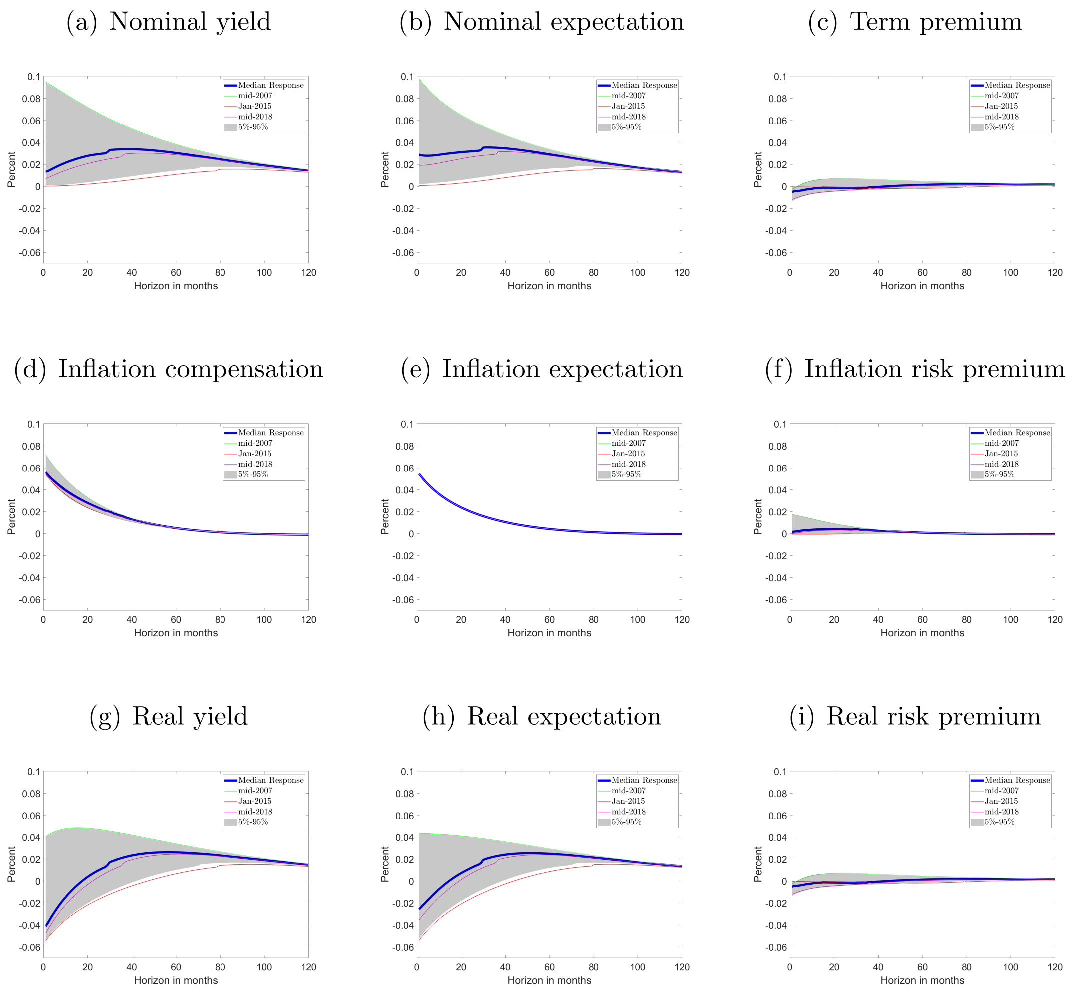
As the comparison of impulse responses over the sample reveals, the response of nominal and real yields is highly dependent on the distance to the ELB (Panels (a) to (c) and (g) to (i) of Figure 2.4)). Away from the ELB, the 2-year yield reacts almost one to one to the inflation shock due to the high persistence of the model, and it is mainly driven by a positive response of its expectations component. The closer yields are to the ELB, however, the more muted their reaction, until it is almost zero when at the ELB like in early 2015. This pattern in nominal yields eventually has important implications for real yields. While the latter respond in a muted but positive fashion to an inflation shock when nominal yields are far from the ELB, their response turns quite negative once nominal yields are at the lower bound.

In principal, the muted reaction in nominal yields is well in line with the narrative of a successful implementation of forward guidance by the Eurosystem, anchoring short-rate expectations at the lower bound.[20] Against this background, these results prove

[19]Note that for the computation of the impulse responses to inflation shocks, it might be important that inflation enters the model subject to a measurement error. As inter alia discussed by Joslin, Le and Singleton (2013), this brings about the advantage that the model has greater flexibility for fitting the cross-section of yields. However, the improved fit of yields tends to come at the cost of a worse fit of the macro factor, so that large parts of its volatility are assigned to its measurement error. On the one hand, this helps the modeller to arrive at more reliable yield decompositions. On the other hand, this may imply less reliable impulse responses of the yield curve components to macro shocks.

[20]Feroli, Greenlaw, Hooper and Mishik (2017) for example show that forward guidance can break the

Figure 2.4: Impulse responses to a 10 bps inflation shock at the 2-year maturity




(a) Nominal yield (b) Nominal expectation (c) Term premium

(d) Inflation compensation (e) Inflation expectation (f) Inflation risk premium

(g) Real yield (h) Real expectation (i) Real risk premium

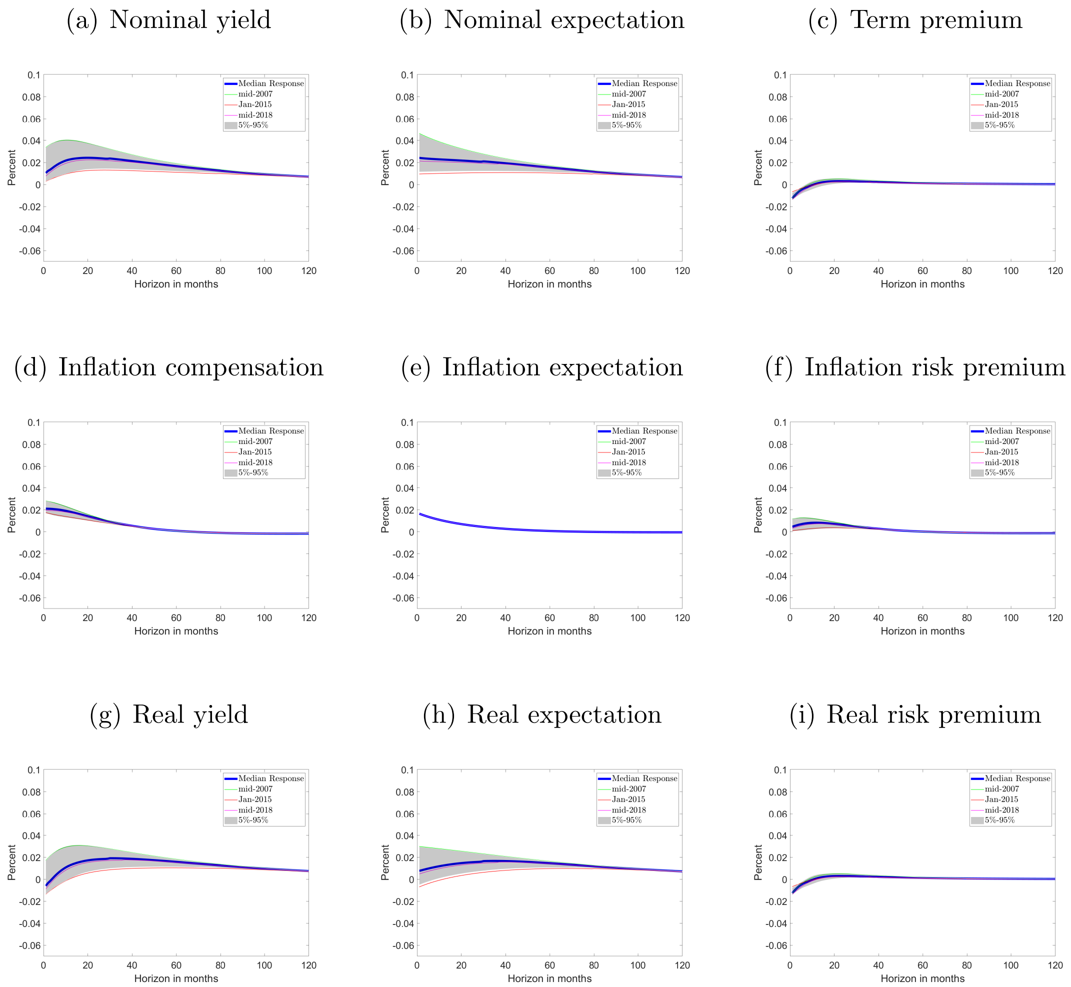
Note: Panel (a)-(i) depict the impulse responses of nominal, inflation and real components of 2-year yields to a 10 bps inflation shock based on the lower bound model $RTSM_{LB}$. In the panels, grey areas depict the range of responses over the sample.

to be meaningful for policy makers as they show that when short-rate expectations are successfully anchored at the lower bound, inflation shocks c.p. can create an additional accommodative impact on the economy by lowering real rate expectations. This opens up an additional transmission channel of forward guidance beyond its direct impact on financing costs through lowering medium- to long-term yields.

It is worth emphasizing that this is not an obvious result, as the ELB naturally restricts interest rates only to the downside and not to the upside. For a rather technical rational for this result, recall that a binding lower bound implies a shadow rate which lies below that lower bound, and the further out the ELB is binding, the more negative this shadow

link between macro news and yields, leaving the latter insensitive to macro shocks.

Figure 2.5: Impulse responses to a 10 bps inflation shock at the 10-year maturity




Note: Note: Panel (a)-(i) depict the impulse responses of nominal, inflation and real components of 10-year yields to a 10 bps inflation shock based on the lower bound model $RTSM_{LB}$. In the panels, grey areas depict the range of responses over the sample.

rate tends to be. Also recall that the shadow rate is nothing more than the sum of all factors, so that the latent factors will be such that smaller shocks to them will not raise the short rate above the ELB. This broadly explains why, in the model, short-term yields would not react to shocks in the inflation factor.

For completeness, Appendix 2.A.6 reports the same exercise conducted in the affine model. Naturally, these shocks are not conditional on date $t$, but are rather similar across the entire sample. Thus, the affine model fails to describe the non-responsiveness of short-term nominal rates potentially implied by monetary policy throughout the ELB period. This implies that the affine model also fails to produce negative responses of the real rate to inflation shocks throughout this period. Given the observed stickiness of nominal short rates and given the forward guidance that was in place, these might be considered unfavorable characteristics for a term structure model if being used for structural analyses of yield curve responses to macro shocks.

These findings are in line with other papers documenting structural non-linearities induced by the ELB. Mertens and Williams (2018), in a small structural model, show that the ELB has direct implications for the distribution of both interest rate expectations and inflation, as the ELB confines the central bank to acting as a stabilizer in the presence of shocks to the economy. With respect to the effectiveness of monetary policy, King (2019) combines a model of Vayanos and Vila (2009) with a lower bound and shows that unconventional monetary policy loses some of its power to affect yields even at longer maturities once closer to the lower bound. Finally, Geiger and Schupp (2018), in a nominal shadow rate term structure model, show that conventional monetary policy becomes less effective at the lower bound as both rate expectations and term premia react less to conventional monetary policy shocks.

### 2.4.4 Quantifying the Impact of the Effective Lower Bound

The following sections discuss the isolated impact of changes in the lower bound on the different yield components. By computing model-implied yield and forward components under different calibrations of the ELB, we are able to quantify the impact that changes in the lower bound have on nominal and real yields, and potentially also on inflation components. Formally, this means that we recompute all yield components conditional on the filtered pricing factors, but differing assumptions about the ELB. For example, the impact of a 10-bp cut in the ELB on forward rates is computed as

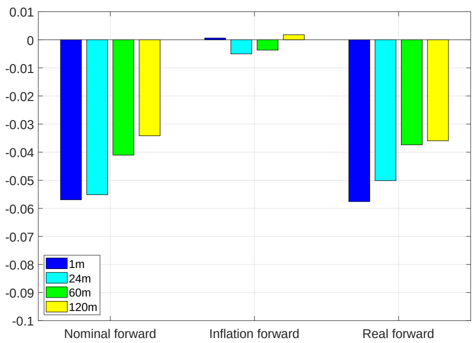
$$\Delta f_t | \Delta ELB_t = f(X_t | ELB_t - 10bps) - f(X_t | ELB_t) \tag{2.29}$$

Along these lines, Figure 2.6 depicts the average changes of forward components over the entire sample due to a 10-bp cut in the ELB at each point in the sample for different maturities.[21] The average impact of such a cut on nominal forwards is around 5 to 6 bps for the 12-month forward rate and decreases to around 2 to 3 bps at the 10-year maturity. As the results for inflation and real forwards shows, the ELB impact works mainly through real components. This is unsurprising, given that the model does not constrain the inflation process, such that non-linearities mainly propagate through nominal and real rates. Interestingly, it shows that changing the ELB mainly affects the

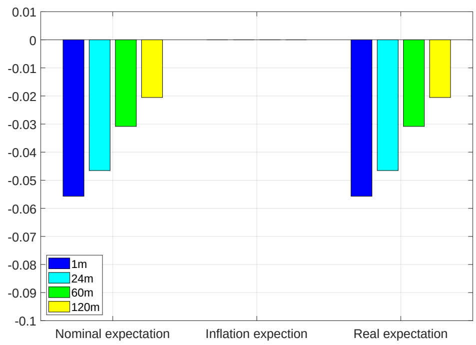
[21] In particular, for each point in time the ELB is lowered by 10 bps from its prevailing level as it is observed by the model at this point in time.

Figure 2.6: Impact of a changing lower bound on yield components

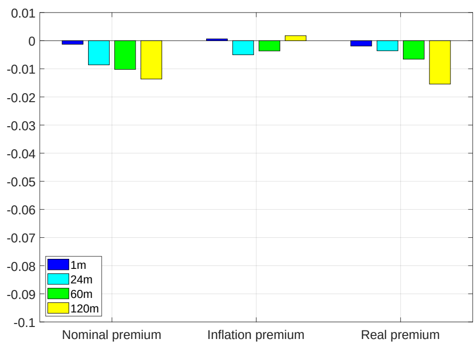
(a) Forwards




(b) Expectations




(c) Premia

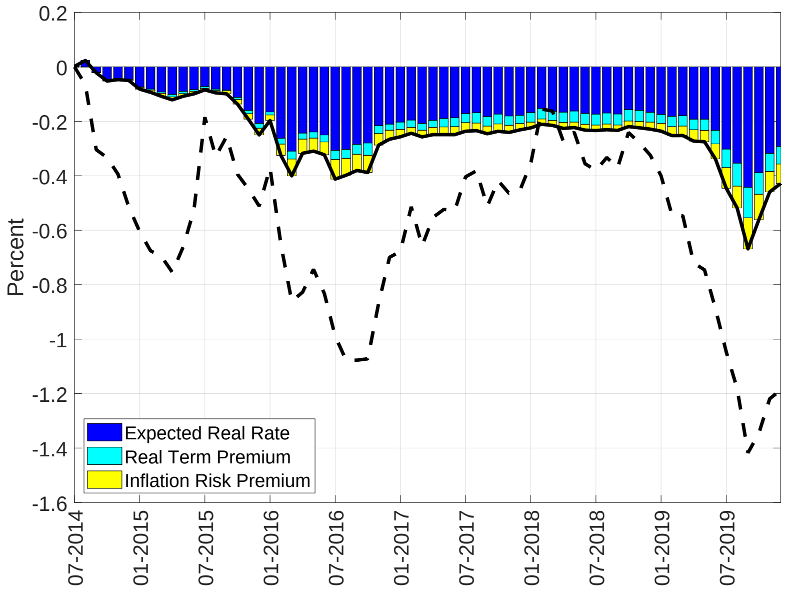



Note: Panel (a) depicts the impact of a 10-bp cut in the effective lower bound on 1-month nominal, real and inflation forwards averaged over the sample at different maturities. Panel (b) depicts the impact of a 10-bp cut in the lower bound on nominal, real and inflation forward expectations averaged over the sample at different maturities. Panel (c) depicts the impact of a 10-bp cut in the lower bound on nominal, real and inflation risk premia averaged over the sample at different maturities.

expectations component, while the effect on premia is only around 1 bps for a 10-bp cut. Naturally, these effects are greater towards the end of the sample, when rates are close to the ELB, and somewhat smaller when rates were still some distance away from it (see Figure 2.A2 and 2.A3).

In the following, we employ our model to estimate the impact monetary policy in the euro area had on long-term yields by allowing interest rates to fall below zero. The assumption of this exercise is that had the ECB never cut rates below zero, market participants would have ruled out negative rates for good, effectively truncating the rate

Figure 2.7: Cumulative impact of lowering the lower bound on the 10-year yield since mid-2014




Note: The chart depicts the isolated cumulative change of the 10-year yield induced only by changes in the effective lower bound since mid-2014. The dashed black line depicts the actual change in the 10-year yield.

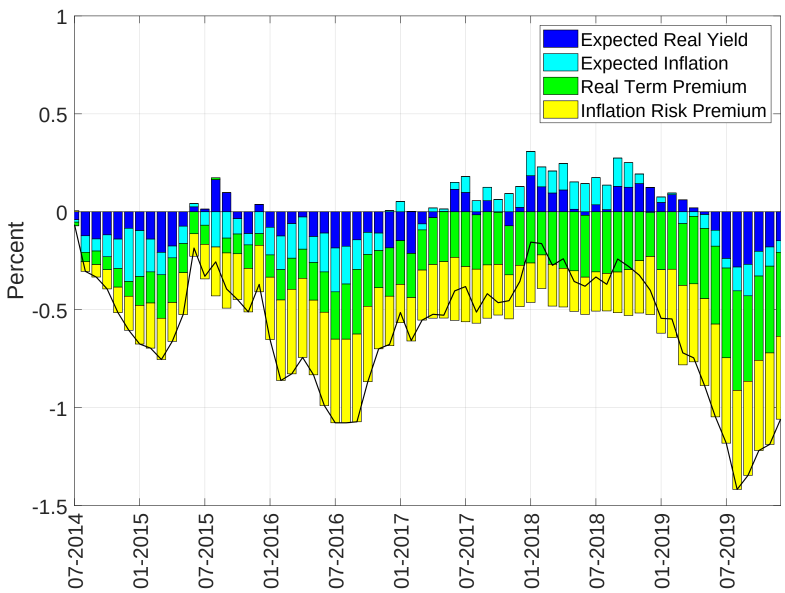
distribution at zero. Technically, the isolated effect of lowering the ELB is computed by keeping a zero lower bound over the entire sample and compare resulting yields and yield components to ones obtained by keeping latent factors and inflation constant as of the introduction of negative rates, but feeding the model with the actual lower bound. Thus, we can obtain the decrease in yields that would have been observed under constant macro conditions, thus only induced by the decreasing lower bound. As can be seen in Figure 2.7, the decreasing lower bound added as much as around 40 bps to the overall cumulative change in the 10-year yield since mid-2014.[22] In particular, in line with the results presented above, this contribution was almost entirely transmitted through lower real rate expectations. This strengthens the conclusion that lowering the lower bound below zero has been an effective tool for injecting real stimulus into the economy.

[22]A similar counterfactual scenario has been computed by Rostagno, Altavilla, Carboni, Lemke, Motto, Saint-Guilhem and Yiangou (2019) who derive the impact of the ECB's negative interest rate policy from simulations based on a 3-month Euribor options-implied distribution. Their results suggest a slightly bigger impact of negative rates, but one that is broadly in the same ballpark as those presented here.

### 2.4.5 The Decline in Long-term Yields in the Context of the Eurosystem's Unconventional Measures

In the following, the proposed model is applied to decompose the change in nominal long-term rates between mid-2014 and mid-2016. This decline is often considered to have been initiated in anticipation of the Eurosystem's unconventional monetary policy measures, in particular its large-scale asset purchases. Commonly, such programmes are considered to affect yields mainly through two channels: 1) the duration extraction or portfolio rebalancing channel affecting risk premia (see Vayanos and Vila (2009)) and 2) the rate signalling channel affecting rate expectations (see Bauer and Rudebusch (2014)). Indeed, the results support the view that monetary policy had an impact through these channels. In particular, this view finds support in the finding that the decline in nominal rate expectations and premia was to a good extent driven by real rate expectations and real risk premia (see Figure 2.8).

Figure 2.8: Decomposition of cumulative change in the nominal 10-year yield




Note: The chart depicts the decomposition of the cumulative changes in the nominal 10-year yield between June 2014 and December 2019.

At the same time, however, model results also imply that the decline in yields also reflects to a large extent a decline in inflation expectations and the inflation risk premium (see Figure 2.8). In fact, almost half of that decline of around 100 bps is accounted for by decreasing inflation components, which implies that the observed change in nominal yields in 2014 or 2016 was also the result of increasing expectations about low future inflation.[23]

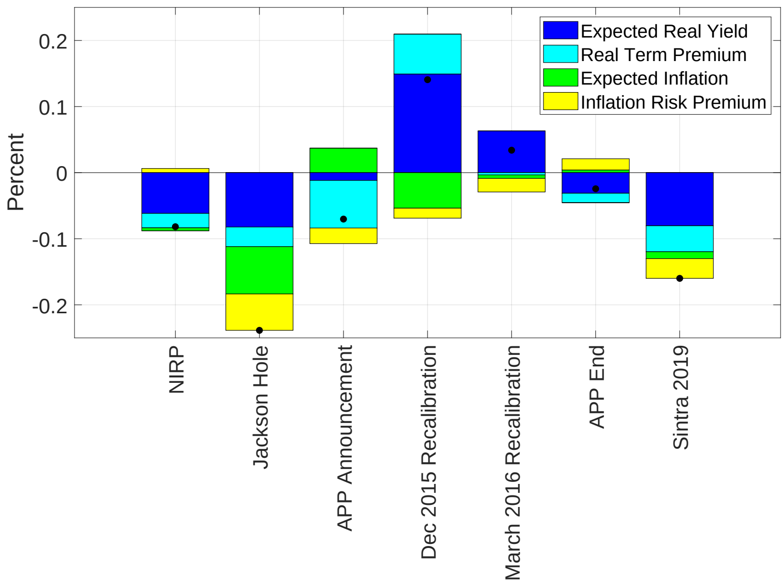
This may seem puzzling given the plethora of monetary policy measures and the accompanying decline in real rate expectations and premia mentioned above. One might be tempted to conclude that the unprecedented measures taken by the ECB – while indeed lowering yields – might have led the market to believe that the economic outlook may be worse than previously expected. In addition, there might even have been a lack of trust in the abilities of monetary policy to reverse the negative inflation trend. In fact, a similar line of argument has been advocated for Japan, for which Christensen and Spiegel (2019) come to the conclusion that the introduction of negative interest rates in January 2016 did indeed have the perverse effect of lowering inflation expectations, contrary to its original intention. Overall, such a pattern would be in line with the interpretation that many of the measures were perceived as negative information shocks rather than accommodative monetary policy shocks as defined by Jarociński and Karadi (forthcoming).[24]

One caveat of the above analysis, of course, is that it is not based on a structural analysis, meaning it remains silent on the exact drivers of the observed change in yields. The analysis takes a closer look at changes in the 10-year yield around important monetary policy events in the euro area in an attempt to close in on the pure policy impact since 2014. Figure 2.9 depicts the decomposed month-on-month changes around selected policy decisions and announcements. The events comprise the first introduction of negative interest rate policy (NIRP), Mario Draghi's Jackson Hole speech in 2014, in which preparations for asset purchases were first mentioned, the official announcement of APP, its recalibrations in December 2015 and March 2016, the first announcement of its end by end-2018, and Mario Draghi's Sintra speech in which he held out the prospect for additional monetary stimulus. While a marked decline in expected real yields and the real risk premium was observed around the majority of these events, it is striking that a marked increase in inflation expectations occurred only around the APP announcement in January 2015. By contrast, in the month of Mario Draghi's Jackson Hole speech in 2014 as well as around the decisions of the Governing Council in December 2015 – widely considered a disappointment – inflation expectations decreased considerably. While these monthly changes again cannot be considered structural responses to monetary policy,

[23]Note that since around 2012 implied levels of the IRP are found to be negative across all maturities (see e.g. Camba-Mendez and Werner (2017) or García and Werner (2012) for the euro area and Carriero et al. (2018) and Christensen and Spiegel (2019) for the UK and Japan, respectively). As can be shown, such negative IRPs would in general be expected in a situation in which investors were anticipating low future growth paired with low inflation (see Appendix 2.A.7).

[24]Alternatively, observations are also in line with results by Vaccaro-Grange (2019), who finds that the ECB's unconventional monetary policy measures have had a negative impact on inflation between 2014 and 2016 via the credit cost channels as they significantly lowered financing costs of firms.

Figure 2.9: Changes in the 10-year yield around selected monetary policy events




Note: The chart depicts decomposed changes in the 10-year yield around selected monetary policy events. The events comprise the first introduction of negative interest rate policy (NIRP), Mario Draghi's Jackson Hole speech in 2014, in which preparations for asset purchases were first mentioned, the official announcement of the ECB's asset purchase programme (APP), its recalibrations in December 2015 and March 2016, the first announcement of its end by end-2018, and Mario Draghi's speech in Sintra in 2019.

they still highlight that monetary policy over the last years has struggled to sustainably create more optimism about long-term inflation expectations with its decisions. In the end, a stronger increase in inflation expectations was only observed late in 2016, well into the ECB's APP and coinciding with a general improvement in the economic outlook on a global level. While not offering final conclusions on the exact impact monetary policy had on long-term yields in the sample considered, the exercise should emphasize the importance of not only looking into nominal yield decomposition, when analyzing the effectiveness of the policy tools used.

## 2.5 Concluding Remarks

We propose a joint real-nominal model for the euro area which incorporates a lower bound for nominal yields as a new and unique feature. Overall, the model is able to produce a satisfying fit of both nominal yields and inflation-linked swap rates. At the same time, it fits survey information about interest rate and inflation expectations quite well, which indicates a plausible decomposition of all yield components despite our small sample, which was limited in size due to constraints on the availability of inflation-linked swap rates.

As is shown by a shock analysis within the proposed model, shock responses of both nominal and real yields are affected by the degree to which the ELB is binding, underlining its importance for structural analysis of the economy. In addition, the importance of the ELB for monetary policy makers is highlighted by further analyses showing that the ELB itself may be a tool for monetary policy to lower real rate expectations and thus induce monetary stimulus.

At the same time, comparing results from the lower bound model with those from an affine version of that model suggests that the incorporation of a lower bound does not necessarily make a substantial difference in terms of the decomposition of yields or inflation components if both models are informed by survey expectations. Nevertheless, the lower bound model is better at replicating observed second moments of yields once they approach the lower bound, as affine models per assumption imply constant conditional volatility of yields.

Based on the proposed model, the decline in long-term yields since mid-2014 is decomposed into real and inflation components. One the one hand, the results support the conclusion that, to some extent, the decline may indeed have been driven by monetary policy, in particular its large-scale asset purchases, which may be the driver of the implied decline in real rate expectations and the real risk premium. On the other hand, according to the model-implied decomposition, the decline was to a large extent also driven by falling inflation expectations and inflation risk premia. This lends some support to the narrative that the Eurosystem's unprecedented unconventional measures might have worsened the perceived outlook for inflation through negative information effects, following the argument of Christensen and Spiegel (2019) in the case of Japan. Indeed, monthly changes in yield components around important monetary policy events show that neither inflation expectations nor the inflation risk premium increased in most months in which policy measures were decided.

Some caveats do remain for the analyses presented in this paper. While our model was able to produce persistent interest rate and inflation expectations, yet allowing for some volatility, including at long-term horizons, the fundamental assumption of stationarity does not allow any conclusions about whether or not the unconditional mean of interest rates or inflation has changed. Hence, while long-term rate and inflation expectations may temporarily decrease, they will always return to their constant unconditional mean. Hence, no conclusions can be drawn about whether or not the real natural rate has decreased permanently. The same holds true for any conclusions about a possible permanent de-anchoring of inflation expectations.

The analysis could thus be extended upon in the future by introducing greater flexibility in this regard as suggested by, e.g., Bauer and Rudebusch (2019) or Brand, Goy and Lemke (2020), who allow for a unit root in their expectations components. Another aspect that could be addressed in future work, is the possibility of a more structural modelling of the inflation process by inter alia adding more macroeconomic structure to the model. This could reduce the reliance on survey information and increase the weight of market data.

# Bibliography


Adrian, T. and Wu, H. (2009). The term structure of inflation expectations, FRB of New York Staff Report 362.

Ajello, A., Benzoni, L. and Chyruk, O. (2012). Core and crust: Inflation dynamics and the term structure of interest rates, Review of Financial Studies **forthcoming**.

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

Ang, A., Bekart, G. and Wei, M. (2008). The term structure of real rates and expected inflation, Journal of Finance **63**(2): 797–849.

Barr, D. G. and Campbell, J. Y. (1997). Inflation, real interest rates, and the bond market: A study of UK nominal and index-linked government bond prices, Journal of Monetary Economics **39**: 361–383.

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

Bauer, M. D. and Rudebusch, G. D. (2019). Interest rates under falling stars, Federal Reserve Bank of San Francisco Working Paper 2017-16.

Black, F. (1995). Interest rates as options, The Journal of Finance **50**(7): 1371–1376.

Brand, C., Goy, G. and Lemke, W. (2020). Natural rate chimera and bond pricing reality, DNB Working Paper 666.

Camba-Mendez, G. and Werner, T. (2017). The inflation risk premium in the post-Lehman period, ECB Working Paper 2033.

Campbell, J. Y., Sunderam, A. and Viceira, L. M. (2016). Inflation bets or deflation hedges? The changing risks of nominal bonds, Critical Finance Review .

Carriero, A., Mouabbi, S. and Vangelista, E. (2018). UK term structure decompositions at the zero lower bound, Journal of Applied Econometrics **33**: 643–661.

Chen, R.-R., Liu, B. and Cheng, X. (2010). Pricing the term structure of inflation risk premia: Theory and evidence from TIPS, Journal of Empirical Finance **17**: 702–721.

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

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

Christensen, J. H. E., Lopez, J. A. and Rudebusch, G. D. (2010). Inflation expectations and risk premiums in an arbitrage-free model of nominal and real bond yields, Journal of Money, Credit and Banking **42**(s1): 143–178.

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

Christensen, J. H. E. and Spiegel, M. M. (2019). Assessing Abenomics: Evidence from inflation-indexed Japanese government bonds, Federal Reserve Bank of San Francisco Working Paper 2019-15.

Cochrane, J. H. and Piazzesi, M. (2008). Decomposing the yield curve, AFA 2010 Atlanta Meetings Paper.

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

Dai, Q. and Singleton, K. J. (2002). Expectation puzzles, time-varying risk premia, and affine models of the term structure, Journal of Financial Economics **63**(3): 415–441.

D'Amico, S., Kim, D. H. and Wei, M. (2018). Tips from TIPS: the informational content of Treasury inflation-protected security prices, Journal of Financial and Quantitative Analysis .

Feroli, M., Greenlaw, D., Hooper, P. and Mishik, F. S. (2017). Language after liftoff: Fed communication away from the zero lower bound, Research in Economics **71**: 452–490.

García, J. A. and Werner, T. (2012). Inflation risks and inflation risk premia, ECB Working Paper Series 1162.

Geiger, F. (2011). The Yield Curve and Financial Risk Premia - Implications for Monetary Policy, Springer.

Geiger, F. and Schupp, F. (2018). With a little help from my friends: Survey-based derivation of euro area short rate expectations at the effective lower bound, Deutsche Bundesbank Discussion Paper 27.

Guimarães, R. (2014). Expectations, risk premia and information spanning in dynamic term structure model estimation, Bank of England Working Papers 489.

Hattori, M., Schrimpf, A. and Sushko, V. (2016). The response of tail risk perceptions to unconventional monetary policy, Amercian Economic Journal: Macroeconomics **8**(2): 111–136.

Hördahl, P. and Tristani, O. (2014). Inflation risk premia in the euro area and the United States, International Journal of Central Banking **10**: 1–47.

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

Jarociński, M. and Karadi, P. (forthcoming). Deconstructing monetary policy surprises - the role of information shocks, American Economic Journal: Macroecnomics .

Joslin, S., Le, A. and Singleton, K. J. (2013). Why Gaussian macro-finance term structure models are (nearly) unconstrained factor-VARs, Journal of Financial Economics **109**: 604–622.

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

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

King, T. B. (2019). Expectation and duration at the effective lower bound, Journal of Financial Economics **in press**.

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

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

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

Mertens, T. M. and Williams, J. C. (2018). What to expect from the lower bound on interest rates: Evidence from derivatives prices, Federal Reserve Bank of San Francisco Working Paper 2018-13.

Priebsch, M. A. (2013). Computing arbitrage-free yields in multi-factor Gaussian shadow-rate term structure models, Finance and Economic Discussion 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, FEDS Notes October 04, 2017.

Rostagno, M., Altavilla, C., Carboni, G., Lemke, W., Motto, R., Saint-Guilhem, A. and Yiangou, J. (2019). A tale of two decades: the ECB's monetary policy at 20, ECB Working Paper 2346.

Vaccaro-Grange, E. (2019). Quantitative easing and the term premium as a monetary policy instrument, AMSE Working Paper 1932.

Vayanos, D. and Vila, J.-L. (2009). A preferred-habitat model of the term structure of interest rates, NBER Working Papers 15487.

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

## 2.A Appendix

### 2.A.1 Nominal Pricing Recursions

In the following nominal bond pricing recursions are derived following Ang et al. (2008). Nominal prices $P_{n+1,t}$ are related to real prices $P^*_{n+1,t}$ via the price deflator $Q_t$:

$$P_{n+1,t} = P^*_{n+1,t}Q_t = E_t[m^*_{t+1}\frac{Q_t}{Q_{t+1}}p^{*n}_{t+1}Q_t] = E_t[m_{t+1}p^n_{t+1}], \tag{2.A1}$$

Further, for the nominal pricing kernel it holds that

$$m_{t+1} = m^*_{t+1}\frac{Q_t}{Q_{t+1}} = m^*_{t+1}exp(-\pi_{t+1}) = exp(-r^*_t - \pi_{t+1} - 0.5\lambda'_t\lambda_t - \lambda'_t\epsilon_{t+1}). \tag{2.A2}$$

Further, nominal prices are assumed to be exponentially affine functions of the factors $X_t$:

$$p^n_t = exp(A_n + B_nX_t) \tag{2.A3}$$

Thus,

$$\begin{aligned}
P_{n+1,t} =& exp(-i^* - \pi_{t+1} - 0.5\lambda'_t\lambda_t - \lambda'_t\epsilon_{t+1})exp(A_n + B'_nX_{t+1}) && (2.A4)\\
=& exp(-i^* - \rho^{\pi,\mathbb{P}}_0 - \rho^{\pi,\mathbb{P}}_1X_t - \Sigma^\pi\epsilon_{t+1} - 0.5\lambda'_t\lambda_t - \lambda'_t\epsilon_{t+1}\dots\\
&+ A_n + B'_n(\rho^{\mathbb{P}}_0 + \rho^{\mathbb{P}}_1X_t + \Sigma\epsilon_{t+1})) && (2.A5)\\
=& exp(-i^* - \rho^{\pi,\mathbb{P}}_0 - \rho^{\pi,\mathbb{P}}_1X_t - 0.5\lambda'_t\lambda_t + A_n + B'_n\rho^{\mathbb{P}}_0 + B'_n\rho^{\mathbb{P}}_1X_t)\dots\\
&E_t[exp(\epsilon_{t+1}(B'_n\Sigma - \lambda'_t - \Sigma^\pi))] && (2.A6)
\end{aligned}$$

To further simplify 2.A6, note that $E(exp(b\epsilon)) = exp(0.5bIb')$, so that

$$\begin{aligned}
P_{n+1,t} =& exp(-i^* - \rho^{\pi,\mathbb{P}}_0 - \rho^{\pi,\mathbb{P}}_1X_t - 0.5\lambda'_t\lambda_t + A_n + B'_n\rho^{\mathbb{P}}_0 + B'_n\rho^{\mathbb{P}}_1X_t)\dots\\
&E_t[exp(0.5B'_n\Sigma'\Sigma B'_n + 0.5\lambda'\lambda + 0.5\Sigma^{\pi'}\Sigma^\pi - B'_n\Sigma\lambda'_t - B'_n\Sigma\Sigma^\pi + \Sigma^\pi\lambda'_t)] && (2.A7)\\
&&& (2.A8)
\end{aligned}$$

Substituting for $i^*, \pi_{t+1}$ and $\lambda_t$

$$\begin{aligned}
=& exp(-\delta_0 - \delta_1X_t - \rho^{\pi,\mathbb{P}}_0 - \rho^{\pi,\mathbb{P}}_1X_t + A_n + B'_n(\rho^{\mathbb{P}}_0 - \Sigma\lambda_0) + 0.5B'_n\Sigma'\Sigma B_n\dots\\
&+ 0.5\Sigma^{\pi'}\Sigma^\pi - B'_n\Sigma\Sigma^\pi - B'_n\Sigma'\lambda_0 - [\delta'_1 - \rho^{\pi,\mathbb{P}}_1 + B'_n(\rho^{\mathbb{P}}_1 - \Sigma\lambda_1) + \Sigma^{\pi,\mathbb{P}}\lambda_1]X_t) && (2.A9)
\end{aligned}$$

From 2.A3 for an n-period bond it then holds that

$$
\begin{aligned}
A_{n+1} =& - \delta_0 - \rho_0^{\pi,\mathbb{P}} + A_n + B_n'(\rho_0^{\mathbb{P}} - \Sigma'\lambda_0) + 0.5B_n'\Sigma'\Sigma B_n \dots \\
& + \Sigma^{\pi}\lambda_0 + 0.5\Sigma^{\pi'}\Sigma^{\pi} - B_n'\Sigma\Sigma^{\pi} \qquad (2.A10) \\
B_{n+1} =& - \delta_1' - \rho_1^{\pi,\mathbb{P}} + B_n'(\rho_1^{\mathbb{P}} - \Sigma'\lambda_1) + \Sigma^{\pi}\lambda_1, \qquad (2.A11)
\end{aligned}
$$

and

$$
\begin{aligned}
A_1 =& - \delta_0 - \rho_0^{\pi,\mathbb{P}} + \Sigma^{\pi}\lambda_0 + 0.5\Sigma^{\pi'}\Sigma^{\pi} \qquad (2.A12) \\
B_1 =& - \delta_1' - \rho_1^{\pi,\mathbb{P}} + \Sigma^{\pi}\lambda_1. \qquad (2.A13)
\end{aligned}
$$

Continuously compounded interest rates then follow

$$
\begin{aligned}
i_{n,t} =& - \frac{1}{n} log(P_{n,t}) \\
=& - \frac{1}{n}(-A_n - B_n X_t) \\
=& a_n + b_n' X_t \qquad (2.A14)
\end{aligned}
$$

with $a_n = -A_n/n$ and $b_n = -B_n/n$.

## 2.A.2 Model performance

**Table 2.A1: In-sample model fit of yields and survey interest rate forecasts of model $RTSM_{LB}$**

| Maturity in months | 1 | 3 | 6 | 12 | 24 | 36 | 60 | 84 | 120 | avg |
|---|---|---|---|---|---|---|---|---|---|---|
| Yields (MAE) | | | | | | | | | | |
| Total sample: | 5 | 4 | 4 | 4 | 3 | 4 | 3 | 3 | 5 | 4 |
| Pre-ELB sample: | 9 | 5 | 4 | 5 | 5 | 5 | 3 | 4 | 6 | 5 |
| ELB sample: | 1 | 3 | 3 | 3 | 2 | 2 | 3 | 2 | 4 | 3 |
| Expected 3M-rate in x months | 3 | 6 | 9 | 12 | 15 | 18 | 21 | $72-120$ | | |
| Interest rate surveys (MAE) | | | | | | | | | | |
| Total sample: | 8 | 11 | 11 | 12 | 13 | 13 | 16 | 13 | | |
| Pre-ELB sample: | 12 | 15 | 15 | 17 | 18 | 18 | 24 | $--$ | | |
| ELB sample: | 5 | 6 | 7 | 8 | 8 | 8 | 9 | 13 | | |

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 obtained based on the model $RTSM_{LB}$. The total sample covers the period June 2005 to December 2019, while the pre-ELB sample covers the period June 2005 to June 2012, and the ELB sample the period July 2012 to December 2019.

**Table 2.A2: In-sample model fit of inflation-linked swap rates and survey inflation forecasts of model $RTSM_{LB}$**

| Maturity in months | 12 | 24 | 36 | 48 | 60 | 84 | 108 | 120 | avg |
|---|---|---|---|---|---|---|---|---|---|
| Yields (MAE) | | | | | | | | | |
| Total sample: | 4 | 3 | 2 | 2 | 2 | 2 | 2 | 3 | 2 |
| Pre-ELB sample: | 4 | 3 | 2 | 3 | 3 | 2 | 3 | 3 | 3 |
| ELB sample: | 3 | 2 | 2 | 1 | 1 | 1 | 2 | 2 | 2 |
| Expected y-o-y inflation in x years | 1 | 2 | 5 | $72 - 120$ | | | | | |
| Inflation expectations surveys (MAE) | | | | | | | | | |
| Total sample: | 31 | 29 | 5 | 7 | | | | | |
| Pre-ELB sample: | 23 | 17 | 3 | 7 | | | | | |
| ELB sample: | 41 | 42 | 7 | 6 | | | | | |

Note: This table shows the mean absolute errors (MAE) of model-implied inflation expectations under the risk-neutral and historical probability measure compared to observed inflation-linked swap rates and survey inflation forecasts for selected sample periods in basis points obtained based on the model $RTSM_{LB}$. The total sample covers the period June 2005 to December 2019, while the pre-ELB sample covers the period June 2005 to June 2012, and the ELB sample the period July 2012 to December 2019.

**Table 2.A3: In-sample model fit of yields and survey interest rate forecasts of model $RTSM_{woLB}$**

| Maturity in months | 1 | 3 | 6 | 12 | 24 | 36 | 60 | | 84 | 120 | avg |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Yields (MAE) | | | | | | | | | | | |
| Total sample: | 6 | 3 | 2 | 5 | 6 | 5 | 4 | | 4 | 7 | 5 |
| Pre-ELB sample: | 9 | 4 | 4 | 9 | 7 | 5 | 5 | | 6 | 8 | 7 |
| ELB sample: | 3 | 2 | 1 | 2 | 4 | 4 | 3 | | 3 | 6 | 3 |
| Expected 3M-rate in x months | 3 | 6 | 9 | 12 | 15 | 18 | 21 | $72-120$ | | | |
| Interest rate surveys (MAE) | | | | | | | | | | | |
| Total sample: | 7 | 11 | 13 | 14 | 14 | 15 | 17 | | 18 | | |
| Pre-ELB sample: | 9 | 13 | 16 | 17 | 18 | 21 | 29 | | $--$ | | |
| ELB sample: | 5 | 9 | 10 | 11 | 11 | 9 | 7 | | 18 | | |

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 obtained based on the model $RTSM_{woLB}$. The total sample covers the period June 2005 to December 2019, while the pre-ELB sample covers the period June 2005 to June 2012, and the ELB sample the period July 2012 to December 2019.

**Table 2.A4: In-sample model fit of inflation-linked swap rates and survey inflation forecasts of model $RTSM_{woLB}$**

| Maturity in months | 12 | 24 | 36 | 48 | 60 | 84 | 108 | 120 | avg |
|---|---|---|---|---|---|---|---|---|---|
| Yields (MAE) | | | | | | | | | |
| Total sample: | 4 | 2 | 3 | 3 | 3 | 2 | 2 | 3 | 3 |
| Pre-ELB sample: | 4 | 3 | 3 | 2 | 3 | 2 | 2 | 3 | 3 |
| ELB sample: | 4 | 2 | 3 | 3 | 3 | 2 | 2 | 3 | 3 |
| Expected y-o-y inflation in x years | 1 | 2 | 5 | $72-120$ | | | | | |
| Inflation expectations surveys (MAE) | | | | | | | | | |
| Total sample: | 29 | 31 | 8 | 10 | | | | | |
| Pre-ELB sample: | 20 | 19 | 7 | 10 | | | | | |
| ELB sample: | 48 | 43 | 10 | 10 | | | | | |

Note: This table shows the mean absolute errors (MAE) of model-implied inflation expectations under the risk-neutral and historical probability measure compared to observed inflation-linked swap rates and survey inflation forecasts for selected sample periods in basis points obtained based on the model $RTSM_{woLB}$. The total sample covers the period June 2005 to December 2019, while the pre-ELB sample covers the period June 2005 to June 2012, and the ELB sample the period July 2012 to December 2019.

**Table 2.A5: Yield forecasts**

| Forecast horizon | 6-months | | | | 12-months | | | | 24-months | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Yield maturity | 6M | 1Y | 5Y | 10Y | 6M | 1Y | 5Y | 10Y | 6M | 1Y | 5Y | 10Y |
| Full Sample: | | | | | | | | | | | | |
| $RTSM_{LB}$: | 0.58 | 0.60 | 0.64 | 1.04 | 0.94 | 0.93 | 0.81 | 1.11 | 1.51 | 1.46 | 1.12 | 1.23 |
| $RTSM_{LB}^{noIRSurveys}$: | 0.63 | 0.68 | 1.08 | 1.36 | 0.98 | 1.00 | 1.25 | 1.46 | 1.53 | 1.54 | 1.60 | 1.69 |
| $RTSM_{woLB}$: | 0.57 | 0.61 | 1.22 | 1.68 | 0.90 | 0.87 | 1.20 | 1.61 | 1.39 | 1.26 | 1.09 | 1.40 |
| $RTSM_{woLB}^{noIRSurveys}$: | 1.20 | 1.19 | 0.97 | 1.63 | 1.71 | 1.60 | 1.03 | 1.61 | 2.64 | 2.34 | 1.09 | 1.43 |
| $RandomWalk$: | 0.63 | 0.67 | 0.64 | 0.49 | 0.99 | 0.96 | 0.74 | 0.74 | 1.47 | 1.43 | 1.11 | 0.95 |
| pre ELB-period: | | | | | | | | | | | | |
| $RTSM_{LB}$: | 0.86 | 0.88 | 0.75 | 0.83 | 1.38 | 1.35 | 0.90 | 0.85 | 2.25 | 2.14 | 1.20 | 0.87 |
| $RTSM_{LB}^{noIRSurveys}$: | 0.92 | 0.97 | 0.80 | 0.62 | 1.42 | 1.41 | 1.00 | 0.71 | 2.26 | 2.18 | 1.46 | 0.99 |
| $RTSM_{woLB}$: | 0.84 | 0.90 | 1.76 | 2.41 | 1.32 | 1.27 | 1.73 | 2.35 | 2.08 | 1.84 | 1.49 | 2.08 |
| $RTSM_{woLB}^{noIRSurveys}$: | 1.60 | 1.54 | 1.16 | 2.33 | 2.37 | 2.15 | 1.25 | 2.34 | 3.79 | 3.26 | 1.26 | 2.17 |
| $RandomWalk$: | 0.63 | 0.64 | 0.55 | 0.49 | 0.99 | 0.96 | 0.74 | 0.66 | 1.47 | 1.43 | 1.11 | 0.95 |
| ELB-period: | | | | | | | | | | | | |
| $RTSM_{LB}$: | 0.08 | 0.10 | 0.49 | 1.20 | 0.14 | 0.17 | 0.66 | 1.28 | 0.29 | 0.35 | 0.91 | 1.50 |
| $RTSM_{LB}^{noIRSurveys}$: | 0.09 | 0.20 | 1.28 | 1.78 | 0.17 | 0.31 | 1.40 | 1.89 | 0.41 | 0.59 | 1.67 | 2.15 |
| $RTSM_{woLB}$: | 0.08 | 0.10 | 0.34 | 0.51 | 0.14 | 0.17 | 0.47 | 0.55 | 0.30 | 0.36 | 0.77 | 0.72 |
| $RTSM_{woLB}^{noIRSurveys}$: | 0.64 | 0.71 | 0.79 | 0.55 | 0.72 | 0.79 | 0.84 | 0.55 | 1.03 | 1.07 | 1.03 | 0.62 |
| $RandomWalk$: | 0.08 | 0.09 | 0.27 | 0.37 | 0.13 | 0.14 | 0.40 | 0.54 | 0.23 | 0.23 | 0.52 | 0.67 |

Note: This table shows the root mean squared errors (RMSE) of in-sample model-implied yield forecasts for 6-month, 1-year, 5-year and 10-year yields. Forecasts are computed based on a lower bound model with and without surveys ($RTSM_{LB}$ and $RTSM_{LB}^{noIRSurveys}$) and an affine model with and without surveys ($RTSM_{woLB}$ and $RTSM_{woLB}^{noIRSurveys}$). The total sample covers the period June 2005 to December 2019 while the pre-ELB sample covers the period June 2005 to June 2012 and the ELB sample the period July 2012 to December 2019.

**Table 2.A6: Inflation forecasts**

| Sample | Full Sample | | | pre-ELB period | | | ELB period | | |
|---|---|---|---|---|---|---|---|---|---|
| Forecast horizon | 6M | 1Y | 2Y | 6M | 1Y | 2Y | 6M | 1Y | 2Y |
| $RTSM_{LB}$: | 0.76 | 0.86 | 1.05 | 0.89 | 1.00 | 1.13 | 0.63 | 0.78 | 1.04 |
| $RTSM_{LB}^{noIRSurveys}$: | 0.80 | 0.89 | 1.03 | 0.91 | 0.99 | 1.09 | 0.69 | 0.84 | 1.05 |
| $RTSM_{woLB}$: | 0.75 | 0.85 | 1.05 | 0.88 | 0.99 | 1.14 | 0.61 | 0.76 | 1.04 |
| $RTSM_{woLB}^{noIRSurveys}$: | 0.91 | 1.09 | 1.30 | 1.05 | 1.31 | 1.52 | 0.78 | 0.95 | 1.17 |
| $Surveys$: | $--$ | 0.89 | 1.05 | $--$ | 1.06 | 1.16 | $--$ | 0.75 | 1.04 |
| $RandomWalk$: | 0.78 | 1.21 | 1.49 | 0.99 | 1.57 | 1.71 | 0.55 | 0.85 | 1.31 |

Note: This table shows the root mean squared errors (RMSE) of in-sample model-implied and survey year-on-year inflation forecasts for 6 month, 1 year and 2 years ahead. Model-implied forecasts are computed based on a lower bound model with and without surveys ($RTSM_{LB}$ and $RTSM_{LB}^{noIRSurveys}$) and an affine model with and without surveys ($RTSM_{woLB}$ and $RTSM_{woLB}^{noIRSurveys}$). The total sample covers the period June 2005 to December 2019 while the pre-ELB sample covers the period June 2005 to June 2012 and the ELB sample the period July 2012 to December 2019.

### 2.A.3 Parameter Estimates

**Table 2.A7: Parameter estimates**

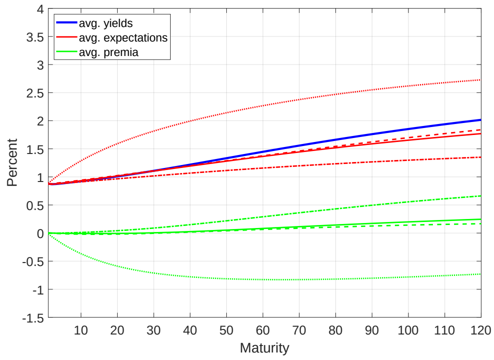
| | $RTSM_{LB}$ | | | | $RTSM_{woLB}$ | | | |
|---|---|---|---|---|---|---|---|---|
| $\rho_0^{\mathbb{Q}}$ | -0.002 | 0 | 0 | 0.137 | 0.015 | 0 | 0 | 0.072 |
| | (0.011) | (-) | (-) | (0.023) | (0.007) | (-) | (-) | (0.030) |
| $\rho_1^{\mathbb{Q}}$ | 0.999 | 0 | 0 | 0 | 0.999 | 0 | 0 | 0 |
| | (–) | (–) | (–) | (–) | (–) | (–) | (–) | (–) |
| | 0 | 0.993 | 0 | 0 | 0 | 0.998 | 0 | 0 |
| | (–) | (0.002) | (–) | (–) | (–) | (0.000) | (–) | (–) |
| | 0 | 0 | 0.859 | 0 | 0 | 0 | 0.949 | 0 |
| | (–) | (–) | (0.026) | (–) | (–) | (–) | (0.010) | (–) |
| | -0.015 | 0.275 | -0.043 | 0.962 | -0.014 | 0.103 | -0.063 | 0.988 |
| | (0.005) | (0.066) | (0.037) | (0.006) | (0.001) | (0.069) | (0.042) | (0.003) |
| $\lambda_0$ | -122.171 | -731.478 | -29.833 | 43.388 | -211.073 | -119.720 | 59.519 | 78.184 |
| | (179.258) | (372.541) | (-29.833) | (87.033) | (136.670) | (159.838) | (322.842) | (90.220) |
| $\lambda_1$ | -28.016 | 48.661 | -5.240 | 88.012 | -6.311 | 192.222 | 62.068 | 119.449 |
| | (42.508) | (411.087) | (150.363) | (69.841) | (53.822) | (52.676) | (392.874) | (48.5413) |
| | 236.948 | -1343.800 | 902.023 | 100.308 | 129.493 | -700.193 | 800.670 | -111.600 |
| | (108.872) | (530.727) | (312.138) | (128.362) | (70.894) | (417.486) | (429.347) | (70.557) |
| | -139.261 | -384.688 | -19.980 | -42.946 | -210.516 | -319.586 | -566.944 | 123.171 |
| | (60.077) | (444.814) | (208.762) | (70.969) | (73.472) | (456.066) | (596.253) | (79.353) |
| | -33.206 | -493.048 | -177.157 | -88.005 | -27.032 | -86.377 | -152.416 | -43.853.345 |
| | (14.493) | (150.363) | (137.567) | (29.316) | (9.912) | (79.744) | (38.476) | (18.668) |
| $\Sigma$ | 0.484 | 0 | 0 | 0 | 0.240 | 0 | 0 | 0 |
| | (0.095) | (–) | (–) | (–) | (0.047) | (–) | (–) | (–) |
| | 0 | 0.042 | 0 | 0 | 0 | 0.041 | 0 | 0 |
| | (–) | (0.007) | (–) | (–) | (–) | (0.006) | (–) | (–) |
| | 0 | 0 | 0.370 | 0 | 0 | 0 | 0.132 | 0 |
| | (–) | (–) | (0.110) | (–) | (–) | (–) | (0.014) | (–) |
| | 0 | 0 | 0 | 0.273 | 0 | 0 | 0 | 0.273 |
| | (–) | (–) | (–) | (0.044) | (–) | (–) | (–) | (0.051) |
| $\delta_0$ | 0 | | | | 0 | | | |
| | (–) | | | | (–) | | | |
| $\delta_1$ | 1 | 1 | 1 | 0.461 | 1 | 1 | 1 | -0.173 |
| | (–) | (–) | (–) | (0.164) | (–) | (–) | (–) | (0.107) |

Note: The table depicts parameter estimates for both the joint real-nominal model incorporating a lower bound ($RTSM_{LB}$) and the joint real-nominal model not including the lower bound ($RTSM_{woLB}$). Asymptotic quasi-maximum standard errors in parentheses.

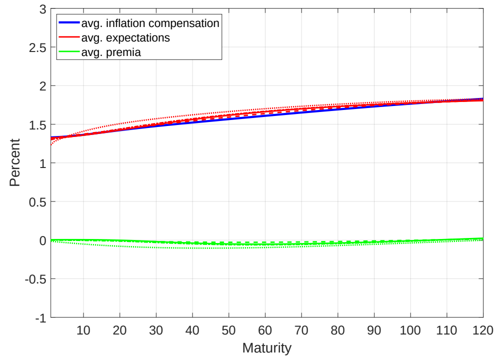
### 2.A.4 Decomposing the term structure with and without surveys

Figure 2.A1: Average decomposition of yield components

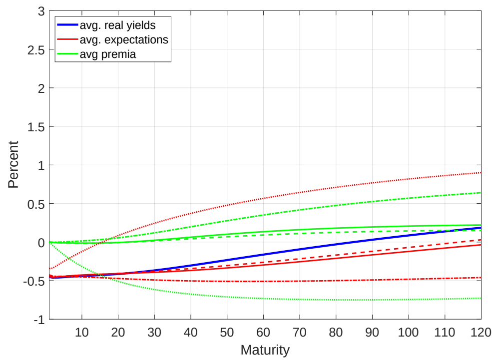
(a) Nominal yields




(b) Inflation-linked swap rates




(c) Real yields

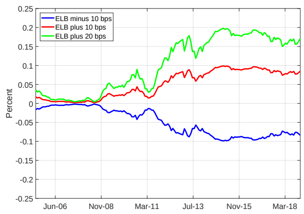



Note: Panel (a) depicts the average model-implied decomposition of the term structure of nominal yields. Panel (b) depicts the average model-implied decomposition of the term structure of inflation-linked swap rates. Panel (c) depicts the average model-implied decomposition of the term structure of real yields. In the panels, solid lines are based on the lower bound model ($RTSM_{LB}$), while dashed lines depict results from the affine model ($RTSM_{woLB}$), and dotted lines from the affine model without surveys, ($RTSM_{woLB}^{noIRSurveys}$) and dashed dotted lines from the lower bound model without surveys ($RTSM_{LB}^{noIRSurveys}$).

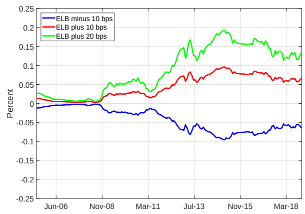
### 2.A.5 Impact of changes in the effective lower bound on yield components

Figure 2.A2: Impact of changes in the ELB on 2-year forward components

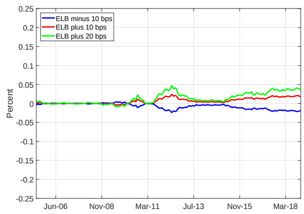
(a) Nominal yield



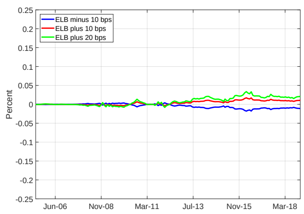

(b) Nominal expectation



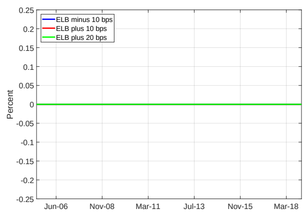

(c) Term premium



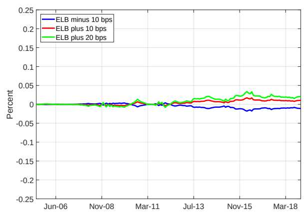

(d) Inflation compensation



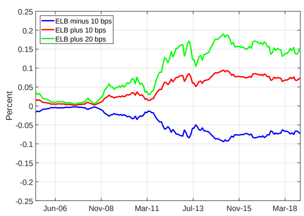

(e) Inflation expectation



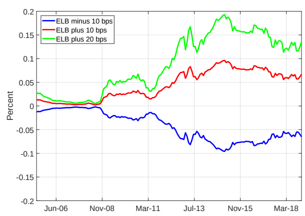

(f) Inflation risk premium



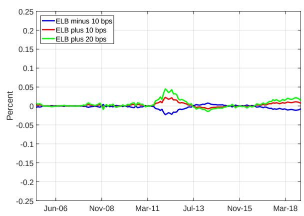

(g) Real yield




(h) Real expectation



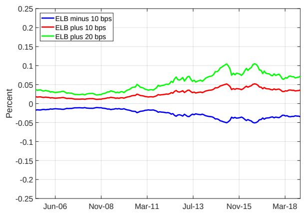

(i) Real risk premium



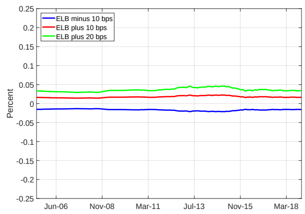

Note: Panels depict the impact of a -10, 10 and 20-bp change in the effective lower bound on 2-year forward components. Impacts are obtained by first computing counterfactual components based on the originally filtered states and estimated parameters but with a changed ELB. Subsequently, the differences between these counterfactuals and actual model-implied components are computed.

Figure 2.A3: Impact of changes in the ELB on 10-year forward components

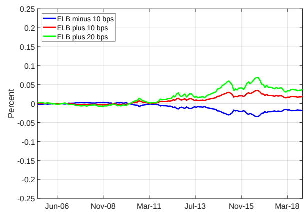
(a) Nominal yield



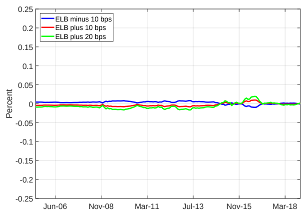

(b) Nominal expectation



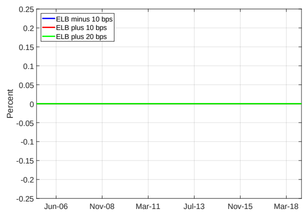

(c) Term premium



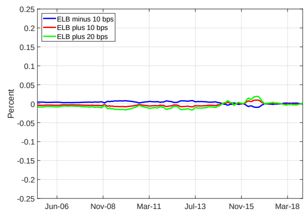

(d) Inflation compensation



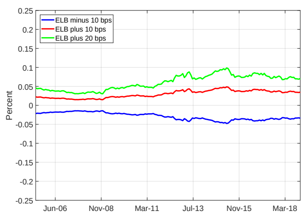

(e) Inflation expectation



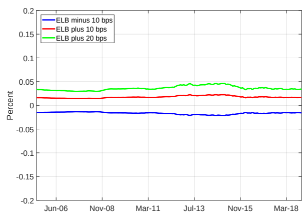

(f) Inflation risk premium



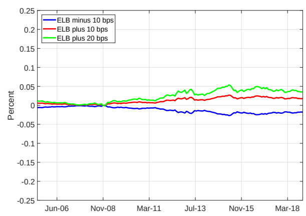

(g) Real yield




(h) Real expectation




(i) Real risk premium

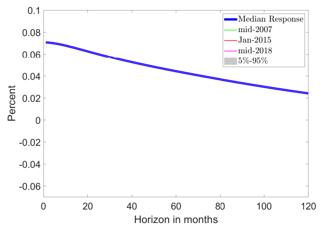



Note: Panels depict the impact of a -10, 10 and 20-bp change in the effective lower bound on 2-year forward components. Impacts are obtained by first computing counterfactual components computed based on the originally filtered states and estimated parameters but with a changed ELB. Subsequently, the differences between these counterfactuals and actual model-implied components are computed.

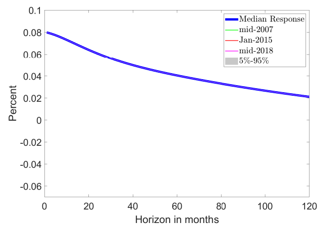
### 2.A.6 Inflation shocks in the affine model

Figure 2.A4: Impulse responses to a 10 bps inflation shock at the 2-year maturity

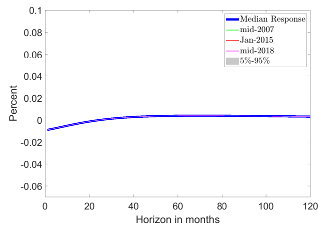
(a) Nominal yield



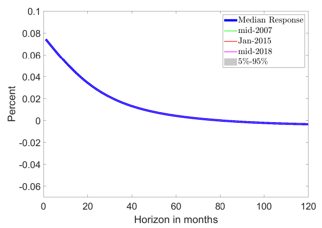

(b) Nominal expectation



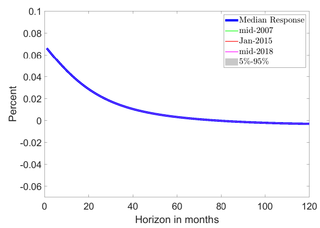

(c) Term premium



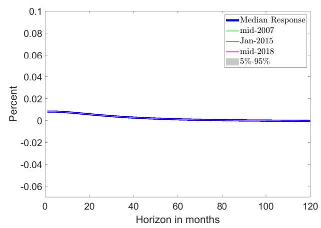

(d) Inflation compensation



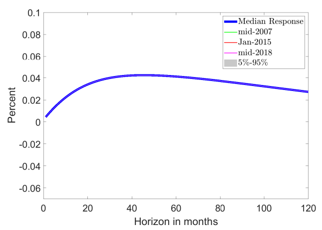

(e) Inflation expectation



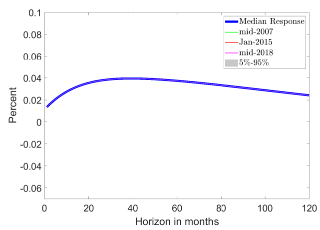

(f) Inflation risk premium



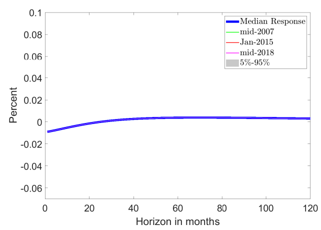

(g) Real yield




(h) Real expectation



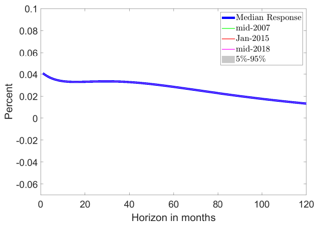

(i) Real risk premium



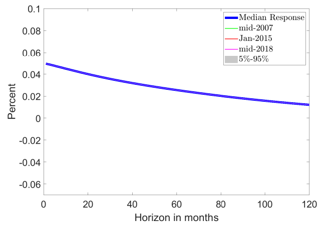

Note: Note: Panel (a)-(i) depict the impulse responses of nominal, inflation and real components of 10-year yields to a 10 bps inflation shock based on the lower bound model $RTSM_{woLB}$. In the panels, grey areas depict the range of responses over the sample.

Figure 2.A5: Impulse responses to a 10 bps inflation shock at the 10-year maturity

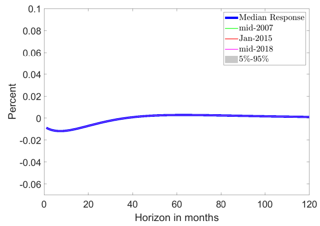
(a) Nominal yield



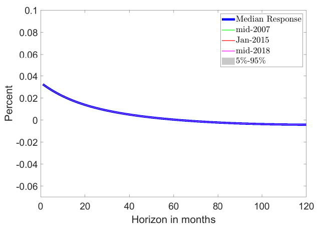

(b) Nominal expectation



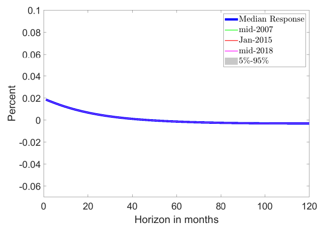

(c) Term premium



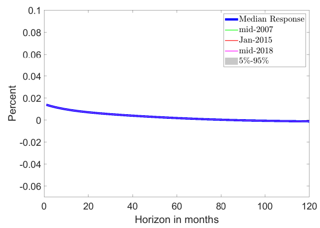

(d) Inflation compensation



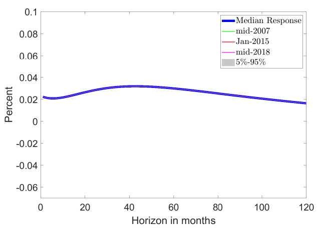

(e) Inflation expectation



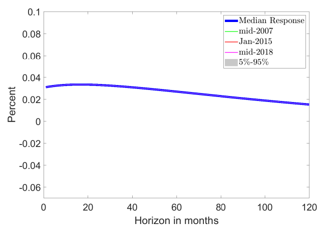

(f) Inflation risk premium



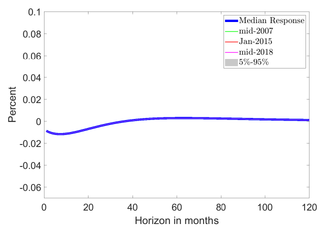

(g) Real yield




(h) Real expectation




(i) Real risk premium




Note: Note: Panel (a)-(i) depict the impulse responses of nominal, inflation and real components of 10-year yields to a 10 bps inflation shock based on the affine bound model $RTSM_{woLB}$. In the panels, grey areas depict the range of responses over the sample.

### 2.A.7 Negative inflation risk premia

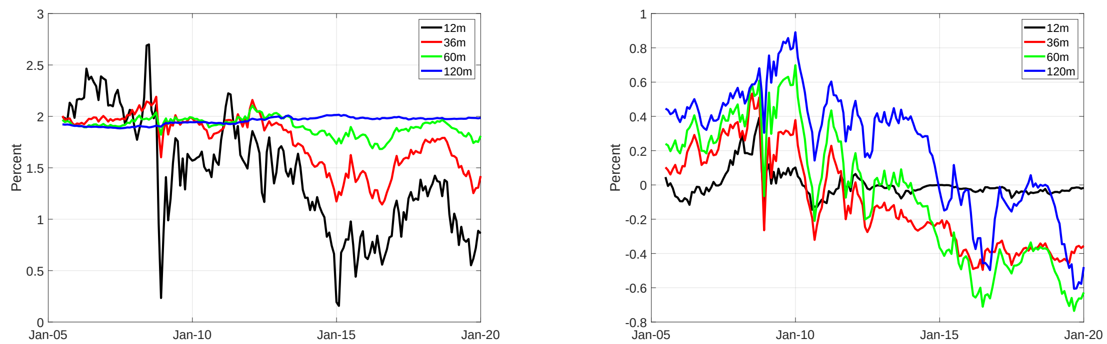
The appendix focuses on the model-implied inflation risk premia and in particular on the finding that these have been negative since around 2011. In general, market-based inflation compensation is the sum of genuine inflation expectations and the inflation risk premia demanded by investors. In the model, inflation compensation is defined as the $\mathbb{Q}$-expectation about the inflation factor $\Pi$, while genuine inflation expectations are obtained under the historical probability measure $\mathbb{P}$. It then holds, that

$$E_t^{\mathbb{Q}}(\Pi_{t+h}) = E_t^{\mathbb{P}}(\Pi_{t+h}) + IRP_t, \tag{2.A15}$$

with the inflation risk premium ($IRP$) obtained as described by Equation 2.25. The model identifies the dynamics of the inflation factor under the $\mathbb{Q}$- and $\mathbb{P}$-measure and thus, the inflation risk premium, on the back of the information included on survey inflation expectations and ILS rates. The model implies an unconditional mean of inflation of around 1.9% (see Table 2.1), which seems to be in line with the Eurosystem's declared intention of keeping inflation below, but close to, 2% over the medium term.

Figure 2.A6: Inflation expectations and inflation risk premia

(a) Expectations (b) Premia




Note: Panel (a) depicts the model-implied expectations about the 1-month inflation 1 year, 3 years, 5 years and 10 years ahead. Panel (b) depicts the normalized model-implied 1-month inflation risk premia 1 year, 3 years, 5 years and 10 years ahead.

Our model generates negative inflation risk premia, in particular at short- and medium-term maturities, since roughly the beginning of 2013, confirming the results by Camba-Mendez and Werner (2017). While negative inflation risk premia were also observed temporarily in the course of the financial crisis, this phenomenon is far more persistent over the second half of the sample (see Figure 2.A6). Since they turned negative in around early 2013, they followed a remarkable downward trend down to levels of below -0.6% in fall 2016 and late 2019. Economically, this may be interpreted as investors demanding a positive inflation risk premium, insuring against a higher-than-expected inflation outcome prior to 2013. Since 2013, they have since been willing to accept negative inflation risk premia, which may reflect some concerns about lower-than-expected inflation outcomes.

While negative risk premia are neither a new nor abnormal phenomenon, they often raise eyebrows when mentioned as their economic interpretation is not straightforward. It is easiest to think about negative premia as an insurance premium. If a given asset is promising safe returns in adverse states of the world, any risk-averse investor may be willing to pay more than the expected return to alleviate his situation, were this adverse state to materialize. Even though this is a generally applicable explanation for negative rates, it is still worth investigating, how risk premia and their signs are determined for any given asset.

Readers may recall, that any asset pricing model including those discussed in this paper build on a fundamental pricing equation:[25]

$$P_{n,t} = E_t[M_{t+1}, X_{n,t+1}], \tag{2.A16}$$

where $M_{t+1}$ is the stochastic discount factor and $X_{n,t+1}$ the asset's payoff in $t+1$. One-period gross holding returns are further defined as

$$1 + R_{n,t+1} = \frac{X_{n,t+1}}{P_{n,t}}, \tag{2.A17}$$

so that Equation 2.A16 can be expressed as

$$1 = E_t[M_{t+1}(1 + R_{1,t+1})] \tag{2.A18}$$

As both $M_{t+1}$ and the one-period return $R_{n,t+1}$ are considered random variables, it holds that

$$E_t[M_{t+1}(1 + R_{n,t+1})] = E_t(M_{t+1})E_t(1 + R_{n,t+1}) + cov_t(M_{t+1}, R_{n,t+1}) \tag{2.A19}$$

[25] The following derivations follow Geiger (2011).

Substituting 2.A19 into 2.A18 yields

$$1 + E_t(R_{n,t+1}) = \frac{1 - cov_t(R_{n,t+1}, M_{t+1})}{E_t(M_{t+1})} = \frac{1}{M_{t+1}} - \frac{cov_t(R_{n,t+1}, M_{t+1})}{E_t(M_{t+1})} \tag{2.A20}$$

If the covariance between the one-period return and the stochastic discount factor is zero, 2.A20 collapses to

$$1 + E_t(R_{n,t+1}) = \frac{1}{E_t(M_{t+1})} = 1 + R^f_{n,t+1} \tag{2.A21}$$

Hence, when the covariance term is zero, the return is considered to be risk-free.[26] The risk premium is positive only if $cov_t(R_{n,t+1}, M_{t+1}) < 0$ and vice versa.

At this point, we know the conditions for the risk premium to be zero, positive or negative. To further gain some economic intuition of what these conditions imply, it is helpful to consider a simple two-period optimization problem some investor might be facing.

Let us assume that the investor wants to maximize her utility through the current and next period's consumption subject to some budget constraint.

$$\begin{aligned} &\max_{C_t, C_{t+1}} U(C_t, C_{t+1}) \\ &s.t. \;\; C_t = e_t - P_t \\ &and \;\; C_{t+1} = e_{t+1} + P_t(1 + R_{t+1}) \end{aligned} \tag{2.A22}$$

where $C$ denotes consumption, $e$ endowments and $R$ the return of assets held, which are denoted by $P$. Further, we assume additive intertemporal utility

$$U(C_t, C_{t+1}) = u(C_t) + \beta E_t[u(C_{t+1})] \tag{2.A23}$$

From the first-order conditions (FOCs) it then follows

[26] To see that this holds in the model presented in the main text, recall that we assume the real pricing kernel to equal $m^*_{t+1} = exp(-si^*_1 - 0.5\lambda_t\prime\lambda_t - \lambda_t\epsilon_t)$. Recall that if $x$ is a normally distributed random variable, $Y = e^x$ is log-normally distributed with $E(Y) = exp(E(x) + 0.5var(x))$. Thus $E(m^*_{t+1}) = exp(-i_{1,t})$, where $i_{1,t}$ is the one period risk-free rate.

$$P_t = E_t\left[\beta\frac{u\prime(C_{t+1})}{u\prime(C_t)}X_{t+1}\right]. \tag{2.A24}$$

From Equation 2.A24 and Equation 2.A16 (the no-arbitrage pricing formula), it then follows that

$$E_t(M_{t+1}) = E_t\left[\beta\frac{u\prime(C_{t+1})}{u\prime(C_t)}\right], \tag{2.A25}$$

saying that the SDF in this set-up equals the marginal rate of substitution multiplied by the investor's subjective discount factor. Dividing Equation $X$ by the price $P_t$ then yields

$$1 = E_t\left[\beta\frac{u\prime(C_{t+1})}{u\prime(C_t)}\frac{X_{t+1}}{P_t}\right], \tag{2.A26}$$

with $X_{t+1}/P_t = 1 + R_{t+1}$ as the gross return of the asset held, such that it holds that

$$1 = E_t\left[\beta\frac{u\prime(C_{t+1})}{u\prime(C_t)}R_{t+1}\right]. \tag{2.A27}$$

Note that for any two random variables $x$ and $y$ it holds that $E_t(xy) = E_t(x)E_t(y) + cov_t(x,y)$. Therefore, Equation 2.A27 can be rewritten as

$$E_t(1 + R_{t+1}) = \frac{1 - cov_t\left(R_{t+1}\beta\frac{u\prime(C_{t+1})}{u\prime(C_t)}\right)}{E_t\left(\beta\frac{u\prime(C_{t+1})}{u\prime(C_t)}\right)}. \tag{2.A28}$$

Equation 2.A28 illustrates that the risk premium and its sign crucially depend on the covariance between the asset's gross return and the stochastic future consumption. Assume a situation, in which the marginal rate of substitution is high, i.e. expected marginal utility in the next period is higher than marginal utility today, which means that the investor would prefer some more consumption in the next period over consumption today. If the asset in such situations typically yields a lower return, such that the covariance term in 2.A28 is negative, the investor overall demands a higher gross return. Note that while the covariance between asset returns and consumption growth determines the sign of the asset-specific risk premium, volatility in returns and consumption also plays a role for its size, as it holds that

$$cov_t\left((1+R_{t+1})\beta\frac{u\prime(C_{t+1})}{u\prime(C_t)}\right)=corr\left((1+R_{t+1})\beta\frac{u\prime(C_{t+1})}{u\prime(C_t)}\right)\sqrt{var(1+R_{t+1})}\sqrt{var(M_{t+1})} \tag{2.A29}$$

To derive the gross return for a risk-free asset, all that needs to be done is to set the covariance term in Equation 2.A28 to zero and assume that the risk-free asset's return is known with certainty, yielding

$$E_t(1+R_t^f)=\frac{1}{E_t\left(\beta\frac{u\prime(C_{t+1})}{u\prime(C_t)}\right)}=\frac{1}{E(M_{t+1})}. \tag{2.A30}$$

### Pricing nominal assets

The above is easily translated into nominal space. Let $CPI_t$ be the price index, then a nominal bond costs in nominal terms $P_{i,t}^{\$}$ and in units of goods $\frac{P_{i,t}^{\$}}{CPI_{,t}}$; it pays \$1 or equivalently $\frac{\$1}{CPI_t}$ in units of goods. An investor is faced with a maximization problem according to Equation 2.A31 with a modified budget constraint

$$\begin{aligned}&\max_{C_t,C_{t+1}} U(C_t,C_{t+1}) \\ &s.t.\;\; C_t=e_t-\frac{P_t^{\$}}{CPI_t} \\ &and\;\; C_{t+1}=e_{t+1}+\frac{P_t^{\$}(1+R_{t+1}^{\$})}{CPI_{t+1}}\end{aligned} \tag{2.A31}$$

The FOCs then yield

$$\frac{1}{1+R_{n,t+1}^{\$}}=E_t\left[M_{t+1},\frac{CPI_t}{CPI_{t+1}}\right] \tag{2.A32}$$

so that it now holds that

$$E_t(1+R_{t+1}^{\$})=\frac{1-cov_t\left(\frac{CPI_t}{CPI_{t+1}},\beta\frac{u\prime(C_{t+1})}{u\prime(C_t)}\right)}{E_t\left(\beta\frac{u\prime(C_{t+1})}{u\prime(C_t)}\right)}. \tag{2.A33}$$

Hence, nominal gross returns now comprise a risk premium which depends on inflation and is non-zero if and only if the covariance between the stochastic discount factor and inflation is non-zero. Importantly, it is positive if and only if this covariance is negative; otherwise it's negative. The covariance between the SDF and inflation is positive if inflation is expected to be low, whenever expected future marginal utility is expected to be higher compared to current marginal utility. This is the case when future consumption is expected to be lower. Thus, we would expect to see negative inflation risk premia if investors were to expect states in which low consumption growth comes with low inflation. Note that this does not require investors to expect deflation. In fact, given 2.A33 no conclusions about deflation expectations can be drawn from the sign of the inflation risk premium.

# Chapter 3

# The Role of Structural Funding for Stability in the German Banking Sector

*Joint with Leonid Silbermann*

## 3.1 Introduction

The financial crisis revealed a large vulnerability of banks originating from money market funding. It showed that liquidity problems were among the main causes of distress in the global financial sector as banks failed to prepare themselves for short-term liquidity stress. As countermeasures, the Basel Committee on Banking Supervision (BCBS) introduced the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR). While the former requires banks to hold enough unencumbered highly liquid assets to withstand a 30 day liquidity stress scenario, the latter stipulates that banks procure sufficient stable funding over a time horizon of one year. Although a full assessment of how successful the NSFR might be at addressing excessive maturity mismatches in the banking sector is not feasible at this stage, we investigate what the impact of stable funding on the probability of banks experiencing financial distress has been in the past. To this end, we use supervisory data on critical events of financial institutions spanning a time period of 19 years and combine it with balance sheet data as well as other supervisory data in order to estimate the effect of stable funding on banks' probabilities of financial distress. Due to the fact that the NSFR cannot be calculated exactly for the time period prior to its implementation, we use the loan-to-deposit ratio and the loan-to-interbank-liabilities ratio as proxies for stable funding. As a result of our empirical work, we find evidence that stable funding makes critical events significantly less likely for savings banks and credit cooperatives, suggesting a stabilizing effect of the NSFR. This effect cannot be found for the banking group of commercial banks. We corroborate our findings in a series of robustness checks.

The remainder of this paper is organized as follows. Section 3.2 discusses the related theoretical and empirical literature. Section 3.3 describes the data, presents the estimation approach, the results, and provides a critical discussion of our findings. Section 3.4 concludes.

## 3.2 Literature

The most recent experience during the financial crisis serves as anecdotal evidence for the importance of funding structures, including in Europe. At the beginning of the crisis, major strains on European money markets were observed (BIS (2008)) to which the ECB reacted by providing €95 bn of funding into the interbank market (Brunnermeier (2009)). Northern Rock is one of the most prominent examples of how funding freezes can put otherwise sound institutions on the brink of bankruptcy. Money market withdrawals caused severe trouble at Northern Rock, long before the bank's depositors even anticipated its financial problems (Shin (2009)).[1] For the German Hypo Real Estate, trouble began with its subsidiary DEPFA plc having problems rolling over its wholesale funding following the Lehmann collapse (Deutscher Bundestag (2009)). In response, the regulator decided that banks should therefore make themselves more resilient against stress on the interbank funding market. Building on past experience, the NSFR considers interbank funding with maturities below one year to be unstable and incentivizes banks to fund themselves using more stable sources of funding like deposits from households and non-financial corporations. These deposits are considered stable despite their short-term maturity due to very low run-off rates.

*a) Stable funding in theoretical literature*

In theory, wholesale funding, especially owing to its short-term maturity structure, is often thought to have a disciplining effect on banks as it prompts them to rollover their debt frequently. Given their high expertise, wholesale investors would also be expected to provide better and closer monitoring than depositors would; at the same time opening

[1] Northern Rock funded its rapid growth mainly through wholesale funding. While the bank's deposit share basically stagnated, its wholesale funding share declined to merely 23% by July 2007, which was well before the depositor run. The latter occurred despite the public announcement of the liquidity assistance by the government. Also, 2/3 of the drained deposits are accounted for by postal, telephone or internet accounts and only 1/3 by classic bank accounts (Shin (2009)).

up more investment opportunities for banks (Brunnermeier (2009), Calomiris and Kahn (1991), Huang and Ratnovski (2011)).

However, a sufficiently high degree of wholesale funders' seniority might force otherwise financially sound banks into inefficient liquidation given publicly available but imprecise information like market prices and credit ratings. Using a noisy negative public signal on banks' project quality, wholesale investors have the incentive to reduce their monitoring and withdraw their funds if their seniority governing the division of banks' liquidation value is sufficiently high. This holds true especially for large and publicly traded banks, while traditional banks holding opaque and non-tradable loans should still profit from wholesale funding and its disciplining character.[2] A higher share of deposit funding (along with a higher precision of the public signal) might even fortify this mechanism, given that more deposits incentivize early withdrawals by wholesale creditors, as they raise the liquidation value (Huang and Ratnovski (2011)).

Another source of instability of wholesale funding that is transmitted through the interbank market structure which is prone to sudden market freezes, as could be observed during the financial crisis, are the so called liquidity spirals (Brunnermeier and Pedersen (2009)). A major part of wholesale funding is obtained by borrowing against assets subject to haircuts. Operating at the edge of being equity constrained, these haircuts determine a bank's maximum leverage[3], so that rising haircuts force banks to either raise more equity or deleverage by selling off assets in order to hold their leverage constant.[4] If there is a general increase in haircuts due to rising volatility in the market, the banking system might experience extreme funding stress.

On the other hand, due to very low run-off rates, deposits are perceived to be a very stable form of funding in the Basel accords on liquidity regulation (BCBS (2014)).[5] This can be attributed to the switching costs that depositors incur whenever they move

[2]This is especially relevant when analyzing the German banking system, as savings banks and credit cooperatives are a lot more opaque for outside investors than many commercial banks. Of course, there is also a high degree of heterogeneity within the commercial banking sector itself. Small institutions, in particular, do not necessarily disclose much information on their business, and thus, are not any more easily monitored than are savings banks and credit cooperatives.

[3]Brunnermeier (2009) describes how banks maximize their leverage under the constraints implied by haircuts.

[4]Shin (2009) provides an easy example of this mechanism. Assuming a bank holds assets worth 100 units and the haircut applied is 2%. This means, that the bank can borrow 98 units against this asset and has to obtain 2 units of equity funding. Its leverage would then be $100/2 = 50$. Were the haircut to rise to 4%, equity would have to double to 4 to reach the new maximum leverage of 25. However, increasing equity would probably be even harder in times of stress. Alternatively, the bank can sell off assets. According to Shin, they usually decide on the latter. Additionally, banks always hold enough equity to cover their Value-at-Risk which amplifies the mechanism even more and adds to its procyclicality, as Value-at-Risk and leverage are inversely related (see Shin (2009)).

[5]Hong, Huang and Wu (2014) confirm the run-off rates applied by the LCR and NSFR regulation quantitatively.

money to a new bank, as well as to deposit insurances (Flannery (1982), Sharpe (1997), Diamond and Dybvig (1983)). However, insured deposits might also destabilize banks by being less disciplining than market funding (Billett, Garfinkel and O'Neal (1998) and Demirgüç-Kunt and Detragiache (1998)).[6]

Another reason why deposits are stable relates to liquidity services provided by the bank which, in a distress event, make depositors withdraw later than wholesale creditors. It is also argued that there is a link between a bank's assets and its choice of funding. Banks that engage primarily in relationship lending rely more on deposits due to their lower risk of sudden withdrawal (Song and Thakor (2007)).[7] This is not exactly in line with the argument brought forward by Huang and Ratnovski (2011), which is that banks with intransparent assets should profit more from wholesale funding as wholesale investors' greater monitoring effort imposes market discipline.

*b) Stable funding in empirical literature*

Theory points towards a relevant but to some extent arbitrary effect of more stable funding for systemic stability. Empirical evidence can be found in Hong et al. (2014) who find a small but significant stabilizing effect of the NSFR. In their study, they examine the role of stable funding by using monthly bank-level balance sheet data from the *call reports* published by the Fed. Their dependent variable in a dynamic discrete-time hazard model[8] is a failure dummy constructed from data on bank failures available from the *Federal Deposit Insurance Corporation* (FDIC).[9] They emphasize the role of the NSFR in lowering systemic risk, in particular. Similarly, Bologna (2015) finds a positive impact of the foreseen regulation on bank stability by using the same data sources in a pooled multivariate logit estimation.[10] In his work, the failure dummy as the dependent variable is regressed on a set of different bank performance indicators and on a loan-to-deposit ratio as a measure for stable funding. He concludes that a greater deposit base for loans

[6]See also Bologna (2015) who, by further differentiating between different types of deposits, can show that depending on whether one regards core deposits or brokered deposits and whether they are small or large, they differ in their stability, with small core deposits being the most stable kind.

[7]Song and Thakor (2007) also show that banks might deviate from that behaviour when exposed to more competition, which then raises the riskiness of the bank.

[8]Their model is based on the Moody's RiskCalc Model.

[9]The FDIC defines defaults "[...] with respect to an insured depository institution any adjudication or other official determination by any court of competent jurisdiction, the appropriate Federal banking agency, or other public authority pursuant to which a conservator, receiver, or other legal custodian is appointed for an insured depository institution or, in the case of a foreign bank having an insured branch, for such branch.", see the FDIC's website, https://www.fdic.gov/regulations/laws/rules/1000-400.html, December 2015.

[10]The approach followed by Bologna (2015) is adapted in this paper. In particular, his proxy for the NSFR, the loan-to-deposit ratio, is central to our empirical analysis.

would have led to fewer bank defaults in the US between 2007 and 2009. However, the economic significance of the effect of funding on the probability of default clearly trails the effects of higher capitalization, higher profitability and lower asset risk.

Peresetsky, Karminsky and Golovan (2004) combine quarterly balance sheet data with macro variables and construct a failure dummy to run a logit estimation for Russian banks with a sample spanning the period from 1997 to 2003. They find a higher share of deposit funding to be beneficial with regard to lowering the default risk of small, but not of large banks in Russia. This emphasizes the need to control for bank size when examining the effect of stable funding. According to Wong, Fong, Li and Choi (2010), in Hong Kong the NSFR also reduces the probability of banking distress. Their results are based on a linear regression of an estimated banking distress probability on aggregated bank balance sheet measures accounting for capital adequacy and funding structure as well as macro variables accounting for inflation and output covering the period from 1998 to 2010.

Focusing on macro effects of the new regulation in the U.K., Yan, Hall and Turner (2012) find a negative impact on GDP in the short run, mainly based on bank lending rates. The effect on bank profitability in the long run is, however, positive. Utilizing a binary response model, they estimate the probability of a banking crisis occuring conditional on aggregate bank capital adequacy, the NSFR and macro variables. They conclude that the NSFR helps to reduce the probability of banking crises and expect it to have a positive impact on output in the long run.

Using a CoVaR approach[11] López-Espinosa, Moreno, Rubia and Valderrama (2012) address systemic risks, finding wholesale funding to be a key determinant in triggering systemic risk episodes. This is true even from a global perspective, according to which money markets can be considered an important distribution channel of risk across countries. The authors used disaggregated data on 54 international banks from 18 countries covering the period from July 2001 until December 2009.

Gobat, Yanase and Maloney (2014) deliver some insights into the extent to which banks have adjusted to the upcoming implementation of the new funding regulation to date. They calculate the NSFR for over 2000 banks in 128 countries including Germany at end-2012. They show that at that point in time more than half of all German banks included had already addressed their funding risk by fulfilling the NSFR minimum requirements.[12] If those results could be generalized, this would suggest that the final implementation of the new regulation will not lead to much further change in the German banking sector.

To the best of the authors' knowledge, there is no study that quantifies the impact of stable funding on bank stability in Germany. However, Porath (2006) analyzes the effect

[11]This risk measure has first been proposed by Adrian and Brunnermeier (2011).

[12]This is also true for the majority of banks in the entire sample. Their results suggest that large banks tend to have the greatest need for adjustment to comply with the NSFR.

of other potential risk drivers found on banks' balance sheets and those caused by changes in the macro environment. He finds the main drivers to be capitalization, return, credit risk, market risk as well as different business cycle indicators and macroeconomic price variables. The author gathers critical events experienced by the German banks from the same supervisory dataset as we use in this paper. Another study that uses these data is Kick and Koetter (2007). In their study, the authors show how the different events recorded by the supervisor can be clustered in different categories of severity in order to estimate a generalized ordered logit model. Their main result is that the probability of the respective critical events responds differently to given changes in the financial profiles of banks.

## 3.3 Empirical analysis

### 3.3.1 Data

In order to answer the question of whether stable funding has been conducive to the overall stability of German banks in the past, we use unique supervisory data that contain information on critical events of German monetary financial institutions, which we combine with banks' balance sheets, profit and loss accounts, and additional supervisory data. We eliminate from our sample branches of foreign banks, special purpose banks, mortgage banks as well as building and loan associations. Branches of foreign banks from the EU and some other jurisdictions are not supervised by the German Federal Financial Supervisory Authority, building and loan associations and special purpose banks have very specific business models that do not focus on traditional loans to consumers and/or firms that are financed by deposits from the private non-financial sector. As far as the mortgage banks are concerned, we do not have data on profitability for almost half of the observations. On average, the remaining banks' loans and deposits account for approximately 95% of the loans and deposits of German monetary financial institutions. Depending on the year, the number of banks in our sample ranges from 3,269 to 1,619.

#### Financial distress events

We have access to a dataset that contains information on critical events of German banks from 1995 to 2013 at an annual frequency.[13] The data have been put together by the Deutsche Bundesbank for microprudential supervisory purposes[14] and have also been

[13]There is also a variable indicating whether or not for a certain bank critical events took place prior to 1995.

[14]The data are used to maintain and validate SRP ratings (SRP: supervisory review process) of banks from several banking groups.

used in academic studies (see Koetter, Bos, Heid, Kolari, Kool and Porath (2007), Kick and Koetter (2007), Porath (2006)). Critical events of banks that comprise the dataset vary with respect to their severity. It is possible for a bank to experience one (several) event(s) in consecutive years as well as several different events in one year. Once a bank has entered into a critical state, subsequent critical events recorded by the supervisor are not treated as new events in the following. Banks are labeled as "cured" in the data only after a one year waiting period. After this time banks might again experience critical events. We map the different critical events listed below to one single category of financial distress events.[15] A financial distress event is classified as such if for bank $i$ in period $t$ at least one of the following critical events occurs:

- Disclosure of facts[16] pursuant to section 29(3) of the Banking Act (BA)
- Operating loss in excess of 25% of liable capital
- Losses of liable capital amounting to at least 25% pursuant to section 24(1) of the BA
- Forbiddance of granting of loans/large exposures pursuant to sections 45 or 46 of the BA
- Moratoriums pursuant to section 4a of the BA
- Capital preservation measures
- Restructuring caused by mergers[17]
- Liquidation or insolvency
- Financial Market Stabilisation Fund (Sonderfonds Finanzmarktstabilisierung: SoFFin) recapitalisation measures and guarantees.[18]

[15]This, of course, is a simplified view and disregards different degrees of severity of the critical events. However, for the sake of having as large a sample size as possible and practicability of our empirical approach, we find it feasible to treat each critical event as a financial distress event. Later on, we confirm this approach in several robustness checks.

[16]This refers to the auditor becoming aware of facts that jeopardize the existence of the institution or fundamentally impair its development. However, for the supervisor, this leads to the recording of a critical event only if at least one of the other events described above occurs in the following year.

[17]Only mergers that come about as a result of at least one bank experiencing financial difficulties are recorded. Ordinary M&A activities are not part of the dataset.

[18]These are measures taken by the Financial Market Stabilisation Fund, that aim to stabilize the financial system in Germany. The guarantees apply to newly issued debt securities and justified other debt issued by financial institutions. The SoFFin recapitalisation measures and guarantees are not an integral part of the data on critical events of German banks. We augment the original dataset by the SoFFin data whenever there is a SoFFin recapitalisation measure or a guarantee for a bank and none of the above criteria has been met to trigger an entry into the original dataset. This applies to

This definition is very closely related to what constitutes a financial distress event of a bank according to Porath (2006) and covers all events indicating that a bank is in danger of ceasing to exist as a going concern[19] without outside intervention. A broad definition of financial distress events as opposed to restricting the analyses to liquidation or insolvency events is necessary for our study as, in particular, savings banks and credit cooperatives are well protected against full-blown defaults which are usually prevented by internal rescue mechanisms.[20]

The critical events are collected by the local banking supervisors on a yearly basis. The exact dates on which these events occurred cannot be retrieved in all cases. For all following analyses, we only consider those bank years in which a bank experiences a critical event after being considered financially healthy for at least one year, while subsequent years already in financial distress are omitted. This is essential because once a bank experiences a critical event, it must be expected that this event affects balance sheet data in the following periods, which leads to endogeneity concerns in the model.

In our estimation, we use 637 critical events (without subsequent critical events), 105 of which were commercial banks, 76 savings banks and Landesbanken, and 456 credit cooperatives and their regional institutions.[21] Appendix 3.A.3 presents a brief descriptive analysis of the critical events used in this study. As far as the nature of critical events is concerned, almost half of the events are capital preservation measures. The second most frequent critical event is restructuring caused by mergers, which could be observed in over 30% of the financial distress events, followed by operating losses in excess of 25% of liable capital in over 10% of the critical events. Table 3.A2 in Appendix 3.A.1 contains a breakdown of the financial distress events experienced by the German banks from 1995 to 2013 by event type and banking group.

Commerzbank in 2008 and BayernLB in 2009. See the Federal Agency for Financial Market Stabilisation (FMSA) website, `http://www.fmsa.de/export/sites/standard/downloads/20140630_Overview_of_SoFFin_measures.pdf`, April 2015.

[19]In case of a liquidation or insolvency, a bank is a gone concern.

[20]Savings banks in Germany collectively hold funds and reserves to guarantee the liquidity and solvency of all members of the *Sparkassen Finanzgruppe* in which all savings banks are included. In this way, they guarantee deposits even beyond the legal minimum of €100.000 (see the *Finanzgruppe and Deutsche Sparkassen- und Giroverbund* website, http://www.dsgv.de/de/sparkassen-finanzgruppe/haftungsverbund/, April 2015 and Simpson (2013)). Credit cooperatives have a similar arrangement: A fund guaranteeing all deposits as well as debt held by customers and by investment companies as long as these liabilities relate to parts of the fund assets (Bundesverband der Deutschen Volksbanken und Raiffeisenbanken (2014)).

[21] The number of critical events is conditional on available observations for our explanatory variables. Throughout the entire sample there are 719 financial distress events. However, in 82 cases, observations for at least one exogenous variable used in the estimation are missing.

**Exogenous variables of interest**

Our aim is to investigate whether stable funding - as envisioned by the Basel Committee on Banking Supervision - would have made German banks safer in the time period before the liquidity regulation was expected to come into force. Within the framework of the Basel III liquidity regulation, the Net Stable Funding Ratio (NSFR) was introduced. According to the BCBS (2014), the NSFR relates *Available Stable Funding* ($ASF$) to *Required Stable Funding* ($RSF$) and is formally defined as

$$\text{NSFR} = \frac{\textit{Available Stable Funding}}{\textit{Required Stable Funding}} = \frac{ASF}{RSF} \geq 100\%.$$

$RSF$ consists of banks' assets, off-balance sheet items and other selected activities that are weighted by the $RSF$ factors based on supervisory assumptions regarding the respective liquidity profile of each exposure. The corresponding $RSF$ factors are the amounts of each exposure that supervisors think should be supported with stable funding reflecting the relative market illiquidity of the respective assets and off-balance sheet items. Funding is regarded as stable if it can be expected not to be withdrawn in an extended period of stress. When determining a bank's $ASF$, each funding source is assigned a factor between 0 and 1. Funding with a factor of 1 includes Tier 1 and Tier 2 capital as well as secured and unsecured funding with a residual maturity of at least one year. Retail deposits of small customers and small non-financial corporations with a residual maturity of less than one year are assigned a factor of 0.95 or 0.9 depending on their respective run-off rate which may lie between 3% and 10% or above 10%[22]. Deposits which are covered by a deposit insurance scheme are also regarded as stable. Unsecured money market funding is seen as much less stable and is assigned a factor of only 0.5. Similarly, deposits of non-banks, governments, central banks, multilateral development banks as well as other public institutions with a residual maturity of less than one year are assigned a factor of 0.5. Money market funding with a residual maturity of less than 6 months is regarded as unstable and is assigned a factor of zero. In each period, banks' $ASF$ should be at least equal to their $RSF$, or put differently, the ratio of $ASF$ over $RSF$ should be equal to or greater than 100%. The aim of the NSFR is

> "[...] to limit over-reliance on short-term wholesale funding during times of buoyant market liquidity and encourage better assessment of liquidity risk across all on- and off-balance sheet items" (BCBS (2014)).

Ideally, we would calculate the Net Stable Funding Ratio according to the Basel III

[22] See BCBS (2013) and BCBS (2014). The exact run-off rate is determined by the responsible regulator and is supposed to mirror the behavior of depositors in the respective jurisdiction in a period of stress.

formula using data from the past.[23] However, the data at our disposal are not granular enough, and hence, do not allow us to do so. Therefore, we use the *loan-to-deposit ratio (LTD)*[24] and the *loan-to-interbank-liabilities ratio (LTIBL)* as our main variables of interest to proxy banks' stable funding.

Our $LTD$ is very similar to that used by Bologna (2015) and is constructed as the ratio of all loans to the non-financial sector over all unsecured liabilities towards non-banks.

$$LTD_{it} = \frac{Loans_{it}}{Deposits_{it}} \cdot 100. \tag{3.1}$$

The $LTD$ is a simple, balance sheet-based measure of stable funding that is established in the literature (see, for example, Bank of England (2014), Van den End (2013)).[25] According to the European Systemic Risk Board, limits on the $LTD$ can be used as one of the macroprudential instruments to address excessive maturity mismatches by increasing the stability of banks' funding base.[26] There is also some empirical evidence that the $LTD$ can be a good predictor of funding vulnerabilities (European Systemic Risk Board (2014)).[27]

Since the NSFR of a bank is a decreasing function of its loans and an increasing function of its deposits, the $LTD$ is related to the NSFR in an inverse fashion. The lower the $LTD$ and the higher the NSFR, the more stable the funding of a bank is. If the $LTD$ of a bank rises (either on account of falling deposits or because loans have increased or both), then the NSFR decreases[28] according to the $ASF$ and the $RSF$ factors outlined in the Basel III liquidity regulation.[29]

[23]In the literature some direct approaches are discussed to get a good approximation of the NSFR. They rely on assumptions about the share of certain asset and liability categories as classified by the NSFR regulation (i.e. categories relating to the maturity and stability of these assets) within the categories reported (Hong et al. (2014), Wong et al. (2010) and Yan et al. (2012)).

[24]The $LTD$ can be regarded as a simple variant of the NSFR (European Systemic Risk Board (2014)).

[25]The drawback of this measure, however, is that it does not completely capture the maturity transformation as it only focuses on certain parts of banks' balance sheets (European Systemic Risk Board (2014)).

[26]As part of the programme on economic and financial assistance, Banco de Portugal introduced an indicative target of 120% for the $LTD$ of the eight largest banking groups to be reached by 2014 as one of several measures to achieve a more balanced funding profile for the banking sector. A mandatory cap of 100% for banks' $LTD$ was introduced in South Korea in the aftermath of the financial crisis and came into force in 2012.

[27]The $LTD$ seems to be used as a measure of stable funding by bank managers as well. According to Moorad Choudhry, the former Head of Business Treasury, Global Banking and Markets at the Royal Bank of Scotland, the $LTD$ "[...] is a standard and commonly used metric, typically reported monthly. It measures the relationship between lending and customer deposits, and is a measure of the self-sustainability of the bank (or the branch or subsidiary). A level above 100% is an early warning sign of excessive asset growth; of course, a level below 70% implies excessive liquidity and implies a potentially inadequate return on funds" (Choudhry (2011)).

[28]A lower deposit base reduces the $ASF$, while a greater volume of loans increases the $RSF$.

[29]Wong et al. (2010) estimate the correlation of the NSFR and their $LTD$ for banks in Hong Kong and find a significant negative linear relation between the two variables.

As wholesale funding is not the residual when equity and deposits are subtracted from liabilities, we also consider the $LTIBL$, defined as

$$LTIBL_{it} = \frac{Loans_{it}}{Interbank\ Liabilities_{it}} \cdot 100. \tag{3.2}$$

It should be noted that the relation between the $LTIBL$ and the NSFR is not as clear-cut as in the case of the $LTD$, as depending on the maturity, an increase in certain interbank liabilities can either lead to an increase or a decrease in the NSFR. The data at our disposal do not allow us to make the relevant distinction.

Appendix 3.A.4 provides a descriptive analysis of our exogenous variables of interest.

### 3.3.2 Econometric specification

Our starting point is the underlying latent-variable model:

$$y^*_{it} = \boldsymbol{x_{i,t-1}}'\boldsymbol{\beta} + \boldsymbol{z_{i,t-1}}'\boldsymbol{\gamma} + \delta RD_i + \boldsymbol{TD}'\boldsymbol{\zeta} + \alpha_i + u_{it}, \quad i = 1, \ldots, n; t = 2, \ldots, T_i$$
$$y_{it} = \begin{cases} 1 & \text{if } y^*_{it} > 0 \\ 0 & \text{otherwise.} \end{cases}$$

$y^*_{it}$ is a latent, continuous variable that reflects bank $i$'s financial health in an inverse fashion, i.e. the larger $y^*_{it}$ is, the closer bank $i$ is to default. The observable dummy $y_{it}$ takes on the value one if bank $i$ experiences financial problems in period $t$, and zero if it is financially healthy in $t$. $\boldsymbol{x_{i,t-1}}$ is a vector of lagged measures of banks' stable funding, i.e. it contains our main exogenous variables of interest.[30] Depending on the specification, it either consists of the loan-to-deposit ratio $LTD$ as defined in (3.1) or the loan-to-interbank liabilities ratio $LTIBL$ as defined in (3.2), or both.[31] Standard deviations in Table 3.A3 in Appendix 3.A.1 reveal that there are several very large values in both ratios, particularly for commercial banks and the group of credit cooperatives. These come about as a consequence of certain banks' business models that use almost no deposits or interbank liabilities to fund loans. Winsorizing both ratios is one possible solution, but this might give rise to a sample selection bias, as specific business models reflected by particularly large or small values of either one of the ratios could be related to financial distress. The fact that the share of bank years in financial distress is higher for the largest 1% of the $LTD$ values than for the overall sample suggests that this might indeed be the case. For this reason, we take the (natural) logarithm of both ratios. Doing so compresses the respective distributions somewhat, such that extremely large values

[30] The exact details and definitions of the variables used in the econometric analysis can be found in Appendix 3.A.2.

[31] Whenever only one measure of stable funding is used, the vector naturally becomes a scalar $x_{i,t-1}$.

do not drive the results so much.[32] Apart from avoiding possible endogeneity problems, this approach is more efficient, as it utilizes all available observations. The vector $\boldsymbol{z_{i,t-1}}$ of lagged explanatory variables contains the following control variables: the return on assets $ROA$ as a measure of banks' profitability[33], the capital ratio $CR$[34] in order to account for banks' capacity to absorb losses, the loan loss ratio $LLR$ to measure the quality of banks' assets, the administrative expenses ratio $AdminR$ as a proxy for banks' efficiency, relative liquid assets $Liquid$ to capture banks' market liquidity[35], $Total\ Assets$ as a proxy for banks' size, and the $Z - Score$ or the distance to default[36] to proxy banks' risk profile as is common in the literature (see, for example, Boyd, Graham and Hewitt (1993), Laeven and Levine (2009), Demirgüç-Kunt and Huizinga (2010)). We take the (natural) logarithm of all explanatory variables[37] but the $ROA$ and the $Z - Score$ because the logarithm cannot be computed, as in some cases, negative returns render both variables negative. We use lagged explanatory variables to mitigate endogeneity concerns and avoid reverse causality. Since it is impossible for us to tell when exactly the financial distress incident took place during a certain year, using lagged explanatory variables is absolutely necessary to make sure that a certain period of time lies between the date on which balance sheet items are disclosed and the financial distress event. Additionally, we control for geographical effects using regional dummies $RD$[38] as well as macroeconomic effects that impact all banks' financial health in a given year (e.g. regulatory changes) captured by the vector of time dummies $\boldsymbol{TD}$. The stochastic error term consists of a time-varying, idiosyncratic component $u_{it}$ and a time-constant, bank-specific unobserved heterogeneity $\alpha_i$. To model the probability for the observed Bernoulli-distributed dummy-variable $y_{it}$, we use the logistic function, i.e. we estimate the following random effects logit

[32] Winsorizing all explanatory variables in $\boldsymbol{x_{i,t-1}}$ and $\boldsymbol{z_{i,t-1}}$ at the 1% and 99% level, respectively, leads to qualitatively similar estimation results.

[33] We prefer the $ROA$ to the return on capital measure of profitability because the former is insensitive to banks' choice of their capital structure.

[34] Due to the fact that for the period before 2008, Tier 1 capital can only be approximated, we use equity from banks' balance sheets to measure their capital.

[35] $CR$, $LLR$, $AdminR$, $ROA$ and $Liquid$ are the so-called **CAMEL** control variables that were applied in a rating system by US regulators and are extensively used in the literature (see, for example, Wheelock and Wilson (2000)). **CAMEL** stands for **C**apital adequacy, **A**sset quality, **M**anagerial efficiency, **E**arnings and **L**iquidity.

[36] The $Z - Score$ is the number of standard deviations that a bank's $ROA$ has to fall to trigger default. To include banks' risk-taking might be important as shown by Vázquez and Federico (2012).

[37] Note that for the $LLR$ there are 618 zeros. In order to compute the respective logarithm, we replace these with $\epsilon = 1 \cdot 10^{-10}$. Using the ratios in place of logarithms does not change the results.

[38] In our case, the term region applies to the German federal states in which banks are headquartered. The regional dummies are supposed to capture region-specific, structural effects that might be relevant for banks' financial health and do not vary over time, e.g. structural unemployment. For banks that operate across different federal states the implicit assumption is that the fraction of activities taking place outside the federal region in which the respective bank is headquartered is relatively small as time-invariant, regional conditions in other federal states are not picked up by the regional dummy associated with the respective bank.

model:

$$Pr(y_{it}=1|\boldsymbol{x_{i,t-1}},\boldsymbol{z_{i,t-1}},RD_i,\boldsymbol{TD},\alpha_i) = \Lambda(\boldsymbol{x_{i,t-1}}'\boldsymbol{\beta}+\boldsymbol{z_{i,t-1}}'\boldsymbol{\gamma}+\delta RD_i+\boldsymbol{TD}'\boldsymbol{\zeta}+\alpha_i) \quad (3.3)$$
$$= \frac{exp(\boldsymbol{x_{i,t-1}}'\boldsymbol{\beta}+\boldsymbol{z_{i,t-1}}'\boldsymbol{\gamma}+\delta RD_i+\boldsymbol{TD}'\boldsymbol{\zeta}+\alpha_i)}{1+exp(\boldsymbol{x_{i,t-1}}'\boldsymbol{\beta}+\boldsymbol{z_{i,t-1}}'\boldsymbol{\gamma}+\delta RD_i+\boldsymbol{TD}'\boldsymbol{\zeta}+\alpha_i)},$$

$$u_{it}|\boldsymbol{x_{i,t-1}},\boldsymbol{z_{i,t-1}},RD_i,\boldsymbol{TD},\alpha_i \sim \mathcal{L}(0;\pi^2/3)^{39}, \qquad \alpha_i|\boldsymbol{x_{i,t-1}},\boldsymbol{z_{i,t-1}},RD_i,\boldsymbol{TD} \sim \mathcal{N}(0;\sigma_\alpha^2),$$

where $\Lambda$ is the cdf of the error term $u_{it}$ that follows the logistic distribution conditional on the regressors. $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ (including an intercept), $\delta$, $\boldsymbol{\zeta}$ are the parameters to be estimated. The bank-specific unobserved heterogeneity $\alpha_i$ is assumed to be conditionally normally distributed around zero with the variance $\sigma_\alpha^2$.

We prefer a logit to a probit model mainly because the logistic functional form allows us to use the log of the odds-ratio[40] and interpret the estimated coefficients directly. Ideally, we would like to compute and interpret the marginal effects, but since they are a function of the unobserved heterogeneity $\alpha_i$, one needs to make assumptions about it, which is why it is convenient to have a superior alternative. Apart from that, we estimate a (conditional) fixed effects logit model to robustify our findings and it seems more natural to use a random effects logit model instead of a random effects probit model[41]. However, applying the random effects probit model yields very similar results.

### 3.3.3 Estimation results

Our main specification (3.3) is estimated via maximum likelihood.[42] Note that we do not use robust standard errors of the estimated coefficients for inference.[43] First, we estimate

[39] The scale parameter is set to one.

[40] The odds ratio is defined as the probability that a bank runs into financial difficulties over the probability that a bank remains financially healthy, and for the random effects logit model its natural logarithm is $log\left\{Pr(y=1)/[1-Pr(y=1)]\right\} = \boldsymbol{x_{i,t-1}}'\boldsymbol{\beta}+\boldsymbol{z_{i,t-1}}'\boldsymbol{\gamma}+\delta RD_i+\boldsymbol{TD}'\boldsymbol{\zeta}+\alpha_i$.

[41] In contrast to the conditional fixed effects logit model, a fixed effects probit model cannot be estimated consistently due to the incidental parameters problem introduced by the unobserved heterogeneity (see, for example, Baltagi (2008)).

[42] The unobserved heterogeneity is integrated out of the likelihood function using a method proposed by Butler and Moffitt (1982).

[43] This is guided by the theoretical consideration that in a binary outcome model such as ours the entire conditional distribution $Pr(y_{it}=1|\boldsymbol{x_{i,t-1}},\boldsymbol{z_{i,t-1}},RD_i,\boldsymbol{TD},\alpha_i)$ including all conditional moments is specified. Thus, it is not possible to correctly model the conditional expected value and at the same time incorrectly specify the conditional variance, which is one of the reasons for using robust standard errors in an OLS-type model (Cameron and Trivedi (2005)). If the random sampling assumption were violated, then cluster-robust standard errors would be required. Also, in a panel model, robust standard errors might be called for to address serial correlation. However, given our sample, we deem the random sampling assumption justified and serial correlation is taken into account by including the unobserved

(3.3) using the entire sample, and hence, additionally include banking group dummies letting commercial banks be our reference group. Table 3.1 summarizes the main results and contains the estimated coefficients as well as the corresponding marginal effects. In a (random effects) logit model, the marginal effect on the probability of a bank experiencing a critical event induced by a small change in an exogenous variable such as stable funding in the form of the $LTD$ is given by

$$\frac{\partial Pr(y_{it} = 1|\boldsymbol{x_{i,t-1}}, \boldsymbol{z_{i,t-1}}, RD_i, \boldsymbol{TD}, \alpha_i)}{\partial LTD_{i,t-1}} = \beta^{LTD} \cdot \Lambda(\bullet) \cdot [1 - \Lambda(\bullet)] \,, \tag{3.4}$$

and always has the same sign as the estimated coefficient $\beta^{LTD}$.[44] A statistically significant positive $\beta^{LTD}$ in Table 3.1 means that a larger $LTD$ of a bank increases its probability of becoming financially distressed, and (3.4) tells us by how much. Since the unobserved heterogeneity is one of the arguments in $\Lambda(\bullet)$, the marginal effect in (3.4) is also a function of $\alpha_i$. To compute the marginal effect, the assumed conditional expected value $\alpha_i = 0$ is used. As this can be a nonrepresentative evaluation point, we have to interpret the marginal effects with caution. For this reason, we take advantage of the specific functional property of the logit model and use the log of the odds ratio, as defined in footnote 40, to interpret the estimated coefficients directly.

The estimated coefficient for the lagged $LTD$ in column (1) equals 0.3302. Since we take the log of $LTD_{i,t-1}$, the interpretation of the marginal effect is that an approximate relative percentage change in stable funding in the form of $LTD$ of bank $i$, given by $\Delta log(LTD_{i,t-1}) \cdot 100$, increases the log of the ratio of the probability of this bank experiencing a critical event over the probability that the bank remains financially healthy by $\frac{\beta^{LTD}}{100} \cdot [\Delta log(LTD_{i,t-1}) \cdot 100]$. That is, a 1% rise in the $LTD$ from 1995 to 2013 increases the log of the odds ratio by 0.003302. Since (the log of) the odds ratio is a non-linear function of the probability of becoming financially distressed, the magnitude of the effect crucially depends on this probability. The predicted mean share of banks experiencing a critical event for the first time, which can be interpreted as a non-parametric empirical distribution measure for the unknown conditional expected value, amounts to 1.2792%, implying 519 bank years in distress.[45] Given the sample of 40,572 bank years, an increase

heterogeneity $\alpha_i$ in the model. Hence, there is no need to resort to the robust standard errors. While, in a random effects logit model, the robust estimator of the variance-covariance matrix is also asymptotically consistent and could, in principle, be applied, it is also more computationally intensive, which is why we choose not to use it.

[44] The marginal effect in a (random effects) logit model depends on the estimated coefficient and the probability density function of $\Lambda(\bullet)$. Since $\Lambda(\bullet)$ is a strictly increasing cdf, the probability density function is always greater than zero, i.e the marginal effect has the same sign as the estimated coefficient. In (3.4), the marginal effect is expressed in terms of the cdf itself.

[45] The actual mean share of banks experiencing a critical event for the first time in all bank years throughout the entire sample, which can be interpreted as a point estimate of the unconditional proba-

## Table 3.1: RE logit estimation – all banks (no subsequent critical events)

| Explanatory variables | (1) Estimates | (1) Marginal effects | (2) Estimates | (2) Marginal effects | (3) Estimates | (3) Marginal effects |
|---|---|---|---|---|---|---|
| $log(LTD_{i,t-1})$ | 0.3302*** | 0.0040*** | | | 0.2715*** | 0.0033*** |
| | (0.0624) | (0.0008) | | | (0.0642) | (0.0008) |
| $log(LTIBL_{i,t-1})$ | | | −0.3319*** | −0.0041*** | −0.3049*** | −0.0037*** |
| | | | (0.0560) | (0.0007) | (0.0604) | (0.0008) |
| $ROA_{i,t-1}$ | −0.2922*** | −0.0036*** | −0.2616*** | −0.0032*** | −0.3264*** | −0.0040*** |
| | (0.0378) | (0.0005) | (0.0339) | (0.0004) | (0.0421) | (0.0006) |
| $log(CR_{i,t-1})$ | −0.9843*** | −0.0120*** | −0.8341*** | −0.0102*** | −1.0080*** | −0.0122*** |
| | (0.1754) | (0.0022) | (0.1703) | (0.0022) | (0.1800) | (0.0023) |
| $log(LLR_{i,t-1})$ | 0.0514*** | 0.0006*** | 0.0804*** | 0.0010*** | 0.0670*** | 0.0008*** |
| | (0.0194) | (0.0002) | (0.0204) | (0.0003) | (0.0205) | (0.0002) |
| $log(AdminR_{i,t-1})$ | 0.9195*** | 0.0112*** | 0.8458*** | 0.0104*** | 0.9559*** | 0.0116*** |
| | (0.1477) | (0.0020) | (0.1389) | (0.0018) | (0.1508) | (0.0019) |
| $log(Liquid_{i,t-1})$ | 0.1961*** | 0.0024*** | 0.0997 | 0.0012 | 0.1834** | 0.0022** |
| | (0.0724) | (0.0009) | (0.0682) | (0.0008) | (0.0723) | (0.0009) |
| $log(Total\ Assets_{i,t-1})$ | 0.1326*** | 0.0016*** | 0.1168*** | 0.0014*** | 0.1115** | 0.0014** |
| | (0.0431) | (0.0005) | (0.0433) | (0.0005) | (0.0439) | (0.0005) |
| $Z-Score_{i,t-1}$ | 0.0001 | $8.04 \cdot 10^{-7}$ | 0.0001* | $9.90 \cdot 10^{-7}$* | 0.0001 | $8.58 \cdot 10^{-7}$ |
| | (0.0001) | $(6.13 \cdot 10^{-7})$ | (0.0000) | $(5.21 \cdot 10^{-7})$ | (0.0000) | $(5.89 \cdot 10^{-7})$ |
| $Constant$ | −6.2626*** | | −2.7561*** | | −4.0733*** | |
| | (0.8469) | | (0.8606) | | (0.9441) | |
| Time dummies | Yes | | Yes | | Yes | |
| Regional dummies | Yes | | Yes | | Yes | |
| Number of banks | 3,497 | | 3,500 | | 3,490 | |
| Number of observations | 40,572 | | 40,432 | | 40,378 | |
| Pseudo $R^2$ | 0.09 | | 0.09 | | 0.10 | |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time after being financially sound for at least one year, and zero if it is financially healthy in $t$. The table reports the estimated coefficients, the corresponding marginal effects and standard errors (in parentheses) using the random effects logit model (3.3) (augmented by banking group dummies). Standard errors of the marginal effects are calculated using the delta method. In column (1), the (natural) log of the loan-to-deposit ratio $LTD$ as defined in (3.1) is used as a lagged measure of banks' stable funding $\boldsymbol{x_{i,t-1}}$, in column (2), the (natural) log of the loan-to-interbank liabilities ratio $LTIBL$ as defined in (3.2) is employed, and in column (3), both measures are used. See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

in the log of the odds ratio of 0.003302 implies a rise in the mean share of bank years in distress of 0.000041767, i.e. approximately two additional banks become financially distressed.[46] Similarly, a 1% decrease in the $LTIBL$ in column (2) leads to an even greater

bility of a bank in distress in the underlying population, is 1.57%. If our model were perfect, then the model-implied mean share of bank years in distress would equal the actual mean share. Taking the actual mean share of banks in distress as a point estimate for the unknown probability of experiencing financial distress would be inappropriate, as the probability used in the odds ratio in the context of our model is a conditional one.

[46] If the estimated mean share of banks in financial difficulties of 1.2792% is used, then the log of the odds ratio is -4.34606. An increase of 0.003302 leads to a new log of the odds ratio of -4.34276, which

rise in the log of the odds ratio of 0.003319 implying an increase in the mean share of bank years in distress of 0.000042458 or stated differently, almost two more banks experience a critical event. Both estimated coefficients are statistically significant indicating the importance of stable funding for the German banking sector. The likelihood ratio test rejects the null that the coefficient on the lagged $LTD$ ($LTIBL$) is zero. The estimated marginal effects suggest a similar effect. If the $LTD$ rises (the $LTIBL$ falls) by one percent, the conditional probability of a bank experiencing a critical event increases by 0.0040 (0.0041) percentage points. Again, if we take the predicted mean share of 1.2792% (1.29308%), then an increase (a decrease) in the probability of 0.0040 (0.0041) percentage points implies approximately two (one) additional bank years in financial distress.[47]

In column (3), both stable funding variables are used simultaneously in order to examine which funding variable is more important for bank distress. It turns out that the estimated effects of both variables retain their relative importance and statistical significance, although both coefficients are slightly smaller.

The estimated coefficients on most control variables are in line with what is expected for these variables in terms of the sign of the respective coefficients. More profitable banks[48], banks holding more capital and banks with qualitatively better credit exposures are associated with a smaller probability of experiencing a critical event. Managerial efficiency negatively affects the likelihood of distress. A bank's size appears to be positively related to the probability of distress. In column (1) (column (2)), liquidity (banks' risk-taking) is significantly different from zero and has a positive sign. As far as liquidity is concerned, banks might accumulate liquid assets when they anticipate financial difficulties. The positive coefficient of the $Z - Score$ is economically immaterial.

Descriptive statistics in Appendix 3.A.1, Table 3.A3 readily show that the German banking sector is very heterogeneous and there are big differences in the bank-specific characteristics across banking groups. To illustrate this from yet another perspective,

corresponds to an odds ratio of 0.0130006. This yields a (conditional) predicted probability of a bank running into financial difficulties for the first time of 0.012834 and a (conditional) predicted probability of a bank staying financially healthy of 0.987166. For the sample of 40,572 bank years, this means that approximately 521 (instead of the model-implied 519) bank years will turn out to be financially distressed.

[47] Alternatively, we can calculate the estimated conditional probability of experiencing a critical event for each bank by keeping all the regressors as they are (using $\alpha_i = 0$), except for the vector of lagged measures of banks' stable funding $\boldsymbol{x_{i,t-1}}$, for which we increase (decrease) the $LTD$ ($LTIBL$) by one percent in every period $t$. These estimated probabilities for individual banks can be used to determine the new overall conditional probability of a bank year becoming financially distressed by taking the mean over the individual ones. The new predicted mean share of 1.283248% (1.297159%) again implies approximately two (one) more banks experiencing financial distress.

[48] Note that the effect of profits has been found to be ambiguous in the literature. Behn, Detken, Peltonen and Schudel (2013) find that large profits in the banking sector can be associated with excessive risk-taking leading to increased vulnerability and subsequent banking crises (see also Drehmann, Borio and Tsatsaronis (2011)). This underscores the importance of including a proxy for risk-taking such as the $Z - Score$.

Figure 3.A4 in Appendix 3.A.5 depicts the evolution of the size of the German banking sector[49] and the shares of the total assets of different banking groups in the total assets of the whole banking sector at three different points in time. Between 1994 and 2012, the total assets of German banks more than doubled from approximately three trillion euro to almost seven trillion euro. However, marked differences in the shares of the total assets of different banking groups have emerged over time. Most strikingly, between 1994 and 2012, the share of commercial banks' total assets increased from approximately 35% to over 50%, which was mostly due to the growth of big banks, and the share of the Landesbanken grew from 24% to 30% between 1994 and 2003 and then decreased to almost 15% between 2003 and 2012. The relative size of credit cooperatives as well as their regional institutions has remained relatively constant, whereas the relative size of savings banks has steadily fallen from almost 24% in 1993 to 15% in 2012. Dynamics-related considerations aside, a look at the proportions shown in Figure 3.A4, Appendix 3.A.5 suggests that it might be appropriate to treat big banks, other commercial banks, the Landesbanken, savings banks, the regional institutions of credit cooperatives and credit cooperatives as separate banking groups.[50] We corroborate this visual conjecture by employing the Mann-Whitney-Wilcoxon test and the Kolmogorov-Smirnov test[51] to see whether each of the variables $LTD$, $LTIBL$, relative loans ($LR$), relative deposits ($DR$) and relative interbank liabilities ($IBLR$)[52] comes from the same underlying distribution for the subgroups of big banks vs. other commercial banks, Landesbanken vs. savings banks and regional institutions of credit cooperatives vs. credit cooperatives, respectively. For each pairing, the null of the same underlying distribution is rejected for almost every variable.[53] As the non-parametric tests confirm that these six subgroups are different from

[49]The German banking sector is approximated by the banks in our sample. As explained in Section 3.3.1, we have excluded a few banking groups for different reasons. The share of the total assets of the banks in our sample in the total assets of monetary financial institutions in Germany amounts to about 80%. In terms of loans/deposits, the share of banks in our sample in the loans/deposits of German monetary financial institutions is around 95%, respectively.

[50] The Landesbanken were founded to act as a sort of central bank for savings banks, thereby also taking care of payment transactions. Only over time have new tasks been added to their portfolio, such as liquidity management, large value credits, securities settlement, foreign transactions etc. (Gubitz (2013)). Over time, their business models have evolved towards that of big banks (Deutsche Bundesbank (2015)). Very similar services are provided by the regional institutions of credit cooperatives to credit cooperatives. These banks are, however, not in public hand (Guinnane (2013)). The big banks can also be argued to have a fundamentally different business model from the much smaller other commercial banks which are much less internationally oriented.

[51]As both these tests are non-parametric tests, they do not require any distributional assumptions and are robust to outliers.

[52]Banks' relative loans, deposits and interbank liabilities are each calculated as a share in the total assets.

[53]The only exception is the $LTD$ for big banks and other commercial banks. The null that the $LTD$ for each subgroup stems from the same distribution cannot be rejected using the Mann-Whitney-Wilcoxon test. However, it is rejected when the Kolmogorov-Smirnov test is applied.

each other with respect to the funding variables, it seems reasonable to assume that the way stable funding affects the probability of financial distress might differ across banking groups as well. Ideally, we would estimate our model for each banking group separately. Unfortunately, samples consisting of just Landesbanken or central institutions of credit cooperatives or big banks turn out to be too small to yield meaningful results. Hence, we exclude all Landesbanken, regional institutions of credit cooperatives as well as big banks from all following analyses.

**Table 3.2: RE logit estimation: main specification – commercial banks without big banks (no subsequent critical events)**

| Explanatory variables | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | Estimates | Marginal effects | Estimates | Marginal effects | Estimates | Marginal effects |
| $log(LTD_{i,t-1})$ | $-0.0701$ | $-0.0022$ | | | $-0.0921$ | $-0.0031$ |
| | (0.0747) | (0.0024) | | | (0.0785) | (0.0026) |
| $log(LTIBL_{i,t-1})$ | | | 0.0074 | 0.0002 | 0.0057 | $-0.0002$ |
| | | | (0.0578) | (0.0019) | (0.0584) | (0.0019) |
| $ROA_{i,t-1}$ | $-0.1190^{***}$ | $-0.0038^{***}$ | $-0.1355^{***}$ | $-0.0044^{***}$ | $-0.1188^{***}$ | $-0.0040^{***}$ |
| | (0.0304) | (0.0010) | (0.0346) | (0.0012) | (0.0343) | (0.0012) |
| $log(CR_{i,t-1})$ | $-0.4542^{**}$ | $-0.0145^{**}$ | $-0.3748^{*}$ | $-0.0122^{*}$ | $-0.3447$ | $-0.0115$ |
| | (0.2113) | (0.0070) | (0.2142) | (0.0072) | (0.2189) | (0.0075) |
| $log(LLR_{i,t-1})$ | $-0.0034$ | $-0.0001$ | $-0.0023$ | $-0.0001$ | $-0.0010$ | $-0.0000$ |
| | (0.0144) | (0.0005) | (0.0148) | (0.0005) | (0.0151) | (0.0005) |
| $log(AdminR_{i,t-1})$ | $0.6037^{***}$ | $0.0193^{***}$ | $0.4644^{***}$ | $0.0151^{***}$ | $0.5358^{***}$ | $0.0178^{***}$ |
| | (0.1621) | (0.0054) | (0.1511) | (0.0050) | (0.1621) | (0.0056) |
| $log(Liquid_{i,t-1})$ | $-0.1233$ | $-0.0039$ | $-0.0553$ | $-0.0018$ | $-0.1229$ | $-0.0041$ |
| | (0.0904) | (0.0029) | (0.0816) | (0.0027) | (0.0919) | (0.0031) |
| $log(Total\ Assets_{i,t-1})$ | $-0.0748$ | $-0.0024$ | $-0.0468$ | $-0.0015$ | $-0.0497$ | $-0.0017$ |
| | (0.0887) | (0.0029) | (0.0916) | (0.0030) | (0.0917) | (0.0031) |
| $Z-Score_{i,t-1}$ | $0.0002^{**}$ | $6.00 \cdot 10^{-6*}$ | $0.0002^{***}$ | $7.33 \cdot 10^{-6***}$ | $0.0002^{**}$ | $6.51 \cdot 10^{-6**}$ |
| | (0.0001) | $(3.18 \cdot 10^{-6})$ | (0.0001) | $(2.77 \cdot 10^{-6})$ | (0.0001) | $(3.24 \cdot 10^{-6})$ |
| $Constant$ | $-1.4096$ | | $-2.2967$ | | $-1.6442$ | |
| | (1.5877) | | (1.6904) | | (1.7136) | |
| Time dummies | Yes | | Yes | | Yes | |
| Regional dummies | Yes | | Yes | | Yes | |
| Number of banks | 295 | | 291 | | 283 | |
| Number of observations | 2,644 | | 2,488 | | 2,443 | |
| Pseudo $R^2$ | 0.13 | | 0.13 | | 0.12 | |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time after being financially sound for at least one year, and zero if it is financially healthy in $t$. The table reports the estimated coefficients, the corresponding marginal effects and standard errors (in parentheses) using the random effects logit model (3.3) on the sample of commercial banks excluding big banks. Standard errors of the marginal effects are calculated using the delta method. In column (1), the (natural) log of the loan-to-deposit ratio $LTD$ as defined in (3.1) is used as a lagged measure of banks' stable funding $\boldsymbol{x_{i,t-1}}$, in column (2), the (natural) log of the loan-to-interbank liabilities ratio $LTIBL$ as defined in (3.2) is employed, and in column (3), both measures are used. See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

We re-estimate our main specification (3.3) for the groups of other commercial banks, savings banks and credit cooperatives respectively.[54] Table 3.2 shows the results for the group of commercial banks without big banks. Most notably, both stable funding variables are not significantly different from zero, i.e. the funding profile does not appear to be of primary importance for explaining distress events for these banks. The only significant variables across all specifications are profitability, managerial efficiency and banks' risk-taking. Commercial banks with a higher $ROA$ are less prone to financial distress. Counterintuitively, a greater distance to default is associated with a higher probability of distress. However, the effect is economically negligible. Note that the number of observations is smaller than the number reported in Table 3.A3 in Appendix 3.A.1. This is due to the fact that no critical events could be observed for commercial banks in the year 2003 or in three federal states. The corresponding observations cannot be used in the estimation because the dependent variable does not display any variation for those values.

The estimation output in Table 3.3 refers to the results for savings banks. As reported in column (1), the estimated coefficient of the $LTD$ is 3.4244, i.e. given 8,423 bank years for savings banks,[55] an increase in the $LTD$ of one percent implies that approximately two more savings banks experience a critical event from 1995 to 2013. The effect of the $LTIBL$ in column (2) is not significant, meaning that interbank funding is not crucial for savings banks. This finding is corroborated in column (3) when both stable funding variables are employed simultaneously.[56] While the $LTIBL$ remains statistically insignificant, the effect of the $LTD$ becomes slightly greater. Interestingly, the coefficient estimated for the $CR$ is not significant either, suggesting that profitability is much more important for savings banks than capital.[57] A lower quality of the assets increases the likelihood of becoming financially distressed, as do more liquid assets[58]. Finally, risk-taking – as proxied by the $Z - Score$ – slightly increases the probability of financial distress, even though the effect is economically not very large.

Table 3.4 contains the results for credit cooperatives. Stable funding positively af-

[54] The alternative is to apply interaction terms involving our stable funding measures and banking groups. However, the interpretation of the interaction effects associated with the interaction terms is more complicated because the interaction effect is not equal to the marginal effect of the interaction term and may have different signs for different values of the independent variables involved (see Ai and Norton (2003)).

[55] Again, the number of observations used in the estimation is smaller than the number reported in Table 3.A3 in Appendix 3.A.1 because there were no critical events for savings banks in the year 2011 or in four federal states. The corresponding 918 bank years cannot be used in the estimation because the dependent variable is zero throughout and does not vary for those values.

[56] Again, the likelihood ratio test rejects the null that the coefficient on the lagged $LTD$ is zero.

[57] However, this might be because we are using equity from banks' balance sheets, which is only a proxy for regulatory capital.

[58] This might reflect savings banks anticipating financial difficulties.

**Table 3.3: RE logit estimation: main specification – savings banks (no subsequent critical events)**

| Explanatory variables | (1) Estimates | (1) Marginal effects | (2) Estimates | (2) Marginal effects | (3) Estimates | (3) Marginal effects |
|---|---|---|---|---|---|---|
| $log(LTD_{i,t-1})$ | 3.4244*** | 0.0247*** | | | 3.4645*** | 0.0250*** |
| | (0.7199) | (0.0057) | | | (0.7335) | (0.0058) |
| $log(LTIBL_{i,t-1})$ | | | −0.2574 | −0.0019 | 0.1507 | 0.0011 |
| | | | (0.4603) | (0.0034) | (0.5035) | (0.0036) |
| $ROA_{i,t-1}$ | −1.9704*** | −0.0142*** | −2.1775*** | −0.0161*** | −1.9739*** | −0.0142*** |
| | (0.4225) | (0.3300) | (0.4062) | (0.0033) | (0.4307) | (0.0033) |
| $log(CR_{i,t-1})$ | −1.1776 | −0.0085 | −1.5009 | −0.0111 | −1.2902 | −0.0093 |
| | (0.9539) | (0.0069) | (0.9662) | (0.0072) | (1.0258) | (0.0075) |
| $log(LLR_{i,t-1})$ | 0.8525*** | 0.0062*** | 0.9248*** | 0.0068*** | 0.8522*** | 0.0062*** |
| | (0.2963) | (0.0022) | (0.2838) | (0.0022) | (0.2968) | (0.0022) |
| $log(AdminR_{i,t-1})$ | 0.1092 | 0.0008 | −1.0792 | −0.0080 | 0.0191 | 0.0001 |
| | (0.9952) | (0.0072) | (1.0480) | (0.0078) | (1.0404) | (0.0075) |
| $log(Liquid_{i,t-1})$ | 0.7875*** | 0.0057*** | 0.5009* | 0.0037* | 0.7813*** | 0.0056*** |
| | (0.2753) | (0.0021) | (0.2681) | (0.0020) | (0.2767) | (0.0021) |
| $log(Total\ Assets_{i,t-1})$ | −0.2596 | −0.0019 | −0.4127*** | −0.0030** | −0.2616 | −0.0019 |
| | (0.1592) | (0.0012) | (0.1591) | (0.0012) | (0.1594) | (0.0012) |
| $Z-Score_{i,t-1}$ | −0.0175* | −0.0001* | −0.0157 | −0.0001 | −0.0179* | −0.0001* |
| | (0.0099) | (0.0001) | (0.0098) | (0.0001) | (0.0100) | (0.0001) |
| $Constant$ | −17.9799*** | | 2.1228 | | −18.7967*** | |
| | (5.0768) | | (3.5074) | | (5.7791) | |
| Time dummies | Yes | | Yes | | Yes | |
| Regional dummies | Yes | | Yes | | Yes | |
| Number of banks | 601 | | 601 | | 601 | |
| Number of observations | 8,423 | | 8,423 | | 8,423 | |
| Pseudo $R^2$ | 0.29 | | 0.26 | | 0.29 | |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time after being financially sound for at least one year, and zero if it is financially healthy in $t$. The table reports the estimated coefficients, the corresponding marginal effects and standard errors (in parentheses) using the random effects logit model (3.3) on the sample of savings banks. Standard errors of the marginal effects are calculated using the delta method. In column (1), the (natural) log of the loan-to-deposit ratio $LTD$ as defined in (3.1) is used as a lagged measure of banks' stable funding $\boldsymbol{x_{i,t-1}}$, in column (2), the (natural) log of the loan-to-interbank liabilities ratio $LTIBL$ as defined in (3.2) is employed, and in column (3), both measures are used. See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

fects the likelihood of staying financially healthy. Given 26,940 observations[59] on credit cooperatives, a 1% increase in the $LTD$ corresponds to two more credit cooperatives experiencing critical events from 1995 to 2013. The estimated effect of the $LTIBL$ is similar, albeit weaker. The results do not change much when both proxies for stable funding are used in column (3). That is, for credit cooperatives, more stable deposits as

[59] As is the case with commercial banks and savings banks, 1,111 bank years cannot be used in the estimation procedure because no financial distress events are available for the year 2013 or in one federal state.

well as fewer interbank liabilities appear to reduce the chances of becoming financially distressed.[60] Again, the expected effects for the $ROA$, $CR$, $LLR$ and the $AdminR$ are found in the estimation. The estimated coefficient of liquidity suggests that more liquid assets are associated with a higher probability of experiencing financial distress, which might be due to credit cooperatives accumulating liquidity in anticipation of financial difficulties. Contrary to the findings for savings banks, size does seem to matter for credit cooperatives, whereas risk-taking does not.

Since both measures of stable funding are ratios, it is insightful to examine whether the numerator or the denominator or both impacts the probability of experiencing a critical event. To that end, we estimate (3.3) using the relative loans ($LR$), relative deposits ($DR$) and relative interbank liabilities ($IBLR$) as defined in footnote 52 in place of the $LTD$ and the $LTIBL$. The results in Appendix 3.A.6, Table 3.A6, Table 3.A7 and Table 3.A8 show that for savings banks and credit cooperatives, both the numerator and the denominator of both stable funding measures are statistically significant and have the expected sign, i.e. more loans, fewer deposits and more interbank liabilities are associated with a higher probability of becoming financially distressed.

All in all, it appears to be crucial to differentiate between banking groups when assessing the importance of stable funding. Stable deposits reduce the likelihood of financial distress for savings banks and credit cooperatives, whereas stable funding does not seem to be important for the more heterogeneous group of commercial banks at all. Credit cooperatives also seem to benefit from relying less on interbank funding.

We conduct several robustness checks to examine how sensitive our findings are. We check whether or not our findings are sensitive to different estimation techniques, more conservative assumptions/definitions of variables as well as alternative/additional variables, and we show that the main results remain unchanged. The exact details can be found in Appendix 3.A.7.

### 3.3.4 Discussion of the results

We now turn to the discussion of the presented results. As shown above, the effect of stable funding differs across banking groups. Perhaps surprisingly, our findings for commercial banks excluding big banks suggest that neither the $LTD$ nor the $LTIBL$ has a significant effect on the probability of occurrence of critical events. This raises questions regarding possible explanations for this result. To begin with, the sample of commercial banks used in the analysis is the most heterogeneous of all three banking groups. Commercial banks can differ a lot in their respective business models, in size and also in their funding

[60] The likelihood ratio statistics are large enough for the test to reject the null that the coefficients on the lagged $LTD$ and/or $LTIBL$ are zero.

**Table 3.4: RE logit estimation: main specification – credit cooperatives (no subsequent critical events)**

| Explanatory variables | (1) Estimates | (1) Marginal effects | (2) Estimates | (2) Marginal effects | (3) Estimates | (3) Marginal effects |
|---|---|---|---|---|---|---|
| $log(LTD_{i,t-1})$ | 0.5830*** | 0.0086*** | | | 0.4481*** | 0.0067*** |
| | (0.1170) | (0.0017) | | | (0.1220) | (0.0018) |
| $log(LTIBL_{i,t-1})$ | | | −0.5292*** | −0.0081*** | −0.4076*** | −0.0061*** |
| | | | (0.1158) | (0.0018) | (0.1201) | (0.0018) |
| $ROA_{i,t-1}$ | −0.2584*** | −0.0038*** | −0.2410** | −0.0037*** | −0.2363** | −0.0035*** |
| | (0.0937) | (0.0013) | (0.0946) | (0.0013) | (0.0941) | (0.0013) |
| $log(CR_{i,t-1})$ | −1.7972*** | −0.0267*** | −1.5026*** | −0.0230*** | −1.6737*** | −0.0251*** |
| | (0.2949) | (0.0047) | (0.2807) | (0.0046) | (0.2916) | (0.0046) |
| $log(LLR_{i,t-1})$ | 0.9746*** | 0.0145*** | 0.9957*** | 0.0152*** | 0.9594*** | 0.0144*** |
| | (0.0859) | (0.0017) | (0.0852) | (0.0017) | (0.0860) | (0.0017) |
| $log(AdminR_{i,t-1})$ | 1.0634*** | 0.0158*** | 1.2009*** | 0.0184*** | 1.1316*** | 0.0169*** |
| | (0.2801) | (0.0042) | (0.2779) | (0.0043) | (0.2813) | (0.0043) |
| $log(Liquid_{i,t-1})$ | 0.3045*** | 0.0045*** | 0.1813* | 0.0028* | 0.3011*** | 0.0045*** |
| | (0.1040) | (0.0016) | (0.1003) | (0.0016) | (0.1031) | (0.0016) |
| $log(Total\ Assets_{i,t-1})$ | 0.1710*** | 0.0025*** | 0.1933*** | 0.0030*** | 0.1741*** | 0.0026*** |
| | (0.0558) | (0.0008) | (0.0559) | (0.0009) | (0.0560) | (0.0009) |
| $Z-Score_{i,t-1}$ | −0.0001 | $-6.72 \cdot 10^{-7}$ | −0.0000 | $-3.91 \cdot 10^{-7}$ | −0.0000 | $-5.31 \cdot 10^{-7}$ |
| | (0.0002) | $(3.19 \cdot 10^{-6})$ | (0.0002) | $(2.49 \cdot 10^{-6})$ | (0.0002) | $(2.87 \cdot 10^{-6})$ |
| *Constant* | −7.1787*** | | −1.7262 | | −4.1824** | |
| | (1.0733) | | (1.1497) | | (1.3558) | |
| Time dummies | Yes | | Yes | | Yes | |
| Regional dummies | Yes | | Yes | | Yes | |
| Number of banks | 2,543 | | 2,542 | | 2,541 | |
| Number of observations | 26,940 | | 26,890 | | 26,885 | |
| Pseudo $R^2$ | 0.15 | | 0.15 | | 0.15 | |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time after being financially sound for at least one year, and zero if it is financially healthy in $t$. The table reports the estimated coefficients, the corresponding marginal effects and standard errors (in parentheses) using the random effects logit model (3.3) on the sample of credit cooperatives. Standard errors of the marginal effects are calculated using the delta method. In column (1), the (natural) log of the loan-to-deposit ratio $LTD$ as defined in (3.1) is used as a lagged measure of banks' stable funding $\boldsymbol{x_{i,t-1}}$, in column (2), the (natural) log of the loan-to-interbank liabilities ratio $LTIBL$ as defined in (3.2) is employed, and in column (3), both measures are used. See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

strategy. As discussed above, for commercial banks in particular, both funding ratios display several very large values, which might give rise to statistical insignificance. These stem from banks' business models that use almost no deposits or interbank liabilities to fund their assets. Although taking the log of both ratios mitigates this problem, it does not alter the results. However, this does not necessarily mean that wholesale funding poses no risk to commercial banks. Even after the log transformation, extreme values still greatly impact the empirical distribution of the $LTD$ and the $LTIBL$, which is apparent when the first two moments of the respective empirical $LTD$ and $LTIBL$ distributions for different banking groups are examined.[61] However, the results do not change much when the sample of commercial banks is restricted to financial institutions whose share of loans and deposits in total assets is at least 15%. This means that extreme values are not the reason why the results for commercial banks are different. Therefore, in future work, the analysis of the German commercial banking sector should put more emphasis on heterogeneity across different financial institutions and the different business models associated with this heterogeneity.

In contrast to the findings for the group of other commercial banks, the results for savings banks and credit cooperatives are in line with the literature on the stability of deposits. For these banks, stable funding is associated with a lower probability of experiencing a critical event and this effect is statistically highly significant.[62] In order to better understand the channel of impact of funding, we have examined how these banks' funding structures have evolved over time ahead of a critical event, conditioning on banks experiencing financial distress.[63] Savings banks and credit cooperatives that experience a critical event tend to constantly increase the share of loans financed through liabilities other than deposits in the periods up until that event.[64] In a complementary manner, the $LTIBL$ tends to decrease in the lead-up to the critical events, which means that the share of interbank funding increases as the event approaches, even though this trend does not exactly mirror the development of the $LTD$. What remains to be explained is how these findings fit in with the institutional set-up of savings banks and credit cooperatives. Both banking groups have established insurance funds that protect each member's solvency and liquidity, which should reduce incentives for early withdrawals. Furthermore, to our knowledge, no bank runs took place in Germany between 1995 and 2013. The reason why we still find significant effects might stem from the fact that the largest share of interbank funding is obtained from within the respective banking group, so that those who provide funding simultaneously guarantee the corresponding liabilities. In this case, the guarantee might not protect the bank from sudden funding withdrawals. Because of this specific feature of both banking groups' interbank funding, the result that credit cooperatives benefit from a higher $LTIBL$ while savings banks do not has to be interpreted with extreme caution. For the most part, interbank liabilities of these two banking groups consist of liabilities vis-à-vis regional institutions of credit cooperatives or Landesbanken

[61]The mean of $log(LTD)$ ($log(LTIBL)$) for commercial banks equals 4.6624 (5.6531), while it is 4.4767 (5.8122) for savings banks and 4.3553 (6.3327) for the group of credit cooperatives. The standard deviations for the respective banking groups amount to 1.8523 (1.9872), 0.3305 (0.4708), and 0.3422 (0.6670).

[62]Note that the data do not allow us to identify exogenous liquidity shocks in order to estimate a causal effect on the probability of financial distress of stable funding.

[63]The plots are available from the authors upon request.

[64]This pattern can also be observed for the group of commercial banks.

and to a lesser extent vis-a-vis other banks and the central bank. That is, it is conceivable that the results are (partly) driven by the liquidity services provided by the regional institutions and Landesbanken as described in footnote 50 in the run-up to the respective distress events. Unfortunately, the available data do not allow us to reliably differentiate between credit cooperatives' and savings banks' interbank liabilities vis-à-vis their regional institutions or Landesbanken and vis-à-vis other banks or the central bank throughout the entire sample.[65] Another conjecture is that funding positions other than deposits are associated with more risks, which are not sufficiently captured by the $Z-Score$. Also, it is conceivable that the ability of savings banks and credit cooperatives to attract deposits varies across regions and that our regional federal state-level dummies are too imprecise to take this into account. All in all, the understanding of the mechanisms through which less stable funding leads to financial distress needs to be further developed. We leave that for future research, as identifying and analyzing those channels is beyond the scope of this paper.

As is apparent in Appendix 3.A.5, Figure 3.A4, savings banks and credit cooperatives account for around 30% of the German banking sector's size.[66] However, there are several reasons why this perspective understates the implications of both banking groups being more stable. Figure 3.A5 in Appendix 3.A.5 shows that in terms of credit exposures, the share of savings banks and credit cooperatives is considerably higher.[67] Moreover, savings banks and credit cooperatives play an important role when it comes to providing loans to small and medium-sized enterprises, which comprise the largest portion of all firms in the German economy by far (Behr, Foos and Norden (2015), IMF (2016)). Apart from that, there is some evidence that savings banks contribute to enhancing local economic development in underdeveloped regions (Hakenes, Hasan, Molyneux and Xie (2015)). All of the above suggests that the benefits of having more stable savings banks and credit cooperatives are substantially greater than it might seem at the first glance.

[65]For the available observations, it turns out that for credit cooperatives the effect of the $LTIBL$ is not significant when only liabilities vis-à-vis their central institutions are considered, whereas the significant negative effect remains when the liabilities vis-à-vis the central institutions are excluded. For savings banks, regressions based on the available observations reveal a significant negative effect of the $LTIBL$ once central bank credit is excluded, while the effect of the $LTIBL$ based solely on central bank credit is significantly positive, suggesting that savings banks financing their loans to a greater extent via the central bank, have experienced fewer critical events. This result could not be found for credit cooperatives.

[66]This share varies between 25% and 38%, depending on the time period. Overall, the relative share of assets of savings banks and credit cooperatives has declined over time.

[67]Over the time horizon of the entire sample, the share of loans of savings banks and credit cooperatives in the overall loans of the entire German banking sector lies between 33% and 45%.

## 3.4 Conclusion

The recent financial crisis has highlighted the importance of stable funding for banks. The regulatory response on the part of the BCBS to the problems caused by the lack of ample liquidity buffers and excessive maturity mismatches has been to introduce the LCR and the NSFR. Although it is difficult at this point to assess whether and to what extent the new regulatory requirements will be instrumental in adequately addressing the problems associated with unstable funding structures in the banking sector, it is possible to infer from the past what difference stable funding has made with respect to the financial health of banks. Quantifying this difference and thus approximating one effect of the NSFR on the probability of banks experiencing financial distress is this paper's main objective.

Our results suggest that for Germany, financial institutions associated with the banking groups of savings banks and credit cooperatives, respectively, have benefited greatly from financing their loans with stable deposits, as they have had a lower probability of experiencing a distress event. Our results, at least partly, confirm the empirical findings in the literature. This suggests that the introduction of the NSFR can be expected to be conducive to the financial health of the corresponding financial institutions, even though a comprehensive analysis of the impact of Basel III liquidity requirements on the German banking sector is beyond the scope of this study.[68] This finding has implications for savings banks' and credit cooperatives' business practices as well as the supervisory process for these banking groups. No positive effect of stable funding could be found for the overall stability of commercial banks (excluding big banks), which are found to be far more heterogeneous with respect to their business models.

[68] The caveat that Goodhart's law, according to which a statistical regularity/measure loses its property as an indicator of economic developments as soon as it is used for regulatory purposes (Goodhart (1975), Daníelsson (2002)), might also apply to the introduction of the NSFR is, of course, valid.

# Bibliography


Adrian, T. and Brunnermeier, M. K. (2011). CoVar, NBER Working Paper 17454, National Bureau of Economic Research.

Ai, C. and Norton, E. C. (2003). Interaction terms in logit and probit models, Economics Letters **80**(1): 123–129.

Baltagi, B. H. (2008). Econometric Analysis of Panel Data, 4th edn, John Wiley & Sons Limited, West Sussex.

Bank of England (2014). The Financial Policy Committee's powers to supplement capital requirements, A Policy Statement.

BCBS (2013). Basel III: The Liquidity Coverage Ratio and liquidity risk monitoring tools, Basel Committee on Banking Supervision .

BCBS (2014). Basel III: The Net Stable Funding Ratio, Basel Committee on Banking Supervision .

Behn, M., Detken, C., Peltonen, T. A. and Schudel, W. (2013). Setting Countercyclical Capital Buffers based on early warning models: Would it work?, ECB Working Paper 1604, European Central Bank.

Behr, P., Foos, D. and Norden, L. (2015). Cyclicality of SME lending and government involvement in banks, Deutsche Bundesbank Discussion Paper 39, Deutsche Bundesbank.

Berger, A. N., Bouwman, C. H., Kick, T. and Schaeck, K. (2016). Bank liquidity creation following regulatory interventions and capital support, Journal of Financial Intermediation p. forthcoming.

Billett, M. T., Garfinkel, J. A. and O'Neal, E. S. (1998). The cost of market versus regulatory discipline in banking, Journal of Financial Economics **48**: 333–358.

BIS (2008). 78th Annual report, Bank for International Settlements .

Bologna, P. (2015). Structural funding and bank failures, Journal of Financial Services Research **47**(1): 81–113.

Boyd, J. H., Graham, S. L. and Hewitt, S. R. (1993). Bank holding company mergers with nonbank financial firms: Effects on the risk of failure, Journal of Banking & Finance **17**(1): 43–63.

Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007-08, Journal of Economic Prespectives **23**(1): 77–100.

Brunnermeier, M. K. and Pedersen, L. H. (2009). Market liquidity and funding liquidity, Review of Financial Studies **22**(6): 2201–2238.

Bundesverband der Deutschen Volksbanken und Raiffeisenbanken (2014). Statutes of the protection scheme.

Butler, J. S. and Moffitt, R. (1982). A computationally efficient quadrature procedure for the one-factor multinomial probit model, Econometrica **50**(3): 761–764.

Calomiris, C. W. and Kahn, C. M. (1991). The role of demandable debt in structuring optimal banking arrangements, American Economic Review **81**(3): 497–513.

Cameron, C. A. and Trivedi, P. K. (2005). Microeconometrics, Cambridge University Press, Cambridge.

Chamberlain, G. (1980). Analysis of covariance with qualitative data, The Review of Economic Studies **47**(1): 225–238.

Choudhry, M. (2011). An Introduction to Banking - Liquidity Risk and Asset-Liability Management, John Wiley & Sons Limited, West Sussex.

Daníelsson, J. (2002). The emperor has no clothes: Limits to risk modelling, Journal of Banking & Finance **26**(7): 1273–1296.

Demirgüç-Kunt, A. and Detragiache, E. (1998). The determinants of banking crises in developing and developed countries, IMF Staff Papers **45**(1): 81–109.

Demirgüç-Kunt, A. and Huizinga, H. (2010). Bank activity and funding strategies: The impact on risk and returns, Journal of Financial Economics **98**(3): 626–650.

Deutsche Bundesbank (2015). Monthly Report April 2015 pp. 35–60.

Deutscher Bundestag (2009). Drucksache **16/14000**: 50–70.

Diamond, D. W. and Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity, Journal of Political Economy **91**(3): 401–419.

Drehmann, M., Borio, C. and Tsatsaronis, K. (2011). Anchoring Countercyclical Capital Buffers: The role of credit aggregates, BIS Working Paper 355, Bank for International Settlements.

European Systemic Risk Board (2014). The ESRB handbook on operationalising macro-prudential policy in the banking sector.

Flannery, M. J. (1982). Retail bank deposits as quasi-fixed factors of production, American Economic Review **72**(3): 527–536.

Foos, D., Norden, L. and Weber, M. (2010). Loan growth and riskiness of banks, Journal of Banking & Finance **34**(12): 2929–2940.

Gobat, J., Yanase, M. and Maloney, J. F. (2014). The Net Stable Funding Ratio: Impact and issues for consideration, IMF Working Paper 106, International Monetary Fund.

Goodhart, C. A. (1975). Problems of monetary management: The U.K. Experience, Papers in Monetary Economics 1, Reserve Bank of Australia.

Greene, W. H. (2012). Econometric Analysis, 7th edn, Pearson Education Limited, Essex.

Gubitz, B. (2013). Das Ende des Landesbankensektors: Der Einfluss von Politik, Management und Sparkassen, Springer Gabler, Wiesbaden.

Guinnane, T. (2013). Die Geschichte der DZ Bank: Das genossenschaftliche Zentralbankwesen vom 19. Jahrhundert bis heute, C.H. Beck, Munich.

Hakenes, H., Hasan, I., Molyneux, P. and Xie, R. (2015). Small banks and local economic development, Review of Finance **19**(2): 653–683.

Hong, H., Huang, J.-Z. and Wu, D. (2014). The information content of Basel III liquidity risk measures, Journal of Financial Stability **15**: 91–111.

Huang, R. and Ratnovski, L. (2011). The dark side of bank wholesale funding, Journal of Financial Intermediation **20**(2): 248–263.

IMF (2016). Germany, Financial Sector Assessment Program, Stress Testing the Banking and Insurance Sectors – Technical Note, International Monetary Fund, IMF Country Report No. 16/191 June 2016 .

Kick, T. and Koetter, M. (2007). Slippery slopes of stress: Ordered failure events in German banking, Journal of Financial Stability **3**: 132–148.

Koetter, M., Bos, J. W., Heid, F., Kolari, J. W., Kool, C. J. and Porath, D. (2007). Accounting for distress in bank mergers, Journal of Banking & Finance **31**(10): 3200–3217.

Laeven, L. and Levine, R. (2009). Bank governance, regulation and risk taking, Journal of Financial Economics **93**(2): 259–275.

López-Espinosa, G., Moreno, A., Rubia, A. and Valderrama, L. (2012). Short-term wholesale funding and systemic risk: A global CoVar approach, Journal of Banking & Finance **36**(12): 3150–3162.

Mundlak, Y. (1978). On the pooling of time series and cross section data, Econometrica **46**(1): 69–85.

Peresetsky, A., Karminsky, A. and Golovan, S. (2004). Probability of default models of russian banks, BOFIT Discussion Paper 21, Bank of Finland Institute for Economies in Transition.

Porath, D. (2006). Estimating probabilities of default for German savings banks and credit cooperatives, Schmalenbach Business Review **58**: 214–233.

Sharpe, S. A. (1997). The effect of consumer switching costs on prices: A theory and its application to the bank deposit market, Review of Industrial Organization **12**(1): 79–94.

Shin, H. S. (2009). Reflections on modern bank runs: A case study of Northern Rock, Journal of Economic Prespectives **23**(1): 101–119.

Simpson, C. V. (2013). The German Sparkassen, Civitas, London.

Song, F. and Thakor, A. V. (2007). Relationship banking, fragility, and the asset-liability matching problem, Review of Financial Studies **20**(6): 2129–2177.

Van den End, J. W. (2013). A macroprudential approach to address liquidity risk with the loan-to-deposit ratio, DNB Working Paper 372, De Nederlandsche Bank.

Vázquez, F. F. and Federico, P. (2012). Bank funding structures and risk: evidence from the global financial crisis, IMF Working Paper 29, International Monetary Fund.

Wheelock, D. C. and Wilson, P. W. (2000). Why do banks disappear? The determinants of U.S. bank failures and acquisitions, Review of Economics and Statistics **82**(1): 127–138.

Wong, E., Fong, T., Li, K.-F. and Choi, H. (2010). An assessment of the long-term economic impact of the new regulatory reform on Hong Kong, Research Note 05, Hong Kong Monetary Authority.

Wooldridge, J. M. (2002). Econometric Analysis of Cross Section and Panel Data, The MIT Press, Cambridge.

Yan, M., Hall, M. J. and Turner, P. (2012). A cost-benefit analysis of Basel III: Some evidence from the UK, International Review of Financial Analysis **25**: 73–82.

# 3.A Appendix

## 3.A.1 Descriptive statistics

**Table 3.A1: Critical events – breakdown by banking group and over time**

| | Number of critical events | | | |
|---|---|---|---|---|
| **Year** | **All banks** | **Commercial banks** | **Savings banks and Landesbanken** | **Credit cooperatives and regional institutions** |
| 1995 | 48 | 5 | 1 | 42 |
| 1996 | 55 | 5 | 4 | 46 |
| 1997 | 64 | 7 | 2 | 55 |
| 1998 | 59 | 5 | 5 | 49 |
| 1999 | 62 | 4 | 1 | 57 |
| 2000 | 54 | 3 | 6 | 45 |
| 2001 | 79 | 16 | 13 | 50 |
| 2002 | 52 | 12 | 11 | 29 |
| 2003 | 24 | 0 | 7 | 17 |
| 2004 | 29 | 2 | 3 | 24 |
| 2005 | 19 | 9 | 2 | 8 |
| 2006 | 13 | 6 | 1 | 6 |
| 2007 | 17 | 3 | 6 | 8 |
| 2008 | 20 | 8 | 5 | 7 |
| 2009 | 21 | 9 | 6 | 6 |
| 2010 | 7 | 5 | 1 | 1 |
| 2011 | 7 | 3 | 0 | 4 |
| 2012 | 5 | 2 | 1 | 2 |
| 2013 | 2 | 1 | 1 | 0 |
| Total | 637 | 105 | 76 | 456 |

**Note:** This table shows the breakdown of financial distress events (without subsequent critical events) as defined in Section 3.3.1.

**Table 3.A2: Critical events – breakdown by event type and banking group**

| | Types of critical events | | | |
|---|---|---|---|---|
| **Critical event** | **All banks** | **Commercial banks** | **Savings banks and Landesbanken** | **Credit cooperatives and regional institutions** |
| • Disclosure of facts pursuant to section 29(3) of the Banking Act | 37 | 4 | 11 | 22 |
| • Operating loss in excess of 25% of liable capital | 64 | 47 | 10 | 7 |
| • Losses of liable capital amounting to at least 25% pursuant to section 24(1) of the Banking Act; | 16 | 11 | 2 | 3 |
| • Forbiddance of granting of loans/ large exposures pursuant to sections 45 or 46 of the Banking Act; | 1 | 0 | 1 | 0 |
| • Moratoriums pursuant to section 4a of the Banking Act | 3 | 3 | 0 | 0 |
| • Capital preservation measures | 302 | 29 | 23 | 250 |
| • Restructuring caused by mergers | 211 | 9 | 28 | 174 |
| • Liquidation or insolvency | 1 | 1 | 0 | 0 |
| • SoFFin recapitalisation measures and guarantees | 2 | 1 | 1 | 0 |
| Total | 637 | 105 | 76 | 456 |

**Note:** This table shows the breakdown of financial distress events (without subsequent critical events) as defined in Section 3.3.1.

**Table 3.A3: Summary statistics for the explanatory variables by banking group**

| | obs | mean | sd | p25 | p50 | p75 |
|---|---|---|---|---|---|---|
| | | | **All banks:** | | | |
| *LTD* | 40,572 | 535.4192 | 21,589.21 | 68.17 | 83.45 | 99.13 |
| *LTIBL* | 40,432 | 6,340.52 | 341,041.7 | 314.81 | 446.01 | 657.49 |
| *ROA* | 40,572 | 0.470 | 0.86 | 0.26 | 0.42 | 0.62 |
| *CR* | 40,572 | 5.400 | 3.8503 | 4.108 | 4.872 | 5.7857 |
| *LLR* | 40,572 | 1.2877 | 59.4566 | 0.3784 | 0.69 | 1.108 |
| *AdminR* | 40,572 | 2.2954 | 1.8202 | 1.851 | 2.146 | 2.479 |
| *Liquid* | 40,572 | 6.5506 | 6.2029 | 3.5149 | 5.2630 | 7.6378 |
| *Total Assets* | 40,572 | 2,321,599 | 25,300,000 | 93,872 | 260,516 | 793,913.5 |
| $Z-Score$ | 40,572 | 49.119 | 391.2474 | 17.971 | 26.043 | 38.251 |
| *LR* | 40,572 | 58.5889 | 14.3476 | 51.873 | 60.855 | 67.69 |
| *DR* | 40,572 | 71.1947 | 13.8737 | 66.367 | 73.529 | 79.622 |
| *IBLR* | 40,572 | 15.1961 | 10.9056 | 8.5771 | 13.251 | 18.962 |
| *AbnormLoangr* | 40,503 | 439.598 | 80,523.85 | -2.78 | 0.203 | 3.738 |
| *RegLoangr* | 40,521 | 4.8343 | 7.0057 | 0.998 | 4.626 | 8.561 |
| *RegDepositgr* | 40,521 | 4.2528 | 5.3036 | 1.89 | 4.64 | 7.2738 |
| | | | **Commercial banks:** | | | |
| *LTD* | 2,925 | 5,959.35 | 79,937.39 | 52.36 | 95.472 | 167.048 |
| *LTIBL* | 2,837 | 65,095.63 | 1,157,305 | 119.1138 | 238.1039 | 625.1888 |
| *ROA* | 2,925 | 0.7331 | 2.8153 | 0.1438 | 0.506 | 1.08199 |
| *CR* | 2,925 | 10.365 | 12.2051 | 4.3618 | 6.7173 | 10.6906 |
| *LLR* | 2,925 | 7.179 | 221.371 | 0.29819 | 0.91512 | 1.94705 |
| *AdminR* | 2,925 | 3.6854 | 6.277 | 1.3608 | 2.1686 | 3.6961 |
| *Liquid* | 2,925 | 13.5809 | 17.2984 | 3.3019 | 7.2596 | 15.3905 |
| *Total Assets* | 2,925 | 13,400,000 | 84,400,000 | 166,094 | 593,997 | 2,738,188 |
| $Z-Score$ | 2,925 | 85.88697 | 736.3427 | 9.28747 | 16.66133 | 36.0171 |
| *LR* | 2,925 | 49.7006 | 30.0829 | 23.2836 | 50.8555 | 75.0138 |
| *DR* | 2,925 | 50.8411 | 28.4837 | 26.6283 | 55.4350 | 76.1873 |
| *IBLR* | 2,925 | 25.876 | 25.2452 | 4.97376 | 17.5633 | 40.8104 |
| *AbnormLoangr* | 2,863 | 6,186.53 | 302,861.3 | -8.1221 | 1.627684 | 15.108 |
| *RegLoangr* | 2,881 | 4.6042 | 7.280282 | 0.91212 | 4.697908 | 8.95849 |
| *RegDepositgr* | 2,881 | 4.732009 | 6.290622 | 1.73019 | 4.979391 | 7.69307 |
| | | | **Savings banks and Landesbanken:** | | | |
| *LTD* | 9,547 | 94.42401 | 31.78976 | 76.6321 | 92.6413 | 109.812 |
| *LTIBL* | 9,547 | 372.8428 | 238.9239 | 237.932 | 319.6606 | 435.328 |
| *ROA* | 9,547 | 0.385896 | 0.284273 | 0.23059 | 0.389409 | 0.54895 |
| *CR* | 9,547 | 4.353592 | 1.106071 | 3.63853 | 4.196681 | 4.9825 |
| *LLR* | 9,547 | 0.913744 | 0.684155 | 0.47663 | 0.746607 | 1.13857 |
| *AdminR* | 9,547 | 1.790906 | 0.333592 | 1.64744 | 1.820822 | 1.98297 |
| *Liquid* | 9,547 | 4.12525 | 2.24523 | 2.5143 | 3.6706 | 5.1991 |
| *Total Assets* | 9,547 | 4,306,836 | 20,500,000 | 637,385 | 1,182,540 | 2,234,355 |
| $Z-Score$ | 9,547 | 51.67706 | 370.1547 | 20.0120 | 28.09728 | 41.7210 |
| *LR* | 9,547 | 59.02045 | 12.44403 | 53.0218 | 61.35803 | 67.2348 |
| *DR* | 9,547 | 65.64215 | 11.14319 | 60.1952 | 66.9744 | 72.9850 |
| *IBLR* | 9,547 | 19.81646 | 9.16117 | 13.0233 | 18.59369 | 25.3852 |
| *AbnormLoangr* | 9,540 | 1.869788 | 16.86038 | -2.44011 | -0.15700 | 2.37632 |
| *RegLoangr* | 9,540 | 4.631268 | 7.669494 | 0.91233 | 3.928161 | 8.38486 |
| *RegDepositgr* | 9,540 | 3.968659 | 5.414738 | 1.45309 | 4.177924 | 7.098978 |
| | | | **Credit cooperatives and regional institutions:** | | | |
| *LTD* | 28,100 | 120.657 | 2,174.201 | 66.88138 | 80.48493 | 93.98087 |
| *LTIBL* | 28,048 | 2,428.84 | 178,489 | 376.2305 | 506.2593 | 733.5483 |
| *ROA* | 28,100 | 0.471442 | 0.4619707 | 0.273917 | 0.429250 | 0.623472 |
| *CR* | 28,100 | 5.238987 | 1.588457 | 4.333921 | 5.025113 | 5.855574 |
| *LLR* | 28,100 | 0.801447 | 0.7775164 | 0.347934 | 0.648863 | 1.052757 |
| *AdminR* | 28,100 | 2.322089 | 0.5979904 | 2.02234 | 2.28186 | 2.572058 |
| *Liquid* | 28,100 | 6.64278 | 3.943463 | 4.10359 | 5.79627 | 8.11926 |
| *Total Assets* | 28,100 | 497,499 | 4,988,774 | 69,652.5 | 150,143 | 346,242 |
| $Z-Score$ | 28,100 | 44.42201 | 343.342 | 18.18525 | 25.93646 | 37.05751 |
| *LR* | 28,100 | 59.36753 | 11.89746 | 52.68924 | 60.98778 | 67.64254 |
| *DR* | 28,100 | 75.19988 | 9.036758 | 70.2444 | 75.8834 | 81.16526 |
| *IBLR* | 28,100 | 12.51462 | 7.111397 | 7.789638 | 11.78918 | 16.23078 |
| *AbnormLoangr* | 28,100 | 2.675052 | 14.92909 | -2.75043 | 0.3104994 | 3.880392 |
| *RegLoangr* | 28,100 | 4.926823 | 6.734028 | 1.07077 | 4.74772 | 8.60905 |
| *RegDepositgr* | 28,100 | 4.300131 | 5.147798 | 2.127622 | 4.746625 | 7.233285 |

Continued on next page

**Table 3.A3: Summary statistics for the explanatory variables by banking group**

| Continued from previous page | | | | | | |
|---|---|---|---|---|---|---|
| | obs | mean | sd | p25 | p50 | p75 |
| **Commercial banks without big banks:** | | | | | | |
| $LTD$ | 2,850 | 6,113.686 | 80,976.99 | 51.24802 | 94.88831 | 168.5997 |
| $LTIBL$ | 2,713 | 68,034.12 | 1,183,384 | 120.381 | 245.6303 | 640.1249 |
| $ROA$ | 2,850 | 0.7484081 | 2.849657 | 0.1463988 | 0.524051 | 1.111011 |
| $CR$ | 2,850 | 10.55456 | 12.30643 | 4.448797 | 6.904447 | 10.83442 |
| $LLR$ | 2,850 | 7.340622 | 224.2636 | 0.2935469 | 0.9217868 | 1.98661 |
| $AdminR$ | 2,850 | 3.742417 | 6.348221 | 1.386909 | 2.204323 | 3.746095 |
| $Liquid$ | 2,850 | 13.76577 | 17.47942 | 3.252019 | 7.380536 | 15.93746 |
| $Total\ Assets$ | 2,850 | 3,649,987 | 11,000,000 | 160,582 | 553,710 | 2,363,413 |
| $Z-Score$ | 2,850 | 87.46222 | 745.8858 | 9.455287 | 16.73799 | 36.12203 |
| $LR$ | 2,850 | 49.94104 | 30.35443 | 22.91734 | 51.86193 | 75.80461 |
| $DR$ | 2,850 | 50.93529 | 28.7441 | 25.36346 | 56.28352 | 76.58227 |
| $IBLR$ | 2,850 | 25.89813 | 25.51466 | 4.769899 | 17.11728 | 42.22281 |
| $AbnormLoangr$ | 2,788 | 6,352.532 | 306,907.6 | -8.137938 | 1.444487 | 15.22671 |
| $RegLoangr$ | 2,806 | 4.588322 | 7.272036 | 0.9121202 | 4.697908 | 8.958492 |
| $RegDepositgr$ | 2,806 | 4.705173 | 6.277733 | 1.73019 | 4.932129 | 7.693069 |
| **Savings banks:** | | | | | | |
| $LTD$ | 9,341 | 92.4525 | 27.98149 | 76.33772 | 92.07174 | 108.4497 |
| $LTIBL$ | 9,341 | 378.556 | 238.3254 | 243.555 | 323.4473 | 438.4264 |
| $ROA$ | 9,341 | 0.391578 | 0.2820592 | 0.2384984 | 0.3946473 | 0.5523934 |
| $CR$ | 9,341 | 4.383198 | 1.059563 | 3.669632 | 4.216748 | 4.997026 |
| $LLR$ | 9,341 | 0.920699 | 0.6864677 | 0.481417 | 0.7543242 | 1.14727 |
| $AdminR$ | 9,341 | 1.821882 | 0.262044 | 1.661232 | 1.82774 | 1.986176 |
| $Liquid$ | 9,341 | 4.156886 | 2.247618 | 2.548492 | 3.694542 | 5.224406 |
| $Total\ Assets$ | 9,341 | 1,896,822 | 2,673,656 | 629,465 | 1,155,496 | 2,123,026 |
| $Z-Score$ | 9,341 | 50.51807 | 368.6469 | 20.00154 | 28.01303 | 41.21417 |
| $LR$ | 9,341 | 59.47948 | 12.10679 | 53.79467 | 61.60516 | 67.36791 |
| $DR$ | 9,341 | 66.59475 | 9.145858 | 60.6842 | 67.23883 | 73.11214 |
| $IBLR$ | 9,341 | 19.46697 | 8.845534 | 12.90444 | 18.38236 | 24.86764 |
| $AbnormLoangr$ | 9,335 | 1.812651 | 16.81694 | -2.431434 | -0.178719 | 2.329706 |
| $RegLoangr$ | 9,335 | 4.620632 | 7.678773 | 0.9123301 | 3.843997 | 8.384861 |
| $RegDepositgr$ | 9,335 | 3.957975 | 5.405501 | 1.45309 | 4.14274 | 7.098978 |
| **Credit cooperatives:** | | | | | | |
| $LTD$ | 28,051 | 120.566 | 2,176.096 | 66.8373 | 80.46535 | 93.92933 |
| $LTIBL$ | 27,994 | 2,433.46 | 178,661 | 376.9081 | 506.7944 | 734.1421 |
| $ROA$ | 28,051 | 0.471725 | 0.4622086 | 0.2742768 | 0.4294842 | 0.6238908 |
| $CR$ | 28,051 | 5.242896 | 1.586864 | 4.337416 | 5.028328 | 5.857646 |
| $LLR$ | 28,051 | 0.800216 | 0.7770149 | 0.3473533 | 0.6477177 | 1.051515 |
| $AdminR$ | 28,051 | 2.325377 | 0.5932935 | 2.023904 | 2.282674 | 2.572609 |
| $Liquid$ | 28,051 | 6.648329 | 3.944079 | 4.107282 | 5.800634 | 8.125089 |
| $Total\ Assets$ | 28,051 | 346,188 | 922,339.5 | 69,518 | 149,608 | 344,755 |
| $Z-Score$ | 28,051 | 44.45206 | 343.6403 | 18.19842 | 25.94434 | 37.05887 |
| $LR$ | 28,051 | 59.44084 | 11.77585 | 52.75204 | 61.01212 | 67.65944 |
| $DR$ | 28,051 | 75.31134 | 8.64041 | 70.28384 | 75.90201 | 81.17254 |
| $IBLR$ | 28,051 | 12.42895 | 6.805807 | 7.78218 | 11.77123 | 16.19441 |
| $AbnormLoangr$ | 28,051 | 2.670382 | 14.92728 | -2.74899 | 0.307313 | 3.870427 |
| $RegLoangr$ | 28,051 | 4.925159 | 6.73288 | 1.07077 | 4.74772 | 8.60905 |
| $RegDepositgr$ | 28,051 | 4.297801 | 5.145128 | 2.117221 | 4.713122 | 7.192748 |

**Table 3.A4: Summary statistics for the stable funding variables by financial distress status and banking group**

| | obs | mean | sd | p25 | p50 | p75 |
|---|---|---|---|---|---|---|
| **All banks:** | | | | | | |
| **Financially healthy bank years:** | | | | | | |
| $LTD_{t-1}$ | 39,935 | 538.8685 | 21,755.18 | 68.1275 | 83.3344 | 98.97538 |
| $LTIBL_{t-1}$ | 39,801 | 6,428.339 | 343,733.4 | 316.1534 | 447.069 | 659.1206 |
| **Bank years in financial distress:** | | | | | | |
| $LTD_{t-1}$ | 637 | 319.1731 | 3,882.533 | 70.7362 | 89.4694 | 107.7242 |
| $LTIBL_{t-1}$ | 631 | 801.3614 | 4,625.522 | 250.2943 | 356.9962 | 545.52 |
| **Commercial banks:** | | | | | | |
| **Financially healthy bank years:** | | | | | | |
| $LTD_{t-1}$ | 2,820 | 6,148.353 | 81,393.8 | 53.0595 | 95.95023 | 167.6354 |
| $LTIBL_{t-1}$ | 2,738 | 67,356.81 | 1,177,986 | 119.8324 | 238.8741 | 622.6769 |
| **Bank years in financial distress:** | | | | | | |
| $LTD_{t-1}$ | 105 | 883.3319 | 7,451.497 | 37.61707 | 88.56574 | 119.599 |
| $LTIBL_{t-1}$ | 99 | 2,559.385 | 11,526.53 | 92.87137 | 174.4209 | 1,166.667 |
| **Savings banks and Landesbanken:** | | | | | | |
| **Financially healthy bank years:** | | | | | | |
| $LTD_{t-1}$ | 9,471 | 94.20008 | 31.52169 | 76.59752 | 92.53974 | 109.5798 |
| $LTIBL_{t-1}$ | 9,471 | 373.777 | 239.2048 | 238.9864 | 320.3487 | 436.0388 |
| **Bank years in financial distress:** | | | | | | |
| $LTD_{t-1}$ | 76 | 122.3301 | 48.69925 | 91.1165 | 116.4177 | 146.9507 |
| $LTIBL_{t-1}$ | 76 | 256.4203 | 164.4315 | 176.2266 | 227.1395 | 285.2223 |
| **Credit cooperatives and regional institutions:** | | | | | | |
| **Financially healthy bank years:** | | | | | | |
| $LTD_{t-1}$ | 27,644 | 118.9838 | 2,160.675 | 66.81621 | 80.39054 | 93.84774 |
| $LTIBL_{t-1}$ | 27,592 | 2,460.544 | 179,957.7 | 377.7126 | 508.2645 | 736.9607 |
| **Bank years in financial distress:** | | | | | | |
| $LTD_{t-1}$ | 456 | 222.0753 | 2,879.134 | 72.34592 | 87.70964 | 102.3842 |
| $LTIBL_{t-1}$ | 456 | 510.5087 | 443.8209 | 301.3046 | 412.1315 | 566.3138 |

**Note:** This table shows the summary statistics of the stable funding measures (loan-to-deposit ratio $LTD$ as defined in (3.1) and loan-to-interbank liabilities ratio $LTIBL$ as defined in (3.2)) by financial distress status (without subsequent critical events as defined in Section 3.3.1) in the following period and banking group.

### 3.A.2 List of variables

**Table 3.A5: Definition of variables used in various estimations**

| Variable | Units | Definition |
|---|---|---|
| Loan-to-deposit ratio | % | $LTD_{it} = \frac{Loans_{it}}{Deposits_{it}} \cdot 100$ |
| Loan-to-interbank liabilities ratio | % | $LTIBL_{it} = \frac{Loans_{it}}{Interbank\ Liabilities_{it}} \cdot 100$ |
| Return on assets | % | $ROA_{it} = \frac{Return_{it}}{Total\ Assets_{it}} \cdot 100$ |
| Capital ratio | % | $CR_{it} = \frac{Equity_{it}}{Total\ Assets_{it}} \cdot 100$ |
| Loan loss ratio | % | $LLR_{it} = \frac{Provisions\ and\ allowances\ for\ credit\ losses_{it}}{Total\ Assets_{it}} \cdot 100$ |
| Administrative expenses ratio | % | $AdminR_{it} = \frac{Personnel\ expenses\ and\ other\ administrative\ expenses_{it}}{Total\ Assets_{it}} \cdot 100$ |
| Liquid assets | % | $Liquid_{it} = \frac{Cash,\ central\ bank\ deposits_{it}\ and\ overnight\ interbank\ loans_{it}}{Total\ Assets_{it}} \cdot 100$ |
| Size | € thousand | $Total\ Assets_{it}$ |

Continued on next page

**Table 3.A5: Definition of variables used in various estimations**

Continued from previous page

| **Variable** | **Units** | **Definition** |
|---|---|---|
| Distance to default | – | $Z - Score_{it} = \frac{CR_{it} + ROA_{it}}{\sigma_{ROA_{it}}}$[69] |
| Loans ratio | % | $LR_{it} = \frac{Loans_{it}}{Total\ Assets_{it}} \cdot 100$ |
| Deposits ratio | % | $DR_{it} = \frac{Deposits_{it}}{Total\ Assets_{it}} \cdot 100$ |
| Interbank liabilities ratio | % | $IBLR_{it} = \frac{Interbank\ Liabilities_{it}}{Total\ Assets_{it}} \cdot 100$ |
| Abnormal loan growth | Percentage points | $AbnormLoangr_{it} = Growth\ rate\ of\ loans_{it} - Median\ growth\ rate\ of\ loans_t$ |
| Regional loan growth | % | $RegLoangr_{it} = \frac{\sum_i^{N^{reg}} Loans_{it} - \sum_i^{N^{reg}} Loans_{i,t-1}}{\sum_i^{N^{reg}} Loans_{i,t-1}} \cdot 100$ |
| Regional deposit growth | % | $RegDepositsgr_{it} = \frac{\sum_i^{N^{reg}} Deposits_{it} - \sum_i^{N^{reg}} Deposits_{i,t-1}}{\sum_i^{N^{reg}} Deposits_{i,t-1}} \cdot 100$ |

[69] The standard deviation of the return on assets $\sigma_{ROA_{it}}$ is computed using all available observations on $ROA$ up to the respective period $t$, i.e. for a given bank $i$, $\sigma_{ROA_{it}}$ is different for every available period $t$ because with each new period an additional observation is used to calculate the standard deviation. At least two observations are needed to compute $\sigma_{ROA_{it}}$ for bank $i$.

### 3.A.3 A descriptive analysis of the critical events used in the study

As can be seen in Figure 3.A1, during the period from 1995 to 2013 there were 637 critical events (without subsequent critical events)[70], 105 of which were commercial banks, 76 savings banks and Landesbanken, and 456 credit cooperatives and their regional institutions[71], i.e. in absolute numbers most critical events have been recorded for the banking group of credit cooperatives.[72]

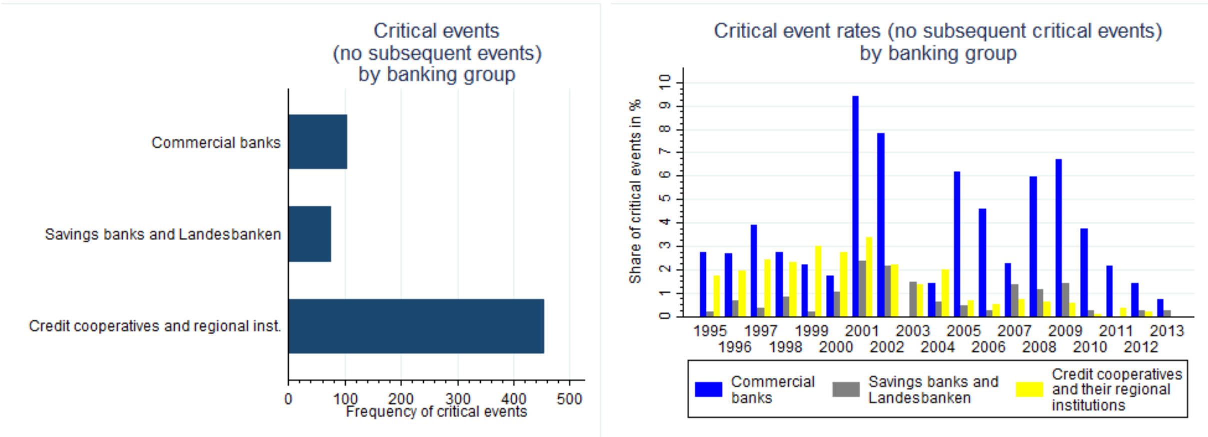



**Figure 3.A1: Critical events by banking group and over time**

For credit cooperatives, the highest annual shares of banks in distress were recorded between 1995 up until 2001.[73] After that period, the share of credit cooperatives experiencing critical events went down to 0.5% in 2006 from over 3% in 2001. Credit cooperatives endured the financial crisis fairly well with a share of banks in distress that hardly rose.[74]

[70] As stated in footnote 21, the number of critical events is conditional on available observations for our explanatory variables. There were 719 critical events during the period from 1995 to 2013, but for 82 of them at least one regressor is missing.

[71] Commercial banks or private banks, public banks (savings banks and Landesbanken), and cooperatives (credit cooperatives and their regional institutions) constitute the three pillars of the German banking sector (see, for example, Berger, Bouwman, Kick and Schaeck (2016), IMF (2016)).

[72] The exact breakdown of critical events by banking group and over time can be found in Appendix 3.A.1, Table 3.A1.

[73] The structural change in the German banking sector in the 1990s had a particularly severe impact on the cooperatives sector which led to a strong consolidation process within the banking group and the relatively high share of credit cooperatives experiencing critical events between 1995 and 2001 (see Guinnane (2013)).

[74] The dataset on critical events also contains information on bank closures. Since this label also applies to financially healthy banks that have been taken over by other banks, closures are not tantamount to critical events. There are 272 bank years in which banks were closed after they were healthy for a number of years prior to the closure, even though they had experienced at least one critical event before becoming financially healthy for at least one year. In 441 cases, a closure is immediately preceded by at least one less severe critical event. In theory, it is conceivable that a bank's financial condition deteriorates so

The share of commercial banks experiencing critical events was similarly high between 1995 and 2001. However, during the years of the dot-com bubble, the share sharply rose towards 9% which implied an increase of more than 400%. While there were not many new events in the years after the bubble for any of the banking groups, commercial banks clearly had the highest share of banks whose status changed from financially healthy to distressed for the first time during that period. The savings banks have emerged to be the most stable sector in Germany over the 19 years observed. On average, their share of institutions in financial distress is below 1%. Only over the course of the dot-com bubble did the share notably rise, but never much higher than 2%. Since then, it has stayed constantly low and just like credit cooperatives, the largest portion of all savings banks got through the financial crisis very much unharmed.

quickly that the bank has to be liquidated within one year. However, this is highly improbable. We conservatively omit those 272 bank years in which banks were closed, whenever those banks were healthy in the years prior to the closure. Because of this, the critical event rates displayed in Figure 3.A1 might be slightly higher than they actually were. Keeping these observations in the dataset and treating them as financially healthy bank years has no bearing on our results.

## 3.A.4 A descriptive analysis of the loan-to-deposit ratio and the loan-to-interbank liabilities ratio

The $LTD$ reveals great differences in the share of loans in deposits across the banking groups in Germany. This particularly refers to the comparison between commercial banks, on the one hand, and savings banks and credit cooperatives on the other. Table 3.A3 in Appendix 3.A.1 shows that the distribution of the $LTD$ of commercial banks has a very large mean of 5,959%. This is mainly due to very high $LTD$s in the 99th percentile. Very large values can be explained by some commercial banks' business models that rely only on a very small deposit base for funding. This is true, for example, for many investment banks. The median values across the banking groups are relatively close to one another, with the median of commercial banks amounting to 95%, and that of savings banks and credit cooperatives being equal to 93% and 80% respectively. However, the respective distributions of the $LTD$ for savings banks and credit cooperatives are characterized by far fewer extreme values.

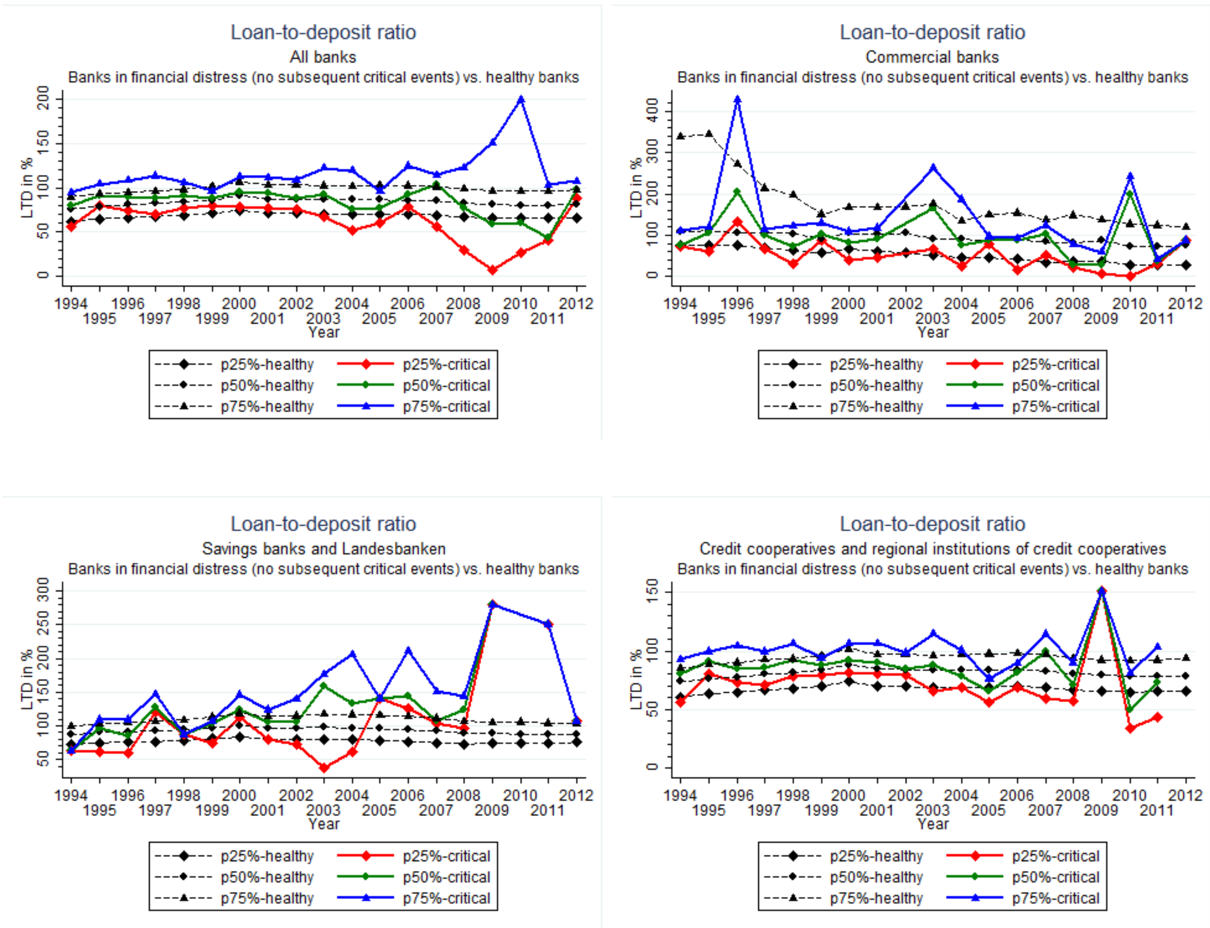



**Figure 3.A2: Loan-to-deposit ratio by banking group and over time**

Figure 3.A2 displays the quartiles and the median of the $LTD$ for banks that become financially distressed in the following year (solid lines) and healthy ones (dashed lines), for each year from 1994 to 2012.[75] The subfigures show the respective percentiles for all banks and for each banking group separately.[76]

The complete sample shows that for the healthy banks, the distribution of the $LTD$ is fairly stable. By contrast, the distribution of the $LTD$ for banks experiencing critical events is far more volatile and this volatility increases in the second half of the 2000s. This is due to a much smaller sample size, but it also suggests that funding is not necessarily the main driver of each critical event. However, for most of the time periods the $LTD$ of banks in critical states lies above that of the healthy banks.[77] This difference is especially pronounced in the 75th percentile. The breakdown by banking group reveals that the picture looks different depending on which banking group is considered. For commercial banks, the distribution of the $LTD$ of banks in critical states tends to lie below that of the healthy banks. This gives rise to the assumption that funding problems have not been the main cause of trouble for this banking group. As far as savings banks are concerned, the distribution of the $LTD$ of banks in financial distress clearly lies above that of the healthy banks in most years. This suggests that savings banks that experience financial distress often turn out to have financed a larger part of their loan portfolio through sources other than deposits, which, in general, is uncommon behavior for savings banks.[78] Indeed, there seems to be some relation between this behavior and the likelihood of critical events in this sector. A similar picture emerges for credit cooperatives. Especially at the beginning of the sample and up until 2002, the $LTD$ of banks in financial distress seems to systematically lie above that of the healthy banks in all considered percentiles. After that period, the distribution displays more volatility over the years which is mainly due to the significantly lower number of critical events. However, there are still a number of banks in critical states that have a higher $LTD$ than most healthy banks.

As for the $LTIBL$, there are vast differences in the use of wholesale funding across banking groups. As would be expected, it is most widely used by commercial banks. Over the period between 1994 and 2012, the mean of the ratio of interbank liabilities to total assets is 26%, as opposed to a mean of 20% for savings banks and 13% for

[75]One has to keep in mind that the figures merely show the quartiles and the median of the $LTD$ for the respective subgroup of banks at each point in time, i.e. the percentiles should not be regarded as time series. As the overall number of banks in distress varies over time, any relation between two points in time is of little informative value.

[76]Table 3.A4 in Appendix 3.A.1 contains a breakdown of the $LTD$ by financial distress status in the following period and banking group.

[77]This is not true for the lower quartile and the median in most of the second half of the 2000s.

[78]Savings banks finance the largest part of their loan growth via deposits (Gubitz (2013)). This is also true for credit cooperatives. The correlation of loan growth and deposit growth is 0.878 for savings banks and 0.697 for credit cooperatives. By contrast, for commercial banks, this correlation is only 0.128.

credit cooperatives. However, commercial banks' standard deviation of this ratio is also the largest. The median of commercial banks' $LTIBL$ amounts to 238%. Again, the distribution of commercial banks is driven by extreme values, while it also shows a large variance pointing towards more heterogeneity in the sector of commercial banks. The 99th percentile is 435,833% which basically means no wholesale funding at all. Slightly fewer extreme values are recorded for the group of credit cooperatives. Their mean still stands at a high 2,429%, the 99th percentile is 5,358%. The median of the $LTIBL$ of credit cooperatives is 506% and more than twice as large as that of commercial banks. For savings banks, this ratio is distributed a lot more narrowly. The mean is 373% and the median amounts to 320%. Overall, savings banks are a lot less active on the interbank market than are commercial banks, but more active than credit cooperatives.[79]

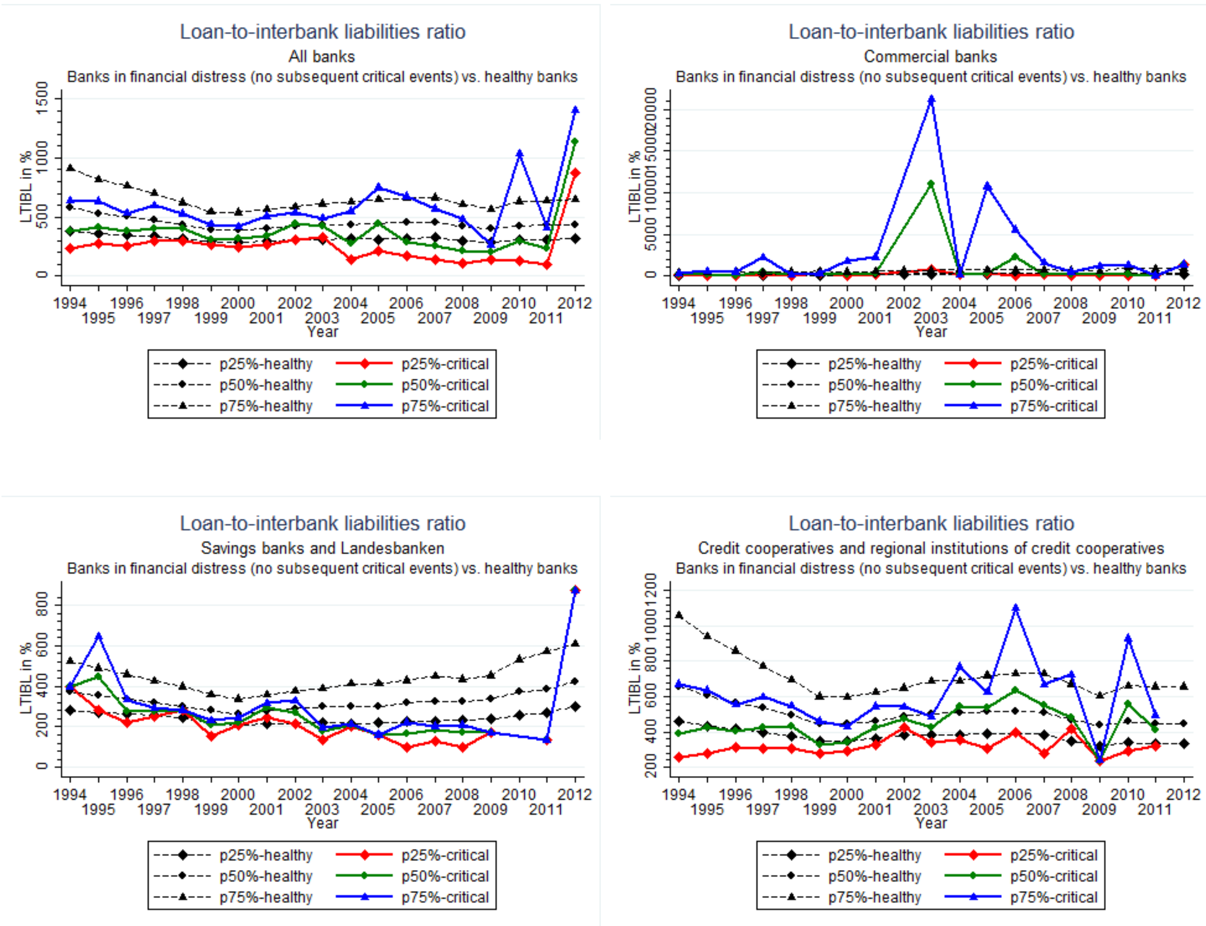



**Figure 3.A3: Loan-to-interbank liabilities ratio by banking group and over time**

[79] It should be noted that the German interbank market is highly segmented. The counterparties that savings banks are most heavily engaged in interbank credit relationships with are other savings banks and the Landesbanken. The same is true of credit cooperatives and their central institutions.

Subfigures in Figure 3.A3 show the quartiles and the median of the $LTIBL$ for banks that become financially unhealthy in the following period (solid lines) and healthy ones (dashed lines) for the entire sample and for each banking group for each year from 1994 to 2012.[80] For the whole sample, unhealthy banks tend to have a lower $LTIBL$, which means that they finance their loans with more funding obtained from the interbank market than do healthy banks. Since banks' financial distress is often associated with liquidity problems, this is not surprising. However, there are marked differences across banking groups. The $LTIBL$ in the commercial banking sector, in particular, can be observed to display a different pattern. Here, the distribution of the $LTIBL$ for banks in financial distress lies above that of healthy banks in most years. This suggests that wholesale funding is not the main cause of their problems. For savings banks, the distribution of the $LTIBL$ of banks in critical states is below that of healthy banks, showing that banks in financial distress financed a higher share of their loan portfolio through wholesale funding. The same holds true for credit cooperatives, although this can most notably be observed for the period from 1995 up until 2003. Thereafter, this relation is reversed in several years, but one must keep in mind that, as can be seen in Appendix 3.A.1, Table 3.A1, from 2005 on, the number of banks in financial distress is much smaller.

[80] Table 3.A4 in Appendix 3.A.1 reports a breakdown of the $LTIBL$ by financial distress status in the following period and banking group.

## 3.A.5 Additional figures

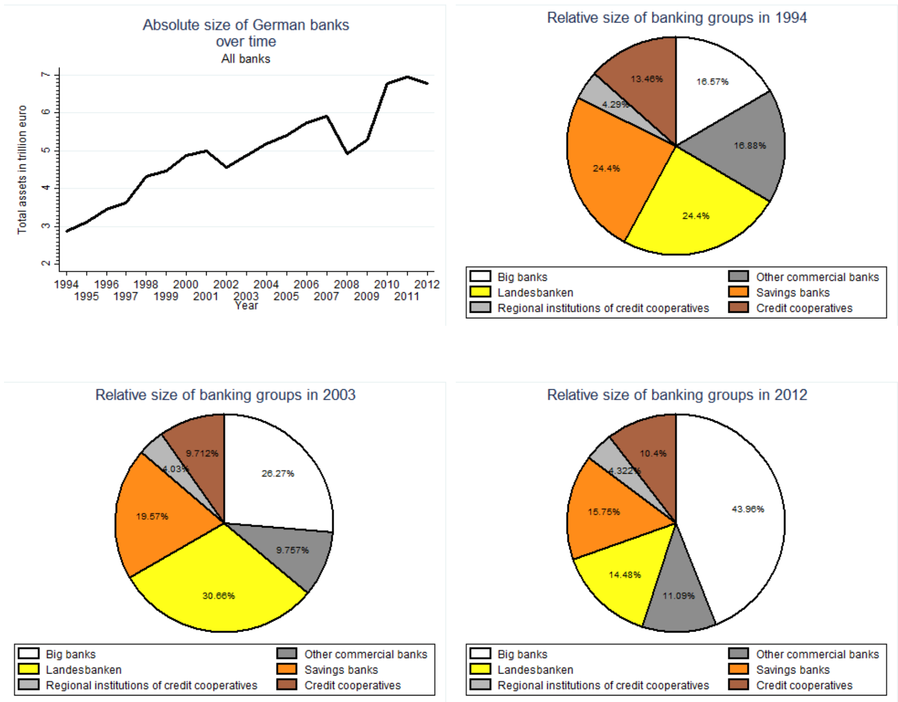



Figure 3.A4: Evolution of the size of the German banks in the sample by banking group and over time

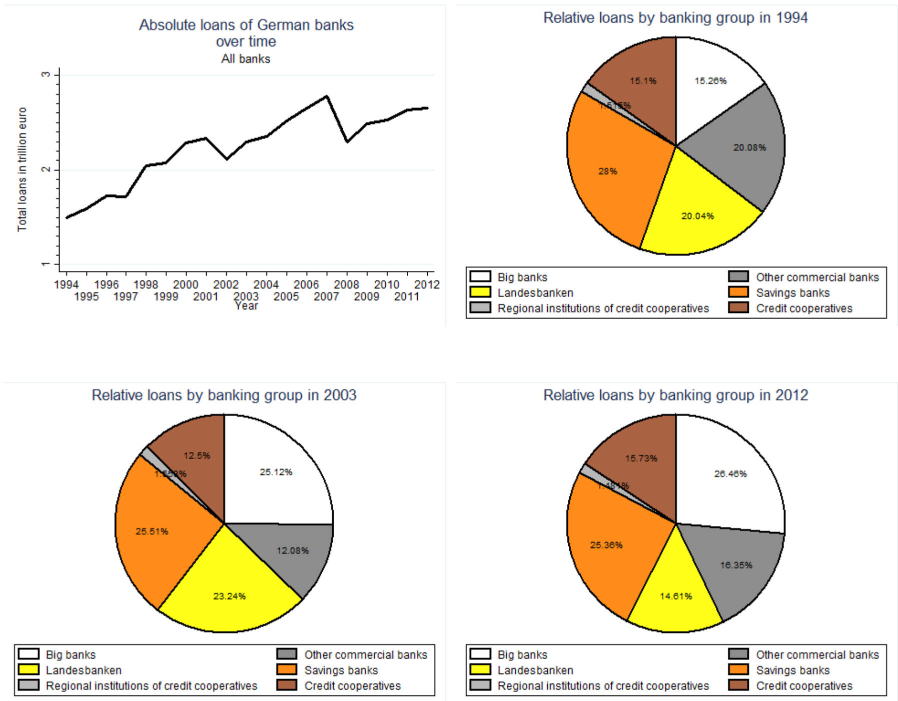



**Figure 3.A5: Evolution of the relative loans to the non-financial sector of the German banks in the sample by banking group and over time**

### 3.A.6 Additional estimation output

**Table 3.A6: RE logit estimation: specification using relative loans in place of the stable funding variables – different banking groups (no subsequent critical events)**

| Explanatory variables | Other commercial banks | Savings banks | Credit cooperatives |
|---|---|---|---|
| $log(LR_{i,t-1})$ | 0.0745 | 4.2409*** | 2.1489*** |
| | (0.0951) | (1.0672) | (0.3218) |
| $ROA_{i,t-1}$ | −0.1327*** | −2.0766*** | −0.2293*** |
| | (0.0320) | (0.4234) | (0.0673) |
| $log(CR_{i,t-1})$ | −0.4706* | −2.1176** | −1.8168*** |
| | (0.2128) | (0.9447) | (0.2911) |
| $log(LLR_{i,t-1})$ | −0.0087 | 0.8743*** | 1.0035*** |
| | (0.0148) | (0.2977) | (0.0854) |
| $log(AdminR_{i,t-1})$ | 0.6250*** | −1.2156 | 1.1073*** |
| | (0.1650) | (0.9359) | (0.2796) |
| $log(Liquid_{i,t-1})$ | −0.0760 | 0.6588** | 0.2393** |
| | (0.0864) | (0.2741) | (0.1015) |
| $log(Total\ Assets_{i,t-1})$ | −0.0792 | −0.2955* | 0.1406** |
| | (0.0896) | (0.1618) | (0.0554) |
| $Z - Score_{i,t-1}$ | 0.0002* | −0.0180* | −0.0000 |
| | (0.0001) | (0.0099) | (0.0002) |
| $Constant$ | −2.0353 | −17.5358** | −12.8806*** |
| | (1.6326) | (5.6336) | (1.5649) |
| Time dummies | Yes | Yes | Yes |
| Number of banks | 295 | 601 | 2,543 |
| Number of observations | 2,644 | 8,423 | 26,940 |
| Pseudo $R^2$ | 0.13 | 0.28 | 0.15 |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time after being financially sound for at least one year, and zero if it is financially healthy in $t$. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3.3). See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

**Table 3.A7: RE logit estimation: specification using relative deposits in place of the stable funding variables – different banking groups (no subsequent critical events)**

| Explanatory variables | Other commercial banks | Savings banks | Credit cooperatives |
|---|---|---|---|
| $log(DR_{i,t-1})$ | 0.1743 | $-4.3928^{***}$ | $-0.3758^{**}$ |
| | (0.1018) | (1.2356) | (0.1498) |
| $ROA_{i,t-1}$ | $-0.1266^{***}$ | $-2.0374^{***}$ | $-0.2631^{***}$ |
| | (0.0307) | (0.4146) | (0.0945) |
| $log(CR_{i,t-1})$ | $-0.3704$ | $-0.5537$ | $-1.6752^{***}$ |
| | (0.2209) | (0.9710) | (0.2887) |
| $log(LLR_{i,t-1})$ | $-0.0076$ | $0.8948^{***}$ | $1.0058^{***}$ |
| | (0.0145) | (0.2839) | (0.0854) |
| $log(AdminR_{i,t-1})$ | $0.6023^{***}$ | 0.4170 | $1.1091^{***}$ |
| | (0.1672) | (1.0817) | (0.2751) |
| $log(Liquid_{i,t-1})$ | $-0.1420$ | $0.6889^{**}$ | $0.1988^{*}$ |
| | (0.0909) | (0.2693) | (0.1035) |
| $log(Total\ Assets_{i,t-1})$ | $-0.0693$ | $-0.3522^{**}$ | $0.1902^{***}$ |
| | (0.0905) | (0.1544) | (0.0555) |
| $Z - Score_{i,t-1}$ | 0.0002 | $-0.0153$ | $-0.0000$ |
| | (0.0001) | (0.0097) | (0.0002) |
| $Constant$ | $-2.4928$ | $16.2331^{**}$ | $-3.2526^{**}$ |
| | (1.6553) | (5.1032) | (1.1342) |
| Time dummies | Yes | Yes | Yes |
| Number of banks | 295 | 601 | 2,543 |
| Number of observations | 2,644 | 8,423 | 26,940 |
| Pseudo $R^2$ | 0.13 | 0.27 | 0.14 |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time after being financially sound for at least one year, and zero if it is financially healthy in $t$. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3.3). See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

**Table 3.A8: RE logit estimation: specification using relative interbank liabilities in place of the stable funding variables – different banking groups (no subsequent critical events)**

| Explanatory variables | Other commercial banks | Savings banks | Credit cooperatives |
|---|---|---|---|
| $log(IBLR_{i,t-1})$ | 0.0206 | 1.3056** | 0.6890*** |
| | (0.0696) | (0.5442) | (0.1095) |
| $ROA_{i,t-1}$ | −0.1384*** | −2.1013*** | −0.2111** |
| | (0.0356) | (0.4177) | (0.0937) |
| $log(CR_{i,t-1})$ | −0.3849* | −0.8630 | −1.5479*** |
| | (0.2145) | (0.9851) | (0.2792) |
| $log(LLR_{i,t-1})$ | −0.0022 | 0.9088*** | 0.9763*** |
| | (0.0146) | (0.2924) | (0.0852) |
| $log(AdminR_{i,t-1})$ | 0.4685** | −0.3014 | 1.2062*** |
| | (0.1521) | (1.0581) | (0.2786) |
| $log(Liquid_{i,t-1})$ | −0.0528 | 0.6455** | 0.2334** |
| | (0.0820) | (0.2773) | (0.1003) |
| $log(Total\ Assets_{i,t-1})$ | −0.0558 | −0.3553** | 0.1766*** |
| | (0.0929) | (0.1659) | (0.0556) |
| $Z-Score_{i,t-1}$ | 0.0002*** | −0.0147 | −0.0000 |
| | (0.0001) | (0.0098) | (0.0002) |
| $Constant$ | −2.1980 | −5.3731 | −6.4957*** |
| | (1.6015) | (4.0390) | (0.9932) |
| Time dummies | Yes | Yes | Yes |
| Number of banks | 291 | 601 | 2,542 |
| Number of observations | 2,488 | 8,423 | 26,890 |
| Pseudo $R^2$ | 0.13 | 0.27 | 0.15 |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time after being financially sound for at least one year, and zero if it is financially healthy in $t$. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3.3). See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

### 3.A.7 Robustness checks

We conduct several robustness checks to examine how sensitive our findings are. A random effects logit model relies on several restrictive assumptions that are needed for obtaining a tractable likelihood function and in order for the estimator to be consistent.[81] One crucial assumption is $\alpha_i|\boldsymbol{x_{i,t-1}}, \boldsymbol{z_{i,t-1}}, RD_i, \boldsymbol{TD} \sim \mathcal{N}(0; \sigma_\alpha^2)$, i.e. conditional on the regressors, the time-invariant unobserved heterogeneity is independent of the vector of the explanatory variables (and follows a normal distribution). However, instances are conceivable where regressors and the bank-specific unobserved heterogeneity might be (at least) correlated. For example, if $\alpha_i$ captures bank managers' (constant fraction of) risk appetite, then it might be related to the values of regressors such as the capital ratio, the return on assets or the loan-to-deposit ratio, for example. There are several ways around this assumption. In our robustness checks we resort to the (conditional) fixed effects logit model and the linear probability model with fixed effects.[82]

Because of their non-linear nature, it is not possible in binary response models to treat $\alpha_i$ as 'fixed' effects, i.e. not making any assumption about how $\alpha_i$ and $\boldsymbol{x_{i,t-1}}$, $\boldsymbol{z_{i,t-1}}$ might be related and thus allowing them to be correlated, by transforming the data to deviations from banks-specific means over time like it is in the linear regression case. The alternative is to estimate the unobserved heterogeneity parameters for each bank, which can be shown to render the maximum likelihood estimator inconsistent, given small $T_i$ (Greene (2012)). However, one can circumvent this incidental parameters problem and still 'eliminate' the unobserved heterogeneity using a conditional logit model, which is an advantage over a probit model. The term 'conditional' refers to the finding that once we condition on $\sum_{t=2}^{T_i} y_{i,t-1}$, the likelihood function is no longer a function of $\alpha_i$, i.e. in a logit model for panel data $\sum_{t=2}^{T_i} y_{i,t-1}$ is a minimum sufficient statistic for the unobserved heterogeneity (Chamberlain (1980)). Essentially, this means that we condition on banks which change their financial distress status at least once. Observations belonging to all the other banks contribute no additional information to the likelihood function, and hence end up being discarded. Results from the estimation of the model via the conditional fixed effects procedure can be found in Table 3.A9. At least for credit cooperatives, the positive impact on the likelihood of becoming financially distressed of the $LTD$ can be confirmed. However, one has to keep in mind that only 418 banks (out of 2,541) change

[81] For a discussion of the assumptions, see Wooldridge (2002).

[82] Alternatively, one might still use the random effects model, but assume that the unobserved heterogeneity is a certain function of the regressors. Mundlak (1978) proposes that $\alpha_i$ depends on the bank-specific time average of $\boldsymbol{v}_{i,t-1}$, where $\boldsymbol{v}_{i,t-1}$ is a vector containing $\boldsymbol{x_{i,t-1}}$, $\boldsymbol{z_{i,t-1}}$, $RD_i$ and $\boldsymbol{TD}$, i.e $\alpha_i = \psi + \overline{\boldsymbol{v}_i}'\boldsymbol{\xi} + c_i$, $\overline{\boldsymbol{v}_i} = \frac{1}{T_i}\sum_{t=2}^{T_i} \boldsymbol{v}_{i,t-1}$. The assumption then becomes $\alpha_i|\boldsymbol{v}_{i,t-1} \sim \mathcal{N}(\psi + \overline{\boldsymbol{v}_i}'\boldsymbol{\xi}; \sigma_c^2)$. While one very restrictive assumption is essentially being replaced by another, some dependence between $\alpha_i$ and $\boldsymbol{v}_{i,t-1}$ is allowed. We corroborated our findings using this model as well. The results are available upon request.

their status, which is why we are merely interested in the sign of the estimated coefficient. For savings banks, it is positive but statistically insignificant, presumably because only 66 (out of 601) savings banks could be used in the estimation.[83]

While the fixed effects logit model has its merits, it is not without drawbacks. Because we have to condition on banks that have been in financial distress, the number of observations is substantially reduced. That is why we deploy the linear probability model with fixed effects to estimate the effect of stable funding on the financial distress of banks. Since we are not interested in predicting probabilities of banks getting into financial difficulties, the problem that coefficients from the estimated linear probability model might result in predicted probabilities that are greater than one and/or less than zero is not a serious concern.[84] We estimate the following model using OLS with fixed effects:

$$y_{it} = \boldsymbol{x_{i,t-1}}'\boldsymbol{\beta} + \boldsymbol{z_{i,t-1}}'\boldsymbol{\gamma} + \boldsymbol{TD}'\boldsymbol{\delta} + \alpha_i + u_{it}, \quad i = 1, \ldots, n; t = 2, \ldots, T_i \tag{3.A1}$$

Note that (3.A1) does not explicitly contain regional dummies, as they do not vary over time and cannot be distinguished from the bank-specific fixed effects.[85] For this reason, they are part of $\alpha_i$ and are 'eliminated' when the variables are transformed to deviations from banks-specific means over time. The results in Table 3.A10 corroborate our earlier findings with respect to the loan-to-deposit ratio. For the group of other commercial banks, the coefficient is not statistically different from zero, for savings banks and credit cooperatives the effect is positive and larger than in the baseline estimation (3.3).[86] For savings banks (credit cooperatives), a relative rise in the $LTD$ of one percent is associated with an increase in the expected value of critical events of 0.000344 (0.000418) from 1995 to 2013. The $LTIBL$ is found to have no effect on the probability of experiencing financial distress for either banking group. Interestingly, the estimated coefficient on size is negative for credit cooperatives, so the positive effect reported in Table 3.4 cannot be corroborated.

As far as different functional forms for modelling the probability parameter are concerned, it might be argued that the employed random effects logit model might not work very well because there are too few critical events.[87] When one of the outcomes is rare, the

[83]Because so many observations are discarded, a Hausmann-Test of whether or not the random effects model is justified is not sensible.

[84]Another disadvantage of a linear probability model like (3.A1) is that the marginal effects are constant, regardless of the regressor values.

[85]The same is true for the conditional fixed effects logit model.

[86]Note that the number of observations is larger than the number reported in Table 3.2, Table 3.3 and Table 3.4. This is because the within transformation generates variation across banks even for years/federal states for which no critical events could be observed.

[87]As previously mentioned, the mean share of banks in financial difficulties throughout the entire sample is 1.57%.

**Table 3.A9: Conditional FE logit estimation: main specification – different banking groups (no subsequent critical events)**

| Explanatory variables | Other commercial banks | Savings banks | Credit cooperatives |
|---|---|---|---|
| $log(LTD_{i,t-1})$ | 0.0611 | 5.3394 | 3.0843*** |
| | (0.2899) | (8.8898) | (1.0049) |
| $log(LTIBL_{i,t-1})$ | 0.0570 | −1.6933 | −0.5395 |
| | (0.1593) | (2.7358) | (0.3483) |
| $ROA_{i,t-1}$ | −0.3090 | −1.2604 | −0.9173*** |
| | (0.1956) | (1.5566) | (0.2663) |
| $log(CR_{i,t-1})$ | −1.0515* | −2.7563 | −1.9062 |
| | (0.4396) | (5.9443) | (1.2746) |
| $log(LLR_{i,t-1})$ | 0.0503 | 1.0931 | 0.6684*** |
| | (0.0476) | (1.7358) | (0.1408) |
| $log(AdminR_{i,t-1})$ | 1.5853* | −1.9126 | 2.4189** |
| | (0.6231) | (3.7123) | (1.1194) |
| $log(Liquid_{i,t-1})$ | −0.1695 | 0.6638 | 0.1178 |
| | (0.3024) | (1.0659) | (0.1432) |
| $log(Total\ Assets_{i,t-1})$ | 0.1593 | −1.1134 | −2.4494*** |
| | (0.5592) | (3.7678) | (0.5766) |
| $Z - Score_{i,t-1}$ | 0.0001 | −0.0251 | −0.0001 |
| | (0.0051) | (0.0411) | (0.0039) |
| Time dummies | Yes | Yes | Yes |
| Number of banks | 76 | 66 | 418 |
| Number of observations | 696 | 670 | 3,686 |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time after being financially sound for at least one year, and zero if it is financially healthy in $t$. The table reports the estimated coefficients and bootstrapped standard errors (in parentheses) using the conditional fixed effects logit model (3.3). See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

complementary log-log model is called for (Cameron and Trivedi (2005)).[88] Table 3.A11

[88] In the complementary log-log model, the error term follows a conditional extreme-value Gumbel distribution and the cdf, given by $Pr(y_{it} = 1|\boldsymbol{x_{i,t-1}}, \boldsymbol{z_{i,t-1}}, RD_i, \boldsymbol{TD}, \alpha_i) = 1 - exp(-exp(\boldsymbol{x_{i,t-1}}'\boldsymbol{\beta} +$

reports the results, which are very similar to our benchmark findings.

One important assumption needed for the random effects logit model is that the regressors are strictly exogenous (conditional on the unobserved heterogeneity). For one, strict exogeneity rules out past dependent variables in $\boldsymbol{x_{i,t-1}}$, $\boldsymbol{z_{i,t-1}}$, but it also means that $y_{it}$ values cannot be correlated with the future realizations of the regressors. However, it is conceivable that once a bank is in financial distress, certain measures are taken that systematically affect future balance sheet variables of that bank. We take this assumption seriously and estimate (3.3) without observations that follow any distress event, i.e. we consider all observations of banks that remain healthy throughout the sample and observations up until the first distress event of banks (including that event) which experience financial difficulties. Doing so leaves us with 556 bank years in financial distress.[89] Table 3.A12 shows that the results basically remain the same.

As previously mentioned, we lag the explanatory variables to make certain that balance sheet data precede financial distress events. However, since we do not have information on when exactly critical events took place during a year, it is possible that very little time lies between the date on which balance sheet items are disclosed and the financial distress event. For this reason, we re-estimate (3.3) and use two lags for the explanatory variables. The results that are reported in Table 3.A13 in are not much different from the ones for the baseline specification.

When defining financial distress events in Section 3.3.1, we have explained that there are several types of critical events with varying severity. Even though we believe that our definition captures all relevant instances in which a bank should be labeled financially distressed, we re-estimate (3.3) using a very conservative definition of financial distress. We only regard bank years as critical if capital preservation measures and/or restructuring caused by mergers and/or liquidation/insolvency and/or SoFFin recapitalisation measures and guarantees have taken place. Bank years with less severe events are omitted for the purpose of this robustness check. Applying this definition reduces the number of bank years in financial distress to 513. Table 3.A14 demonstrates that restricting the analysis to conservatively defined critical events hardly alters the results.

Another potential concern is that the 'operating loss in excess of 25% of liable capital' – as one of the criteria constituting a critical event – is related to a reduction in capital, which is also a right-hand side variable in our model. In order to exclude the possibility that our results are driven by this mechanical statistical association, we estimate (3.3) again, additionally including a dummy that is one whenever the (negative) return on cap-

$\boldsymbol{z_{i,t-1}}'\gamma + \delta RD_i + \boldsymbol{TD}'\boldsymbol{\zeta} + \alpha_i$)), is not symmetric around zero.

[89] There are 66 critical events for the group of other commercial banks, 67 for savings banks, and 423 for credit cooperatives.

ital[90] in a given year is less than -25%. The estimation output is reported in Table 3.A15. Not surprisingly, the estimated coefficient for the dummy is positive and highly significant and accordingly, the estimated coefficient on $ROA$ becomes lower and insignificant for credit cooperatives.[91] The effect of the stable funding variables on the likelihood of encountering financial difficulties remains unchanged.

It can also be argued that the $Z-Score$ – as a backward-looking measure of risk – does not adequately account for banks' risk profiles. In this check we employ an alternative. We use the lagged abnormal loan growth to capture bank risk. The abnormal loan growth is defined as the difference between the growth rate of bank $i$'s loans at time $t$ and the median growth rate of loans over all banks in that year. The idea is that loan growth is not necessarily risky per se, but if in a given year, the growth rates are higher than that year's median loan growth, it might be an indication of excessive credit growth and high risk, especially if lending standards and/or collateral requirements are lowered. Apart from that, banks exhibiting higher loan growth rates may attract more risky customers that have been denied loans by their competitors with more moderate loan growth (Foos, Norden and Weber (2010)). We employ the abnormal loan growth instead of the $Z-Score$ in (3.3). The results in Table 3.A16 corroborate our earlier findings.[92] Similar to the $Z - Score$, our alternative measure does not suggest that there is a noteworthy effect of a risk-taking variable on the probability of becoming financially distressed.

Another possibility is that the results are influenced by regional economic booms where banks fund regional projects (i.e. increase their supply of credit) and finance them with an increased share of wholesale funding. In order to address this issue, we additionally include the regional loan growth and the regional deposit growth[93] in the lagged vector of explanatory variables $\boldsymbol{z_{i,t-1}}$ in (3.3).[94] The regional loan growth is defined as the relative change in loans summed over all banks in a federal state. The regional deposit growth is defined accordingly with respect to the deposits instead of loans. As is shown in Table 3.A17, our baseline results are confirmed. The coefficients associated with the regional growth rates are economically small and mostly insignificant, suggesting that regional trends do not seem to matter for the critical events of banks, at least at the level of federal states.

To summarize, we have checked whether or not our findings are sensitive to different

[90] The return on capital is defined as the ratio of banks' returns over their respective capital from the balance sheet.

[91] For savings banks, the $ROA$ is still highly significant.

[92] Except for credit cooperatives, the number of bank years is slightly less than in the baseline estimation. This is because generating growth rates requires two consecutive observations for each cross-sectional unit.

[93] The regional deposit growth can be seen as a proxy for the regional saving rate.

[94] The results remain qualitatively the same if we augment $\boldsymbol{z_{i,t-1}}$ by either the regional loan growth or the regional deposit growth.

estimation techniques, more conservative assumptions/definitions of variables as well as alternative/additional variables, and we show that the main results remain unchanged.

**Table 3.A10: FE OLS estimation: main specification – different banking groups (no subsequent critical events)**

| Explanatory variables | Other commercial banks | Savings banks | Credit cooperatives |
|---|---|---|---|
| $log(LTD_{i,t-1})$ | 0.0006 | 0.0344*** | 0.0418*** |
| | (0.0036) | (0.0101) | (0.0089) |
| $log(LTIBL_{i,t-1})$ | 0.0028 | 0.0034 | 0.0009 |
| | (0.0038) | (0.0037) | (0.0018) |
| $ROA_{i,t-1}$ | −0.0076** | −0.0288*** | −0.0198*** |
| | (0.0031) | (0.0076) | (0.0041) |
| $log(CR_{i,t-1})$ | −0.0209 | −0.0232 | −0.0094 |
| | (0.0162) | (0.0147) | (0.0081) |
| $log(LLR_{i,t-1})$ | 0.0008 | 0.0035 | 0.0009*** |
| | (0.0012) | (0.0021) | (0.0002) |
| $log(AdminR_{i,t-1})$ | 0.0254* | −0.0029 | 0.0182** |
| | (0.0137) | (0.0304) | (0.0088) |
| $log(Liquid_{i,t-1})$ | −0.0047 | 0.0028 | 0.0024 |
| | (0.0048) | (0.0031) | (0.0021) |
| $log(Total\ Assets_{i,t-1})$ | −0.0020 | 0.0042 | −0.0192*** |
| | (0.0099) | (0.0087) | (0.0050) |
| $Z - Score_{i,t-1}$ | 0.0000 | −0.0000 | 0.0000 |
| | (0.0000) | (0.0000) | (0.0000) |
| $Constant$ | 0.0444 | −0.1958 | 0.0342 |
| | (0.1483) | (0.1265) | (0.0721) |
| Time dummies | Yes | Yes | Yes |
| Number of banks | 295 | 632 | 2,545 |
| Number of observations | 2,709 | 9,342 | 27,994 |
| $R^2$ within | 0.04 | 0.02 | 0.02 |
| $R^2$ between | 0.01 | 0.02 | 0.00 |
| $R^2$ overall | 0.03 | 0.02 | 0.01 |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time after being financially sound for at least one year, and zero if it is financially healthy in $t$. The table reports the estimated coefficients and robust standard errors (in parentheses) using the fixed effects OLS regression (3.A1). See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

**Table 3.A11: Complementary log-log estimation: main specification – different banking groups (no subsequent critical events)**

| Explanatory variables | Other commercial banks | Savings banks | Credit cooperatives |
|---|---|---|---|
| $log(LTD_{i,t-1})$ | $-0.0798$ | 3.3755*** | 0.4109*** |
| | (0.0733) | (0.7032) | (0.1079) |
| $log(LTIBL_{i,t-1})$ | $-0.0100$ | 0.1916 | $-0.3872$*** |
| | (0.0558) | (0.4901) | (0.1145) |
| $ROA_{i,t-1}$ | $-0.0841$*** | $-1.8314$*** | $-0.0922$ |
| | (0.0235) | (0.3984) | (0.0548) |
| $log(CR_{i,t-1})$ | $-0.3227$ | $-1.3802$ | $-1.6710$*** |
| | (0.2091) | (0.9915) | (0.2734) |
| $log(LLR_{i,t-1})$ | $-0.0016$ | 0.8011** | 0.9613*** |
| | (0.0143) | (0.2857) | (0.0823) |
| $log(AdminR_{i,t-1})$ | 0.5054** | 0.2171 | 1.0422*** |
| | (0.1536) | (1.0060) | (0.2560) |
| $log(Liquid_{i,t-1})$ | $-0.1126$ | 0.7011** | 0.2948** |
| | (0.0878) | (0.2641) | (0.0969) |
| $log(Total\ Assets_{i,t-1})$ | $-0.0521$ | $-0.2489$ | 0.1696** |
| | (0.0903) | (0.1546) | (0.0536) |
| $Z-Score_{i,t-1}$ | 0.0002* | $-0.0176$ | $-0.0000$ |
| | (0.0001) | (0.0097) | (0.0002) |
| $Constant$ | $-1.7665$ | $-18.6937$*** | $-4.0604$** |
| | (1.6812) | (5.6000) | (1.2964) |
| Time dummies | Yes | Yes | Yes |
| Number of banks | 283 | 601 | 2,541 |
| Number of observations | 2,443 | 8,423 | 26,885 |
| Pseudo $R^2$ | 0.13 | 0.29 | 0.15 |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time after being financially sound for at least one year, and zero if it is financially healthy in $t$. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects complementary log-log model. See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

**Table 3.A12: RE logit estimation: specification using financially healthy bank years and only the first distress event of the respective banks experiencing financial distress – different banking groups (no subsequent critical events)**

| Explanatory variables | Other commercial banks | Savings banks | Credit cooperatives |
|---|---|---|---|
| $log(LTD_{i,t-1})$ | $-0.1172$ | 3.6078*** | 0.6382*** |
| | (0.1803) | (0.7567) | (0.1670) |
| $log(LTIBL_{i,t-1})$ | 0.0918 | 0.1245 | $-0.4452$** |
| | (0.1264) | (0.5145) | (0.1360) |
| $ROA_{i,t-1}$ | $-0.2029$** | $-1.9910$*** | $-0.3289$** |
| | (0.0767) | (0.4388) | (0.1155) |
| $log(CR_{i,t-1})$ | $-1.3031$* | $-1.2920$ | $-1.7679$*** |
| | (0.5858) | (1.0472) | (0.3468) |
| $log(LLR_{i,t-1})$ | 0.0240 | 0.8541** | 0.9880*** |
| | (0.0346) | (0.3038) | (0.0945) |
| $log(AdminR_{i,t-1})$ | 1.1802* | 0.1451 | 1.4626*** |
| | (0.4697) | (1.0661) | (0.3420) |
| $log(Liquid_{i,t-1})$ | $-0.1861$ | 0.9007** | 0.3150** |
| | (0.1961) | (0.2821) | (0.1145) |
| $log(Total\ Assets_{i,t-1})$ | 0.2201 | $-0.2433$ | 0.2350*** |
| | (0.2148) | (0.1615) | (0.0680) |
| $Z - Score_{i,t-1}$ | 0.0004 | $-0.0175$ | $-0.0000$ |
| | (0.0002) | (0.0100) | (0.0002) |
| $Constant$ | $-8.2906$* | $-19.7221$*** | $-5.9947$*** |
| | (4.0103) | (5.9332) | (1.7281) |
| Time dummies | Yes | Yes | Yes |
| Regional dummies | Yes | Yes | Yes |
| Number of banks | 256 | 599 | 2,486 |
| Number of observations | 1,951 | 8,300 | 25,272 |
| Pseudo $R^2$ | 0.14 | 0.26 | 0.15 |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time, and zero if it is financially healthy in $t$. The estimation only uses observations of banks that remain healthy throughout the sample and observations up until the first distress event of banks (including that event) which experience financial difficulties. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3.3). See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

**Table 3.A13: RE logit estimation: specification using two lags for the explanatory variables – different banking groups (no subsequent critical events)**

| Explanatory variables | Other commercial banks | Savings banks | Credit cooperatives |
|---|---|---|---|
| $log(LTD_{i,t-2})$ | 0.0118 | 4.2432*** | 0.7100*** |
| | (0.0903) | (0.9549) | (0.1391) |
| $log(LTIBL_{i,t-2})$ | 0.0185 | 0.4095 | −0.3780** |
| | (0.0694) | (0.5404) | (0.1221) |
| $ROA_{i,t-2}$ | −0.0963* | −1.4788** | −0.1429 |
| | (0.0401) | (0.5125) | (0.0811) |
| $log(CR_{i,t-2})$ | −0.4224 | −1.7569 | −1.3147*** |
| | (0.2592) | (1.1592) | (0.3060) |
| $log(LLR_{i,t-2})$ | −0.0141 | 1.0976*** | 0.5594*** |
| | (0.0175) | (0.3302) | (0.0831) |
| $log(AdminR_{i,t-2})$ | 0.5129** | −0.0111 | 0.6536* |
| | (0.1940) | (1.1394) | (0.2788) |
| $log(Liquid_{i,t-2})$ | −0.0783 | 0.2625 | 0.4593*** |
| | (0.1169) | (0.3016) | (0.1082) |
| $log(Total\ Assets_{i,t-2})$ | −0.1280 | −0.4317* | 0.1959*** |
| | (0.1053) | (0.1859) | (0.0592) |
| $Z - Score_{i,t-2}$ | 0.0003* | −0.0054 | −0.0001 |
| | (0.0001) | (0.0065) | (0.0003) |
| $Constant$ | −2.6502 | −19.5669** | −8.2200*** |
| | (2.2792) | (6.7155) | (1.6827) |
| Time dummies | Yes | Yes | Yes |
| Regional dummies | Yes | Yes | Yes |
| Number of banks | 260 | 559 | 2,448 |
| Number of observations | 2,149 | 7,473 | 24,175 |
| Pseudo $R^2$ | 0.12 | 0.23 | 0.12 |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time after being financially sound for at least one year, and zero if it is financially healthy in $t$. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3.3). See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

**Table 3.A14: RE logit estimation: specification using a conservative definition of financial distress – different banking groups (no subsequent critical events)**

| Explanatory variables | Other commercial banks | Savings banks | Credit cooperatives |
|---|---|---|---|
| $log(LTD_{i,t-1})$ | 0.0286 | 4.1655*** | 0.4050** |
| | (0.1133) | (0.9494) | (0.1307) |
| $log(LTIBL_{i,t-1})$ | 0.0254 | 0.7522 | −0.4432*** |
| | (0.0831) | (0.5881) | (0.1245) |
| $ROA_{i,t-1}$ | −0.0851* | −2.3320*** | −0.2541** |
| | (0.0421) | (0.5046) | (0.0973) |
| $log(CR_{i,t-1})$ | −0.2521 | −1.0467 | −1.6935*** |
| | (0.3219) | (1.2236) | (0.2996) |
| $log(LLR_{i,t-1})$ | −0.0011 | 0.7482* | 0.9392*** |
| | (0.0220) | (0.3422) | (0.0883) |
| $log(AdminR_{i,t-1})$ | 0.2109 | 0.2122 | 1.4243*** |
| | (0.2322) | (1.2359) | (0.2956) |
| $log(Liquid_{i,t-1})$ | 0.0305 | 1.0466** | 0.2827** |
| | (0.1413) | (0.3284) | (0.1063) |
| $log(Total\ Assets_{i,t-1})$ | 0.0049 | −0.2160 | 0.1841** |
| | (0.1254) | (0.1863) | (0.0576) |
| $Z - Score_{i,t-1}$ | 0.0002 | −0.0153 | −0.0000 |
| | (0.0001) | (0.0105) | (0.0002) |
| $Constant$ | −4.2445 | −25.5586*** | −3.9976** |
| | (2.4504) | (7.5977) | (1.4047) |
| Time dummies | Yes | Yes | Yes |
| Regional dummies | Yes | Yes | Yes |
| Number of banks | 255 | 547 | 2,533 |
| Number of observations | 1,806 | 6,863 | 26,740 |
| Pseudo $R^2$ | 0.07 | 0.30 | 0.15 |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time after being financially sound for at least one year, and zero if it is financially healthy in $t$. In this estimation, financially distressed bank years comprise the following critical events: capital preservation measures or restructuring caused by mergers or liquidation/insolvency or SoFFin recapitalisation measures and guarantees. The less severe bank years are omitted. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3.3). See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

**Table 3.A15: RE logit estimation: specification including a dummy that is one whenever the return on capital is less than -25% – different banking groups (no subsequent critical events)**

| Explanatory variables | Other commercial banks | Savings banks | Credit cooperatives |
|---|---|---|---|
| $log(LTD_{i,t-1})$ | $-0.0648$ | 3.3684*** | 0.4299** |
| | (0.0816) | (0.8607) | (0.1347) |
| $log(LTIBL_{i,t-1})$ | 0.0129 | $-0.0832$ | $-0.4027$** |
| | (0.0616) | (0.5686) | (0.1247) |
| $ROA_{i,t-1}$ | $-0.0373$ | $-1.9265$*** | $-0.0518$ |
| | (0.0338) | (0.5104) | (0.0885) |
| $log(CR_{i,t-1})$ | $-0.3330$ | $-0.7229$ | $-1.7160$*** |
| | (0.2323) | (1.1487) | (0.3096) |
| $log(LLR_{i,t-1})$ | $-0.0034$ | 0.6480* | 0.9235*** |
| | (0.0160) | (0.3239) | (0.0888) |
| $log(AdminR_{i,t-1})$ | 0.4620** | $-0.2889$ | 1.3128*** |
| | (0.1756) | (1.1709) | (0.2908) |
| $log(Liquid_{i,t-1})$ | $-0.1911$* | 0.9504** | 0.3200** |
| | (0.0966) | (0.3090) | (0.1085) |
| $log(Total\ Assets_{i,t-1})$ | $-0.0754$ | $-0.3268$ | 0.2118*** |
| | (0.0961) | (0.1868) | (0.0600) |
| $Z-Score_{i,t-1}$ | 0.0002* | $-0.0180$ | $-0.0000$ |
| | (0.0001) | (0.0110) | (0.0002) |
| $Dummy_{Capital\ Loss<-25\%}$ | 3.4216*** | 4.8773*** | 4.1247*** |
| | (0.4371) | (0.6936) | (0.2958) |
| $Constant$ | $-1.4905$ | $-17.7408$** | $-5.0040$*** |
| | (1.7614) | (6.5204) | (1.4397) |
| Time dummies | Yes | Yes | Yes |
| Regional dummies | Yes | Yes | Yes |
| Number of banks | 283 | 601 | 2,541 |
| Number of observations | 2,443 | 8,423 | 26,885 |
| Pseudo $R^2$ | 0.21 | 0.37 | 0.20 |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time after being financially sound for at least one year, and zero if it is financially healthy in $t$. $Dummy_{Capital\ Loss<-25\%}$ is a dummy that is one whenever a bank's (negative) return on capital in a given year is less than -25%, and zero otherwise. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3.3). See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

**Table 3.A16: RE logit estimation: specification using the abnormal loan growth in place of the $Z-Score$ – different banking groups (no subsequent critical events)**

| Explanatory variables | Other commercial banks | Savings banks | Credit cooperatives |
|---|---|---|---|
| $log(LTD_{i,t-1})$ | $-0.0644$ | $3.3997^{***}$ | $0.4480^{***}$ |
| | (0.0822) | (0.7326) | (0.1220) |
| $log(LTIBL_{i,t-1})$ | 0.0172 | 0.0412 | $-0.4073^{***}$ |
| | (0.0602) | (0.5077) | (0.1201) |
| $ROA_{i,t-1}$ | $-0.1788^{***}$ | $-2.2335^{***}$ | $-0.2381^{*}$ |
| | (0.0433) | (0.4094) | (0.0944) |
| $log(CR_{i,t-1})$ | $-0.3394$ | $-1.3736$ | $-1.6732^{***}$ |
| | (0.2296) | (1.0260) | (0.2917) |
| $log(LLR_{i,t-1})$ | $-0.0026$ | $0.9059^{**}$ | $0.9588^{***}$ |
| | (0.0157) | (0.2985) | (0.0861) |
| $log(AdminR_{i,t-1})$ | $0.5452^{**}$ | 0.0727 | $1.1339^{***}$ |
| | (0.1678) | (1.0155) | (0.2818) |
| $log(Liquid_{i,t-1})$ | $-0.1128$ | $0.7862^{**}$ | $0.3012^{**}$ |
| | (0.0935) | (0.2765) | (0.1032) |
| $log(Total\ Assets_{i,t-1})$ | $-0.0340$ | $-0.2967$ | $0.1761^{**}$ |
| | (0.0929) | (0.1592) | (0.0562) |
| $AbnormLoangr_{i,t-1}$ | $-0.0000$ | 0.0051 | $-0.0011$ |
| | (0.0000) | (0.0054) | (0.0027) |
| $Constant$ | $-1.9594$ | $-18.1408^{**}$ | $-4.2099^{**}$ |
| | (1.7546) | (5.7960) | (1.3574) |
| Time dummies | Yes | Yes | Yes |
| Regional dummies | Yes | Yes | Yes |
| Number of banks | 276 | 601 | $2,541$ |
| Number of observations | $2,393$ | $8,418$ | $26,885$ |
| Pseudo $R^2$ | 0.13 | 0.28 | 0.15 |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time after being financially sound for at least one year, and zero if it is financially healthy in $t$. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3.3). See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

**Table 3.A17: RE logit estimation: specification including the regional loan growth and the regional deposit growth – different banking groups (no subsequent critical events)**

| Explanatory variables | Other commercial banks | Savings banks | Credit cooperatives |
|---|---|---|---|
| $log(LTD_{i,t-1})$ | −0.0998 | 3.4611*** | 0.4469*** |
| | (0.0810) | (0.7339) | (0.1229) |
| $log(LTIBL_{i,t-1})$ | −0.0231 | 0.1257 | −0.4279*** |
| | (0.0598) | (0.5048) | (0.1214) |
| $ROA_{i,t-1}$ | −0.1246*** | −1.9798*** | −0.2397* |
| | (0.0346) | (0.4311) | (0.0950) |
| $log(CR_{i,t-1})$ | −0.2914 | −1.2533 | −1.6727*** |
| | (0.2238) | (1.0251) | (0.2936) |
| $log(LLR_{i,t-1})$ | −0.0017 | 0.8550** | 0.9665*** |
| | (0.0154) | (0.2969) | (0.0864) |
| $log(AdminR_{i,t-1})$ | 0.5315** | 0.0267 | 1.1270*** |
| | (0.1636) | (1.0413) | (0.2829) |
| $log(Liquid_{i,t-1})$ | −0.1236 | 0.7838** | 0.3033** |
| | (0.0940) | (0.2768) | (0.1034) |
| $log(Total\ Assets_{i,t-1})$ | −0.0413 | −0.2627 | 0.1733** |
| | (0.0912) | (0.1594) | (0.0563) |
| $Z-Score_{i,t-1}$ | 0.0002 | −0.0178 | −0.0000 |
| | (0.0001) | (0.0100) | (0.0002) |
| $RegLoangr_{i,t-1}$ | −0.0604 | −0.0068 | 0.0029 |
| | (0.0316) | (0.0282) | (0.0114) |
| $RegDepositsgr_{i,t-1}$ | 0.0102 | −0.0051 | −0.0248 |
| | (0.0272) | (0.0388) | (0.0138) |
| $Constant$ | −1.3839 | −18.4078** | −3.7696** |
| | (1.7298) | (5.8256) | (1.3833) |
| Time dummies | Yes | Yes | Yes |
| Regional dummies | Yes | Yes | Yes |
| Number of banks | 279 | 601 | 2,541 |
| Number of observations | 2,407 | 8,418 | 26,885 |
| Pseudo $R^2$ | 0.13 | 0.29 | 0.15 |

**Notes:** The dependent variable is a dummy $y_{it}$ that takes on the value one if bank $i$ experiences financial distress in period $t$ for the first time after being financially sound for at least one year, and zero if it is financially healthy in $t$. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3.3). See Appendix 3.A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

# Conclusion

Over the last 15 years, the world of economics has changed considerably. A part of this change has come at the wake of the GFC in 2008, consequences of which have shaped the economic debate until today. However, only a few years after the GFC, Europe had to go through a sovereign debt crisis and lately, it looks as if climate change will be one of the greater challenges in the times ahead. All of these events and certainly much more than that will shape the field of economics for some time to come.

Certainly, central banks and regulators are among those that stand at the frontier of any economic debate and one of the first who are asked to respond and extend their toolkit adequately. It is undoubtedly within their responsibilities to contribute to this debate and to find answers to the questions and challenges these changes in the global environment hold in store.

Of course, each of these actors has topics of primary concern. For central banks, the greatest challenge may be the regime of persistently low inflation paired with very low interest rates, which demands unconventional and sometimes untested measures. For regulators and governments, on the other hand, it is of utmost importance to understand the triggers of the GFC, to find regulatory solutions that help to increase the resilience of the financial sector and reduce the probability of the recurrence of such crises, also in light of the challenges related to climate change that may reasonably be expected.

The ambition of this dissertation is to contribute to the ongoing debate about the former two of these topic: First, Chapters 1 and 2 focus on some of the challenges of monetary policy and offer new approaches that help to assess its effectiveness and transmission along the yield curve in a low interest rate environment which is characterized by a large number of unconventional monetary policy measures. Second, Chapter 3 offers an empirical analysis of one of the most prominent new regulatory measures aimed at increasing the resilience of the banking sector.

More in detail, Chapter 1 and Chapter 2 are concerned with modelling the term structure of risk-free interest rates in the euro area. In general, such analysis is impeded by interest rates' high persistence paired with a relatively short sample. Over the last years, a further challenge appeared in form of very low interest rates close to their ELB, which implies non-linearities in the asset pricing process. As has been shown in the literature, not accounting for these data features might lead to inaccurate inference of the drivers of interest rates. Thus, the new economic environment calls for term structure models that do account for those features.

Against this backdrop, Chapter 1 adds to the literature by introducing a shadow rate term structure model for the euro area term structure of risk free rates, which includes a lower bound specification that allows for current as well as future changes in the ELB. As an important feature, the model incorporates survey information on interest rate forecasts which helps to better identify the expected future path of the short rate and alleviates the problems caused by high persistence in short samples. All this is essential for a reliable decomposition of interest rates into expectations and term premia, which both are a key ingredient to the analysis and assessment of monetary policy measures.

Based on this model, Chapter 1 assesses through which channels conventional and unconventional monetary policy affects the yield curve. It finds that conventional monetary policy works mostly through expectations at short maturities, but also affects the premium component which adds to the its overall effect. Importantly, both impacts are dampened when interest rates approach their ELB, leading to weaker effects of conventional monetary policy. At the same time, unconventional measures, like the ECB's large-scale asset purchases, foremost affect longer maturities. In line with the duration extraction channel, they affect long-term rates mainly through compressing their premium component. However, analyses show that they also work through rate expectations, highlighting the signalling channel of non-standard monetary policy.

While Chapter 1 is primarily concerned with the term structure of nominal rates, Chapter 2 turns the focus of this dissertation towards real rates and inflation compensation embedded in nominal yields. The Chapter proposes a model that jointly describes euro area nominal and inflation-linked swap rates, which allows isolating the real and inflation components of nominal interest rates. This is essential for monetary policy analyses since policy makers need to effectively influence real rates in the intended manner as, according to economic theory, it is the level of real rates that matters for consumption and investment and thus ultimately drives inflation.

Like in Chapter 1, the model in Chapter 2 accounts for the ELB for nominal interest rates, which, as it shows, also introduces non-linearities for real rates and the inflation components. The model implies that isolated changes in the ELB impact both nominal and real rates mainly through their expectations component. This highlights that, via lowering the ELB, monetary policy can add accommodation to the economy. Furthermore, an analysis of the instantaneous response of the yield curve components to inflation shocks reveals that the magnitude and sign of these responses are conditional on the degree to which the ELB is binding. The closer nominal yields are to the ELB, the less they react to shocks. On the flipside, this implies that the response of real rates changes as well. While they respond positively to such shocks, when nominal rates are sufficiently far from the ELB, they respond negatively to inflation shocks when nominal rates are at the ELB.

The proposed model is further applied to a decomposition of the change in nominal long-term rates between mid-2014 and mid-2016. This decline is often considered to have been initiated in anticipation of the Eurosystem's unconventional monetary policy measures, in particular, its large-scale asset purchases. Commonly, such programmes are considered to affect yields mainly through two channels: 1) the duration extraction or portfolio rebalancing channel affecting risk premia, and 2) the rate signalling channel affecting rate expectations. Indeed, the results show that both, nominal rate expectations and premia contributed to the decline which is principally in line with both these transmission channels mentioned above. At the same time, however, the reduction to a large extent also reflected declines in inflation expectations and inflation risk premia, which may be an expression of market's anticipating an increased probability of low inflation or even deflation scenarios. Overall, this lays the ground for the supposition that monetary policy may have had adverse effects through negative information effects.

Following these two contributions to the term structure modelling literature, Chapter 3 turns the focus to financial regulation. In particular, it evaluates the potential effectiveness of liquidity and funding regulations. Both of these have been implemented in reaction to the GFC and are based on the insight that liquidity and funding strains were at the heart of this crisis. This was the case as banks previously had failed to prepare themselves for short-term liquidity and funding stress. In response, the Basel Committee on Banking Supervision introduced the LCR, which obliges banks to ensure a sufficient amount of unencumbered highly liquid assets to withstand a 30 day liquidity stress scenario. In addition, the newly introduced Net Stable Funding Ration (NSFR) demands that banks procure sufficient stable funding over a time horizon of one year.

The Chapter presents empirical evidence based on superivsory data on critical events of financial institutions, which is combined with balance sheet data as well as other supervisory data in order to estimate the effect of stable funding on banks' probabilities of distress. Results suggest that stable funding makes critical events significantly less likely for savings banks and credit cooperatives, suggesting a stabilizing effect of the NSFR. Overall, these results indicate that these regulations go in the right direction.

Afterall, it may be both a blessing and curse that uncertainty is a fundamental feature of economic research. On the one hand, it means that economic theory and empirical analyses are unlikely to reach final answers. On the other hand, it means that there is always room for improvement. As this true in general, it is true for the analyses in this dissertation.

The the term structure models presented in Chapter 1 and Chapter 2 offer valuable insights about the importance of modelling the ELB in order to understand how monetary policy transmits along the yield curve and its real and inflation components. However, some open issues remain. For example, these models remain somewhat sensitive to the choice the modeler makes about the level of the ELB which is unobservable in practice. In this regard, future research should focus on pinning down this level. Another important topic for future reasearch on the term structure of interest rates is their level in the very long-run. The models presented here are stationary by assumption and thus consider this level as constant. However, latest research on the natural rate of interest suggests that this assumption may be false, and that interest rates may converge towards a moving target. Accounting for this may have a substantial impact on the decomposition of interest rates and should thus be another focus for future reasearch on this topic.

As regards the empirical work on banking regulations presented in Chapter 3 it is obvious to state that ultimate conclusions about whether they increased the resilience of the financial sector may only be drawn once these regulations have been put in place for a longer period of time. This will allow for a direct analysis of the impact of liquidity and funding regulations. Future research should therefore certainly revisit the empirical analysis of the newly implemented regulation once the relevant data is available.

# Eidesstattliche Erklärung

„Ich erkläre hiermit, dass ich die vorgelegten und nachfolgend aufgelisteten Aufsätze selbstständig und nur mit den Hilfen angefertigt habe, die im jeweiligen Aufsatz angegebenen oder zusätzlich in der nachfolgenden Liste aufgeführt sind. In der Zusammenarbeit mit den angeführten Koautoren war ich mindestens anteilig beteiligt. Bei den von mir durchgeführten und in den Aufsätzen erwähnten Untersuchungen habe ich die Grundsätze guter wissenschaftlicher Praxis, wie sie in der Satzung der Justus-Liebig-Universität Gießen zur Sicherung guter wissenschaftlicher Praxis niedergelegt sind, eingehalten.“

Fabian Schupp
Frankfurt, den 21. März 2020

## Eingereichte Aufsätze

Geiger, F. and Schupp, F. (2018). With a little help from my friends: Survey-based derivation of euro area short rate expectations at the effective lower bound, Deutsche Bundesbank Discussion Paper 27.

Schupp, F. (2020). The (ir)relevance of the nominal lower bound for real yield curve analysis, forthcoming.

Schupp, F. and Silbermann, L. (2017). The role of structural funding for stability in the German banking sector, Deutsche Bundesbank Discussion Paper 3.