DEUTSCHE
BUNDESBANK
EUROSYSTEM

Discussion Paper

Deutsche Bundesbank
No 24/2017

Euro area banks' interest rate risk exposure to level, slope and curvature swings in the yield curve

Daniel Foos
(Deutsche Bundesbank)

Eva Lütkebohmert
(University of Freiburg)

Mariia Markovych
(University of Freiburg)

Kamil Pliszka
(Deutsche Bundesbank)

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

Tel +49 69 9566-0

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

Internet http://www.bundesbank.de

ISBN 978–3–95729–386–2 (Printversion)
ISBN 978–3–95729–387–9 (Internetversion)

Non-technical summary

Research question

Maturity-transforming banks are significantly exposed to interest rate risk. Consequently, the present value of a bank's equity should decrease as a result of rising interest rates. However, given the current low interest rate environment, an increased level of interest rates in conjunction with a steeper term structure could also improve the prospect of higher interest income which may, in turn, have an impact on the economic value of equity. Both interpretations show that the effect of an interest rate hike on the value of bank's equity can go in either direction – this explains why the current literature on this topic is inconclusive. We analyze bank-level data spanning the period from 2005 to 2014 to shed light on the question which bank-specific indicators allow us to explain SSM banks' share price sensitivities to interest rate movements.

Contribution

First, we estimate the sensitivity of share prices for each individual bank to various types of interest rate movements. Our approach allows us to consider movements in the level, the slope and the curvature of the yield curve. We employ the Bayesian DCC M-GARCH model, which enables us to capture risks in the tail of a distribution. This is of particular importance as our considered time period contains major crises. Second, we explain the previously determined sensitivities in terms of bank-specific characteristics (e.g., balance sheet composition, reliance on interest income).

Results

This paper shows that, on average, rising interest rates and a steepening yield curve correspond with higher share prices. The impact heavily depends on individual banks' business model and on other bank-level characteristics. In particular, banks with larger balance sheets, high capital ratios, a higher part of customer loans and a lower part of deposits are more sensitive to interest rate movements. Further, the impact is clearly time-varying, with stronger effects during the crisis period 2010 to 2014.

Nichttechnische Zusammenfassung

Fragestellung

Eine Bank, die positive Fristentransformation betreibt, ist Zinsänderungsrisiken ausgesetzt. Ökonomisch führt das dazu, dass der Wert des Eigenkapitals bei einem Zinsanstieg sinken sollte. Gerade im vorherrschenden Niedrigzinsumfeld könnte allerdings ein Zinsanstieg sowie eine steilere Zinsstrukturkurve die Aussicht auf künftige Zinserträge erhöhen, was sich wiederum positiv auf den ökonomischen Wert des Eigenkapitals auswirken könnte. Diese beiden Interpretationen zeigen, dass der Effekt eines Zinsanstiegs auf das Eigenkapital in beide Richtungen gehen kann - entsprechend gibt es für beide Sichtweisen Belege in der bisherigen Literatur. Wir nutzen in diesem Papier Einzelbankdaten im Zeitraum von 2005 bis 2014 um zu bestimmen, welche bankindividuellen Kennziffern die Sensitivität von börsennotierten SSM-Banken auf Zinsänderungen erklären können.

Beitrag

Im ersten Schritt ermitteln wir die Sensitivität des Aktienkurses auf verschiedene Bewegungen der Zinsstrukturkurve für jede Bank separat, wobei Änderungen im Niveau, in der Neigung und in der Wölbung der Zinsstrukturkurve betrachtet werden. Methodisch greifen wir hier auf das *Bayesian DCC M-GARCH Modell* zurück, welches Risiken am Rand einer Verteilung besser abbilden kann als gängige Ansätze; das ist vor allem wichtig, da unser Analyszeitraum Krisen beinhaltet. Im zweiten Schritt erklären wir die zuvor ermittelten Sensitivitäten für die unterschiedlichen Zinsbewegungen durch bankindividuelle Daten (z.B. Bilanzstruktur oder Abhängigkeit vom Zinseinkommen).

Ergebnisse

Dieses Forschungspapier zeigt, dass Zinserhöhungen sowie eine steilere Zinsstrukturkurve im Durchschnitt positiv mit dem Aktienkurs von SSM-Banken zusammenhängen. Dabei hängt der Einfluss stark vom Geschäftsmodell und von anderen Charakteristika der Banken ab; insbesondere zeigt sich, dass der Aktienkurs von Banken mit höheren Bilanzsummen, höheren Kapitalquoten, höheren Anteilen von Kundenkrediten und niedrigeren Anteilen von Kundeneinlagen stärker auf Änderungen der Zinsstruktur reagiert. Zudem variieren die Effekte stark im Zeitablauf; insbesondere im Krisenzeitraum von 2010 bis 2014 sind Reaktionen der Aktienkurse auf Zinsänderungen stärker ausgeprägt.

Bundesbank Discussion Paper No 24/2017

Euro area banks' interest rate risk exposure to level, slope and curvature swings in the yield curve*

Daniel Foos
Deutsche Bundesbank

Eva Lütkebohmert
University of Freiburg

Mariia Markovych
University of Freiburg

Kamil Pliszka
Deutsche Bundesbank

Abstract

This paper investigates interest rate risk exposures of listed euro area banks which fall under the Single Supervisory Mechanism (SSM). We analyze the period 2005 to 2014, as it includes times of very low interest rates in which banks may have pursued a more risky maturity transformation strategy. First, we use the Bayesian DCC M-GARCH model to assess banks' stock price sensitivities to principal components of changes in the yield curve describing shifts in its level, slope and curvature. Second, we investigate how these sensitivities vary depending on bank-level characteristics (e.g., balance sheet composition, reliance on interest income). Our findings reveal that, on average, banks benefit from positive level shifts and steepening yield curves. Curvature changes affect banks' share prices as well, particularly in times of crises. Further, these sensitivities change in time and depend heavily on the bank's business model and balance sheet composition. Our analysis reveals that banks with larger balance sheets, higher capital ratios, higher parts of customer loans and lower parts of deposits are particularly sensitive to interest rate movements.

Keywords: Bayesian DCC M-GARCH model, interest rate risk, maturity transformation, swings in the yield curve

JEL classification: C11, C51, C55

*Daniel Foos, Deutsche Bundesbank, Wilhelm-Epstein-Str. 14, 60431 Frankfurt am Main. Phone: +49-69-9566-2665. E-mail: daniel.foos@bundesbank.de. Eva Lütkebohmert, Department of Quantitative Finance, University of Freiburg, Platz der Alten Synagoge 1, 79098 Freiburg. Phone: +49-761-203-9362. E-mail: eva.luetkebohmert@finance.uni-freiburg.de. Mariia Markovych, Department of Quantitative Finance, University of Freiburg, Platz der Alten Synagoge 1, 79098 Freiburg. E-mail: mariia.markovych@gmail.com. Kamil Pliszka, Deutsche Bundesbank, Wilhelm-Epstein-Str. 14, 60431 Frankfurt am Main. Phone: +49-69-9566-6815. E-mail: kamil.pliszka@bundesbank.de. We would like to thank Thomas Kick (the editor), Marco Wilkens and seminar participants at Deutsche Bundesbank for their helpful comments.

1 Introduction

Financial institutions, which usually hold a substantial amount of interest-bearing assets and are traditionally heavily involved in the maturity transformation process, are particularly exposed to interest rate risk. Unexpected changes in interest rates triggered by movements in the yield curve might entail large losses in interest-tied balance sheet positions as well as affect the net present value of future cash flows (thus, market value of equity), which may pose a substantial threat to individual bank's stability and the banking sector as such. Though the above-mentioned risks might not immediately materialize in the bank's profit, the underlying hazards are apparent in banks' equity valuations on the stock market. This indirect link makes a stock market reaction indicative of financial stability as a whole and of vulnerabilities in individual financial institutions with important implications for regulatory and monitoring practices.

While theory indicates that an increase in the level and slope of the term structure should have a negative effect on the stock price of maturity transforming banks, the empirical literature remains inconclusive as to whether this holds true in practice. Given an exceptionally low interest rate environment in the euro area that may stimulate risk taking to boost declining profits and may weaken banks' "vigilance" with regard to interest rate risk, tracking of banks' interest rate risk sensitivity and of the underlying sources is becoming increasingly important again. Correspondingly, the Basel Committee on Banking Supervision (BCBS) has revised the minimum capital requirements for market risk[1] (see BCBS (2016b)) and the Pillar 2 standards for interest rate risk in the banking book (see BCBS (2016a)).

This paper contributes to the subject of banks' interest rate risk exposure in two major aspects. First, we estimate individual banks' sensitivity to changes in the yield curve. Second, we analyze which bank-specific indicators allow us to explain banks' share price sensitivities to interest rate movements. Our data ranges from 2005 to 2014 and covers the global financial crisis and the subsequent European sovereign debt crisis. We deepen the analysis by splitting the data in two subperiods (2005 to 2009 and 2010 to 2014). This adds some value to the literature, as both subperiods encompass different economic circumstances and are characterized by different yield curves. Further, this procedure allows us to capture time-dependent variations regarding, first, the sensitivities and, second, relevant bank-specific characteristics.

Concerning the first part of our contribution, we investigate the interest rate sensitivity of major euro area banks which is caused by movements of (quasi) risk-free euro area interest rates. Specifically, we refer to listed European banks which fall under the Single Supervisory Mechanism (SSM) in the euro area.[2] Though there have been related studies

[1] These standards capture, among other risk types, interest rate risk and credit spread risk in the trading book.

[2] These banks have to meet at least one of the following criteria (see ECB (2014a)): (i) the total value of its assets exceeds 30 billion EUR or – unless the total value of its assets is below 5 billion EUR – exceeds 20% of national GDP; (ii) it is one of the three most significant credit institutions established in a member state; (iii) it is a recipient of direct assistance from the European Stability Mechanism; (iv)

focusing specifically on the German, US and UK markets, this research is, to the best of our knowledge, the first to study SSM banks' interest rate risk exposure. Our methodology for measuring banks' stock price sensitivity to interest rate risk consists of two main building blocks. First, we use principal components of changes in the yield curve, which capture the shape of the euro area yield curve, in order to approximate interest rate risk factors that banks are facing. Such a method allows us to quantify SSM banks' interest rate risk exposure to changes of various interest rate movements, including curvature swings in the yield curve – an element that has barely been covered in the empirical literature (an exception is Czaja, Scholz, and Wilkens (2009)). The banks' interest rate risk exposure is assessed based on the recently developed Bayesian dynamic conditional correlation multivariate GARCH model (Bayesian DCC M-GARCH, see Fioruci, Ehlers, and Filho (2014)). This model allows us to directly infer each bank's exposure from conditional variance-covariance matrices between its stock returns and interest rate risk factors at any point in time. It is robust to multicollinearity that might lead to imprecise estimates and allows us to incorporate interdependent interest rate risk components into a conventional regression. Moreover, the Bayesian DCC M-GARCH model, as pointed out by Virbickaite, Concepcion, and Galeano (2015), is much better at explaining asymmetries in volatilities and heavy-tailed asset return distributions that cannot be captured by parametric models, and is, thus, well suited for our analysis, as crises are included in the covered time period. In particular, in times of crises, asset returns exhibit fat tails, volatility clusters and time-varying correlations.

Conceptually, our approach is based on the idea developed in Hasan, Kalotychou, Staikouras, and Zhao (2013), who identify interest rate risk factors with level and slope parameters in the Nelson-Siegel yield curve model[3] and then estimate banks' time-varying interest rate risk sensitivity by applying the DCC M-GARCH framework. However, in contrast to their approach, we employ the generally more robust principal components of the yield curve instead of the Nelson-Siegel yield curve model and we do not limit banks' interest rate risk exposure to level and slope swings in the term structure of interest rates, but incorporate curvature movements as well. Litterman and Scheinkman (1991) show that these three types of interest rate movements are able to explain, on average, more than 98% of total interest rate variation. Further, a broad variety of (simple or complex) interest rate scenarios like, for example, the six new interest rate shock scenarios introduced in the new Basel standards for interest rate risk in the banking book (see BCBS (2016a, pp. 44-47)) can be assessed within our analysis by combining level, slope and curvature shifts. Besides the requirements from Basel, the euro area yield curve took different shapes in the last decade which calls for more sophisticated approaches for capturing interest rate changes as well. The Bayesian extension of the DCC M-GARCH model, developed by Fioruci et al. (2014), enables us to relax the restrictive assumption regarding the normality in the time series of stock returns and determines the distribution by the Bayesian inference procedure. Finally, rather than pooling the banks into a single

the total value of its assets exceeds 5 billion EUR and the ratio of its cross-border assets/liabilities in more than one other participating member state to its total assets/liabilities is above 20%. A complete list of the SSM banks is provided in ECB (2014b). We refrained from adding further small listed banks (outside the SSM) to our sample because their equity is less likely to exhibit liquid trading.

[3] Details of the Nelson-Siegel model are provided in Nelson and Siegel (1987).

portfolio and calculating an average exposure of the sample, we concentrate on each individual bank, which enables us to study the variation in interest rate risk exposure across SSM banks.

As a second contribution, after having quantified SSM banks' interest rate risk exposure, we investigate how these exposures, as measured by the reaction of banks' equity prices to swings in the yield curve, vary depending on individual banks' characteristics (for example, balance sheet composition and reliance on interest income). Such a step serves both as a validation procedure for the results obtained in the initial stage and as an attempt to determine publicly available indicators that might serve as "warning signs" regarding interest rate risk sensitivity which banks exhibit.

The research in the first part of our paper adds to the literature which adopts an "economic value" perspective on investigating banks' exposure to interest rate risk. The basic idea behind this is that interest rate risk embedded in banks' trading and banking books translates into the corresponding changes in their equity prices on the stock market. We undertake this research direction for several reasons. First, as noted by Van den Heuvel, S. (2014), unlike the accounting-based perspective, which relies on lagged data to measure interest rate risk exposure, an approach that is based on banks' equity valuations is more forward-looking. It takes into account the effect of interest rate changes on the present value of all future cash flows and thus captures the long-term impact of interest rate movements on banks' overall positions. Second, the above-mentioned method enables us to trace banks' interest rate risk exposure over shorter time horizons (i.e., daily, weekly, monthly), which is not possible when using the usually annually published accounting-based business figures. Third, this approach tests implicitly how the stock market processes information about changes in the level and shape of the yield curve.

Most papers in this direction start either with a two-factor model suggested by Stone (1974), who uses a CAPM core enhanced with an interest rate risk component, or with various extensions of the Fama-French three factor model,[4] which incorporate additional regressors to capture the impact of unexpected changes in interest rates on banks' equity valuations (see, for example, Saunders and Yourougou (1990), Schuermann and Stiroh (2006) and Mirza and Dauphine (2010)). The existing literature in this line of research, however, provides rather mixed evidence. The majority of authors report that there is a negative association between changes in interest rates and banks' equity prices, meaning that, on average, banks lose in equity value when interest rates go up (see Benink and Wolff (2000), Fraser, Madura, and Weigand (2002), Esposito, Nobili, and Ropele (2015), English, Van den Heuvel, and Zakrajšek (2014) and Czaja et al. (2009)). Others, in contrast, claim that the relationship is negligible and that interest rate risk has an inconclusive impact on banks' stocks (see Schuermann and Stiroh (2006)). In contrast, Ballester, Ferrer, Gonzales, and Soto (2009) find a positive relation between stock prices and interest rates for Spanish banks in the period 1994 to 2006. This is an indication that the European market might react differently on interest rate changes. Interestingly,

[4]Fama and French extend the basic CAPM model (Sharpe (1964), Lintner (1965)) by taking into account size effects, measured via market capitalization, as well as companies' book-to-market ratios (see Fama and French (1974)).

the discrepancies in the directional impact of rate changes remain even when the authors analyze the same market (see Benink and Wolff (2000) versus Schuermann and Stiroh (2006), who study the US banks' interest rate risk exposure).

The second step in our analysis relates to the literature which tries to explain banks' interest rate risk sensitivity via some bank-level characteristics. Such research usually concentrates on the maturity composition of banks' interest rate risk sensitive assets and liabilities. In this context, among the most discussed "vulnerability" sources, which are documented in earlier studies, are a larger maturity gap, or income gap (see Flannery and James (1984), Kwan (1991), Akella and Greenbaum (1992), Landier, Sraer, and Thesmar (2015)), and a positive duration gap (Czaja, Scholz, and Wilkens (2010), Fraser et al. (2002)). In particular, Landier et al. (2015) demonstrate that an income gap, calculated as the nominal difference between banks' interest rate risk-sensitive assets and liabilities that matures within one year, is a major factor explaining a cross-sectional variation in banks' interest rate risk sensitivity. Czaja et al. (2010) and Fraser et al. (2002) explain the differences in banks' sensitivity to interest rate risk based on the positive duration gap inherent in the balance sheet.[5] In this context, when interest rates change, banks with a non-zero duration gap experience a variation in the market value of their equity. These conclusions are in line with the maturity mismatch and nominal contracting hypotheses, which motivate the above-mentioned line of research.

Though maturity and duration gap hypotheses provide a solid intuition behind the vulnerability to interest rate risk across banks, the limited availability of a broader sample of detailed data on banks' asset/liability structures and maturities of the underlying claims,[6] has meant that several studies have tried to explain banks' interest rate risk exposure through publicly available statistics (e.g., banks' capital structure, reliance on interest income, size, hedging activities, overall liquidity in the balance sheet or some other indicators published in banks' financial and regulatory disclosure). For instance, Ballester et al. (2009), who analyze Spanish banks, find that there is a positive relation between banks' size, derivative activities, granted loans and interest rate risk which Spanish banks undergo. Drakos (2001), who concentrates on Greek banks, claims that working capital, equity capital and total debt ratio can explain heterogeneity in interest rate risk exposure across banks. Reichert and Shyu (2003) explore large international dealer banks in the US, Europe and Japan, and attribute the variation in banks' interest rate risk exposure to variation in capital and liquidity ratios as well as in loan loss provisions. The paper suggests, however, that the impact of these indicators on banks' interest rate risk sensitivity is not the same across the regions. Fraser et al. (2002) reaches similar conclusions for the US market. The authors state that equity capital ratios, demand deposits and loans normalized to total assets have an explanatory power in determining banks' interest rate risk exposure. Furthermore, institutions generating a smaller part of their profit from the interest income are more exposed to interest rate risk, which might be due to their greater

[5] Duration is measured as a weighted average value of assets and liabilities in a bank's portfolio, where each resulting cash flow is weighted by the timing at which the payment occurs.

[6] Deriving maturities for assets and liabilities is very challenging and requires subjective assumptions, as several instruments do not have a contractual maturity or are equipped with embedded optionalities. Examples include non-maturing deposits, prepayable fixed-rate loans and derivatives.

reliance on securities-related activities, such as underwriting or acquisitions. Au Yong, Faff, and Chalmers (2007), in turn, distinguish between time horizons related to interest rate risk exposure. The authors conclude that, in the long-run, derivative usage makes banks more sensitive to interest rate shocks, while, in the short-term, this association is less pronounced. The studies on the German market reach similar conclusions (see Entrop, Memmel, Wilkens, and Zeisler (2008), Czaja and Scholz (2006)). We take the conclusions gathered in the above-mentioned studies as a starting point to investigate which bank-level characteristics make a particular SSM bank sensitive to level, slope and curvature swings in the term structure.

The paper is organized as follows. In Section 2 we describe the methodology based on the Bayesian DCC M-GARCH model used to capture each SSM bank's share price reaction (i.e., sensitivity) to movements in level, slope and curvature of the yield curve. Moreover, we present the data and discuss the results on banks' interest rate sensitivity. Section 3 looks for bank-level characteristics which can best explain the estimated sensitivities from the previous section, while Section 4 concludes. Details of the Bayesian DCC M-GARCH approach are provided in Appendix A, while Appendix B contains descriptive statistics of the data as well as robustness checks.

2 Measuring SSM banks' interest rate risk exposure

In this section we estimate the sensitivity of SSM banks' stock prices to various shifts in the yield curve. The methodology described in Section 2.1 is based on the Bayesian DCC M-GARCH approach to estimate the sensitivity of banks' stock returns with respect to various changes in the yield curve. In particular, we analyze level, slope and curvature shifts of the term structure characterized by the first three principal components of the variance-covariance matrix of changes in the yield curve. Our dataset is presented in Section 2.2, while results are summarized in Section 2.3.

2.1 Methodology

2.1.1 Interest rate risk factors

In order to capture various movements of the term structure of interest rates, we first retrieve interest rates from the ECB's estimates for the Svensson parameters (see Svensson (1994)). Within the Svensson model the term structure of interest rates is fitted to an exponential-polynominal family of functions described by six parameters. It is flexible enough to describe reasonable term structure shapes and the model is used, along with several other central banks (see BIS (2005)), by the Deutsche Bundesbank and the European Central Bank (see ECB (2015)). The ECB publishes estimates of the Svensson parameters on a daily basis. From these we can extract times series of interest rates for different maturities. Then, we calculate the variance-covariance matrix of interest rate changes for various maturities. Finally, we calculate the eigenvectors (factor loadings) of the variance-covariance matrix as well as the principal components, i.e., the projections of the daily interest rate changes onto the eigenvectors.

The principal components allow us to capture banks' exposure to interest rate risk for a broad spectrum of movements of the yield curve. Most papers exploring banks' interest rate risk exposure via the stock market reaction use changes in risk-free interest rates related to certain maturities in order to proxy for interest rate risk. For example, among recent papers, Ferrer, Bolos, and Benitez (2016) use yields on ten-year European government bonds to investigate banks' long-term interest rate risk exposure. Beirne, Caporale, and Spagnolo (2009) adopt daily changes in 90-day Treasury bill rates and in ten-year government bond yields in order to approximate interest rate risk. Schuermann and Stiroh (2006) proxy alterations in the term structure using changes in three-month Treasury rates and the term spread as measured by the difference between ten-year and three-month Treasury rates. While these approaches are reasonable approximations, they do not capture interest rate fluctuations for all relevant interest rate movements. Thus, such an approach may be too rough, as banks, on the one hand, try to reduce volatility in their net interest income in order to generate stable earnings for a one-year period[7] and, on the other hand, hold assets and liabilities mostly to maturities well below ten years.

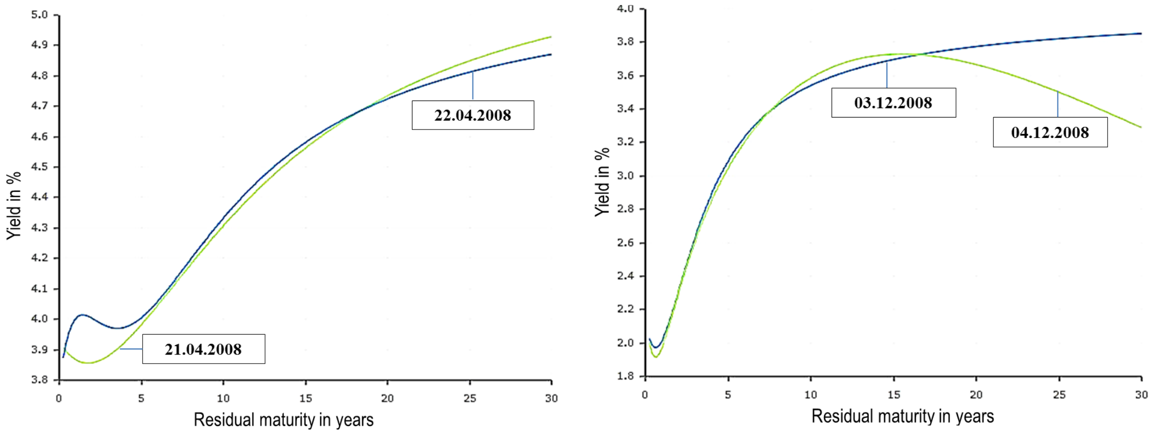
Further, our methodology enables us to estimate banks' interest rate risk exposure not only to linear changes in the term structure, i.e., level or slope surprises, but also to curvature swings in the yield curve. In the empirical literature, this component is usually not analyzed. Unexpected curvature swings in the yield curve, i.e., when short and long-run yields go in one direction while mid-term yields move in another direction, might expose banks to material losses if interest rate risk is not fully hedged. In contrast to the level and slope shifts in the yield curve, movements in curvature are hard to capture analytically when using a standard approach, i.e., calculating differences in term spreads between the observed yields on some securities. This would require a number of subjective judgements regarding which maturities to use in order to locate the humps in the interest rate term structure (see Phoa (2000)). Moreover, at some points in time there might be several humps at different maturities, even though the slope and level may remain the same (see Figure 1); this is clear evidence for incorporating curvature swings in the model.

The approximation of interest rate risk factors through changes in principal components, which describe the shape of the yield curve, addresses this problem and allows us to capture "curvature" risk (along with slope and level changes in the term structure) over the entire maturity spectrum; Figure 1 and our results in Section 2.3 reveal the significance of this additional interest rate risk factor.

[7] The new BCBS standards on interest rate risk in the banking book require banks to measure the net interest income over one year (BCBS (2016a, p. 15)).

Figure 1: Swings in the euro area yield curve

(a) Curvature swing on 22 April 2008 (b) Curvature swing on 4 December 2008



The figures depict the euro area yield curves based on the AAA-rated euro area government bonds estimated on 21 and 22 April (left-hand side) as well as on 3 and 4 December 2008 (right-hand side). The left-hand figure demonstrates a curvature swing in the yield curve that happened in one day at maturities up to 5 and over 20 years. The right-hand figure presents changes in the curvature over the long end of the euro area yield curve (at maturities over 17 years), whereas the short-term yields remained unchanged. In both cases, the level and slope of the yield curve do not change. Source: ECB; details of the estimation procedure may be found in ECB (2015).

2.1.2 Bayesian DCC M-GARCH model for stock price sensitivities

In order to capture SSM banks' interest rate risk exposure to swings in the euro area yield curve we use the Bayesian DCC M-GARCH model. This methodology considers fat tails, volatility clusters and lowers the statistical requirements for the considered time series. Moreover, it allows us to directly estimate banks' time-varying interest rate risk exposure based on the corresponding conditional variance-covariance matrices between banks' equity returns and interest rate risk factors. The sensitivity of banks' stock returns to a particular interest rate risk factor is then expressed as a factor-related beta coefficient (interest rate beta).

More specifically, for each individual bank in the sample, we assess the time-varying interest rate beta coefficient based on the following formula

$$\beta^{(i)}_{\mathrm{IR,t}} = \mathrm{Cov}(\mathrm{r_{it}}, \mathrm{IR_t})/\mathrm{Var}(\mathrm{IR_t}), \tag{1}$$

where $\mathrm{Cov}(\mathrm{r_{it}}, \mathrm{IR_t})$ denotes the conditional covariance between bank i's stock return r_{it} in $(t-1, t]$ and interest rate risk factor $\mathrm{IR_t}$ during $(t-1, t]$ while $\mathrm{Var}(\mathrm{IR_t})$ is the conditional variance of interest rate risk factor $\mathrm{IR_t}$. The interest rate risk factors, in turn, are identified using the first three principal components capturing the yield curve shape, i.e., level (pc_{1t}), slope (pc_{2t}) and curvature (pc_{3t}). Hence, $\beta^{(i)}_{\mathrm{IR,t}}$ represents the interest rate risk exposure of bank i in the period $(t-1, t]$ (i.e., one trading day) to the interest rate risk factor IR during the same time period.[8]

[8]For instance, while assessing bank i's interest rate risk exposure to level swings in the yield curve, the following expression is calculated: $\beta^{(i)}_{pc_{1t}} = \mathrm{Cov}(\mathrm{r_{it}}, \mathrm{pc_{1t}})/\mathrm{Var}(\mathrm{pc_{1t}})$, where pc_{1t} captures changes in

Banks' interest rate risk exposure to swings in level (pc_1), slope (pc_2) and curvature (pc_3) is assessed at each point in time (each bank is considered separately in this step). Conditional variances of risk factors and conditional covariances between banks' stock returns and interest rate risk factors are modeled based on the Bayesian DCC M-GARCH model, which we describe in more detail in Appendix A.1.

In order to derive the sensitivity of each bank's stock returns to changes in the yield curve, we run the Bayesian DCC M-GARCH model separately for each SSM bank. To ensure stable results, we run 100,000 iterations each time when the parameters in the variance-covariance matrices are calibrated. As an output, we obtain conditional variance-covariance matrices estimated at each point in time. Based on these matrices we then assess interest rate beta coefficients $\beta^{(i)}_{\mathrm{IR,t}}$ for exposures to level, slope and curvature changes in the yield curve using Equation 1.

2.2 Data

We apply the analysis to 36 listed banks which fall under the SSM in the euro area (see ECB (2014b)). Among these banks, twelve are headquartered in Italy, four banks are based in Germany, five are domiciled in Spain, and the remaining 15 banks are located in one of the other euro area countries (see Table 1 for details).[9]

Table 1: Euro area SSM banks

Country	AT	BE	CY	DE	ES	FR	GR	IE	IT	PT	Total
Number of banks	1	2	1	4	5	3	4	2	12	2	36

The table shows the number of SSM banks used in the analysis with respect to the countries where their headquarters are registered. The first line corresponds to the widely accepted country abbreviations.

In order to capture the evolution of SSM banks' interest rate risk exposure to swings in the euro area yield curve, we collect a time series of daily stock prices of 36 SSM banks, a time series of the EURO STOXX 50 excluding financials (SX5GNFT) index to control for the overall market conditions, as well as a time series of parameters capturing the shape of the euro area yield curve, which is estimated on a daily basis by the ECB. The analysis overlaps the time period 1/2005 to 12/2014, which was rich in events: In the summer of 2008 the term structure became almost flat; then, after the Lehman failure, the term structure steepened dramatically. Moreover, this period is characterized by declining interest rates, which remained at a low level in the last years.

the yield curve level in the period $(t-1, t]$.

[9] In total, there are 46 listed banks among the SSM banks as of September 2015. However, four banks are excluded from the analysis because the available time series of returns are too short (less than three years), six more banks are excluded because of illiquidity of its stocks, which results in a long series of zero log returns.

Stock prices are obtained from Thomson Reuters Datastream. Banks' closing stock prices are adjusted for splits and dividend payments.[10] Based on these prices we calculate time series of each bank's log returns, $r_t = \ln(P_t/P_{t-1})$, where P_{t-1} and P_t denote bank i's closing stock prices during two subsequent trading days. Overall market conditions are approximated by log returns on EURO STOXX 50 excluding financials index, a blue-chip index capturing the stock market performance of the largest and most liquid non-financial corporates in the euro area. The data on the EURO STOXX 50 excluding financials index is taken from the STOXX website.

Euro area yield curve shape parameters (i.e., Svensson parameters), which are used for calculating the variance-covariance matrix of interest rates for various maturities, are obtained from the ECB website. The ECB's Directorate General Statistics releases the euro area yield curves, including the shape parameters, every trading day. The ECB estimates zero-coupon yield curves based on the Svensson model. A selected bond basket is used to calculate the euro area yield curves consisting of AAA-rated euro area central government zero coupon bonds of different maturities.[11]

We collect daily time series of Svensson model parameters capturing the shape of the euro area yield curve over the period 1/2005 to 12/2014 and retrieve the corresponding interest rates for maturities 0.25, 0.5, 1, 2, 3, 4, 5, 10 and 15 years using the Svensson model. Next, we calculate the variance-covariance matrix for the time series of interest rate changes for the nine above-mentioned maturities. Then, we calculate the first three principal components representing level (pc_1), slope (pc_2), and curvature (pc_3) of the yield curve.

The first principal component explains 76.29%, the second 11.59% and the third 8.21% of the total variation in the yield curve. Accordingly, we explain 96.09% of the total variation by the first three principal components – this is a very parsimonious way of capturing the main properties of yield curve changes and additional principal components would barely increase the explained variation. The relatively high proportions of the second and the third principal component suggest that the interest rate movements in the considered period differ from interest rate fluctuations in normal times indicating that simple measures like the difference of a long-term and a short-term rate would not be sufficient for capturing the observed rate movements.

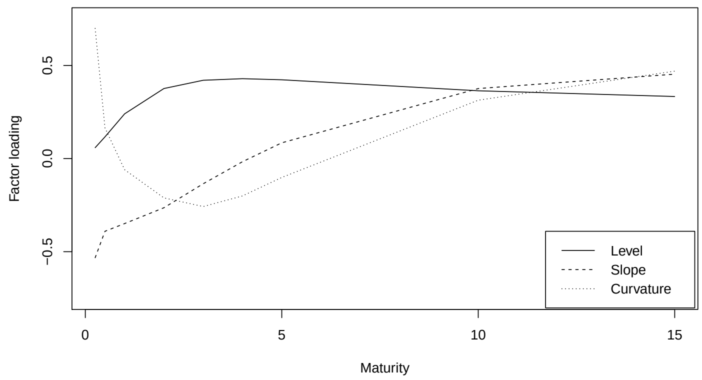
According to Litterman and Scheinkman (1991, pp. 57-58) and as depicted in Figure 2, principal components allow for an economical interpretation. The first principal component is a weighted sum of interest rate changes with the same sign for all maturities and can be interpreted as the level of the change in the yield curve. More precisely, as the coefficients are positive for all maturities, an increase in the first principal compo-

[10] Prices of the stocks, which are listed on more than one stock exchange within a country, are taken from the primary exchange of that country; this is not necessarily the "home" exchange of the stock. Source: Datastream.

[11] The fact that ECB uses only AAA-rated bonds to fit the yield curve also allows us to disentangle effects of changes in risk-free rates from the effects of changes in the risk spreads that would enter the analysis if we had used government bonds of lower ratings. Further details of euro area yield curve estimation are provided in ECB (2015).

nent can be interpreted as an upward shift in the level of the yield curve. The second principal component weights interest rate changes for short maturities with a negative sign and interest rate changes for medium as well as for long maturities with a positive sign and, thus, models the slope of the yield curve. An increase in the second principal component can, therefore, we interpreted as an increase in the slope leading to a steeper yield curve. The third principal component associates positive signs with short-term and long-term interest rate changes and associates negative signs with medium-term interest rate changes. Therefore, it represents a measure of the curvature.

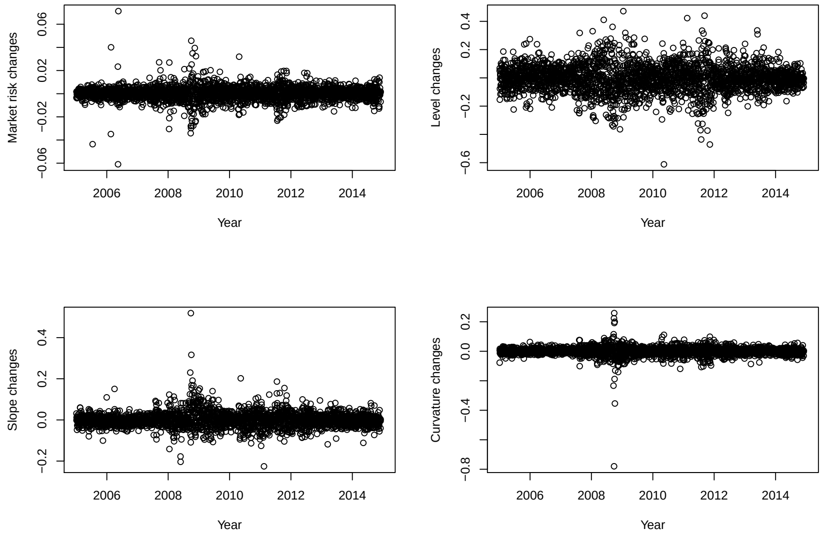
Figure 2: Principal components



Factor loadings for each maturity of the risk-free interest rates for the level (first eigenvector), slope (second eigenvector) and curvature (third eigenvector).

We obtain the daily values of the principal components referring to level, slope and curvature by taking the coefficients as shown in Figure 2 for each maturity and multiply them by the time series of interest rate changes of the same maturity (0.25, 0.5, 1, 2, 3, 4, 5, 10 and 15 years), i.e., the projection of interest rate changes onto the first, second, and third eigenvector. Accordingly, we receive a daily value for each of the three interest rate risk factors; the course in time of the market risk factor and of the principal components is shown in Figure 3.

Figure 3: Course of changes in the market risk and in the interest rate risk factors



The figure shows the course of changes in the market risk and in the interest rate risk factors. The upper left figure shows the changes to the market risk factor. The upper right figure visualizes the level changes, the lower left figure shows the slope changes and the lower right figure depicts the curvature changes of the yield curve.

A pairwise correlation matrix between these components is provided in Table 2. As the principal components are by definition orthogonal to each other, we have no issues with strong correlation or multicollinearity between the considered variables.

Table 2: Pairwise correlation matrix between interest rate risk factors

	Market risk (r_m)	Level (pc_1)	Slope (pc_2)	Curvature (pc_3)
Market risk (r_m)	1.000			
Level (pc_1)	0.2948	1.000		
Slope (pc_2)	0.0608	0.000	1.000	
Curvature (pc_3)	-0.0284	0.000	0.000	1.000

The table shows a pairwise correlation matrix between the market risk factor and the principal components capturing the shape of the euro area yield curve. The variable r_m stands for the market risk as approximated by the EURO STOXX 50 (excluding financials). The variable pc_1 corresponds to level changes in the yield curve reflected in the first principal component; pc_2 represents changes in the yield curve slope captured by the second principal component; pc_3 captures changes in the yield curve curvature corresponding to the third principal component.

Periods during which a big variation in the yield curve model parameters is observed serve as identification events. Two examples of such events are presented in Figure 1, where a substantial change in the yield curve shape happened over night triggering a change in the third principal component pc_3. In Figure 1a and Figure 1b, for instance, curvature swings in the yield curve, which happened at the peak of the global financial crisis (e.g., from 21 to 22 April 2008 and from 3 to 4 December 2008), were accompanied by big jumps in pc_3 (see Figure 3 for curvature changes in 2008).

All the time series used in the analysis are checked for stationarity and normality. We use Augmented Dickey-Fuller, Phillips-Perron unit root tests as well as the KPSS stationarity test to check whether time series are stationary.[12] In each case, time series are stationary (log returns on banks' stocks and EURO STOXX 50 excluding financials index as well as principal components[13]). Furthermore, while the Bayesian methodological approach comes with certain advantages over the conventional regression based methods, we also conduct normality checks on the data to ensure that the additional complexity is warranted. We use Kolmogorov-Smirnov, Shapiro-Wilk and Jarque-Bera normality tests to check whether the return series as well as interest rate risk factors follow a normal distribution. Normality assumption is rejected in all cases. While there is a stylized fact that return distributions might exhibit fat tails as well as leptokurtosis, it is not that obvious for the interest rate risk factors. Thus, we also double-check normality of the EURO STOXX 50 excluding financials index as well as level, slope and curvature interest rate risk factors on QQ plots. QQ plots reconfirm the outcome of the previous tests (see results in Figure 6 in Appendix B).[14]

Each SSM bank is analyzed separately at this stage; thus, in total we consider 36 separate input matrices to analyze each bank's sensitivity to swings in the euro area yield curve. The only difference between these matrices is that the first column, which corresponds to individual bank stock returns, varies.

2.3 Results

We estimate each bank's market risk and interest rate risk exposure to swings in the level, slope and curvature of the euro area yield curve for each trading day during 1/2005 to 12/2014. The exposure to a particular risk factor is calculated as the arithmetic mean over the daily exposures to the corresponding factor observed over each year.[15]

The systematic risk factors (i.e., the market risk factor and the principal components of the yield curve) are economically significant and, hence, attribute a substantial part of the total risk and only a small fraction needs to be explained by idiosyncratic risk. However, some banks were more severely affected by the crises than others and decoupled from general market movements. This becomes apparent in our data set, as the market

[12] KPSS stands for a widely accepted abbreviation of Kwiatkowski-Phillips-Schmidt-Shin stationarity test. Detailed notes on each test can be found in Hamilton (1994).

[13] More specifically, the product of eigenvectors of the variance-covariance matrix of interest rate changes and historical changes in interest rates for various maturities

[14] The results of normality tests also justify the additional complexity that stems from the incorporation of the Bayesian inference procedure into the DCC M-GARCH framework. If the return series and interest rate risk factors were normally distributed, this complication could be avoided.

[15] Less aggregated results, i.e., each individual bank's daily exposure to the risk factors, are available upon request.

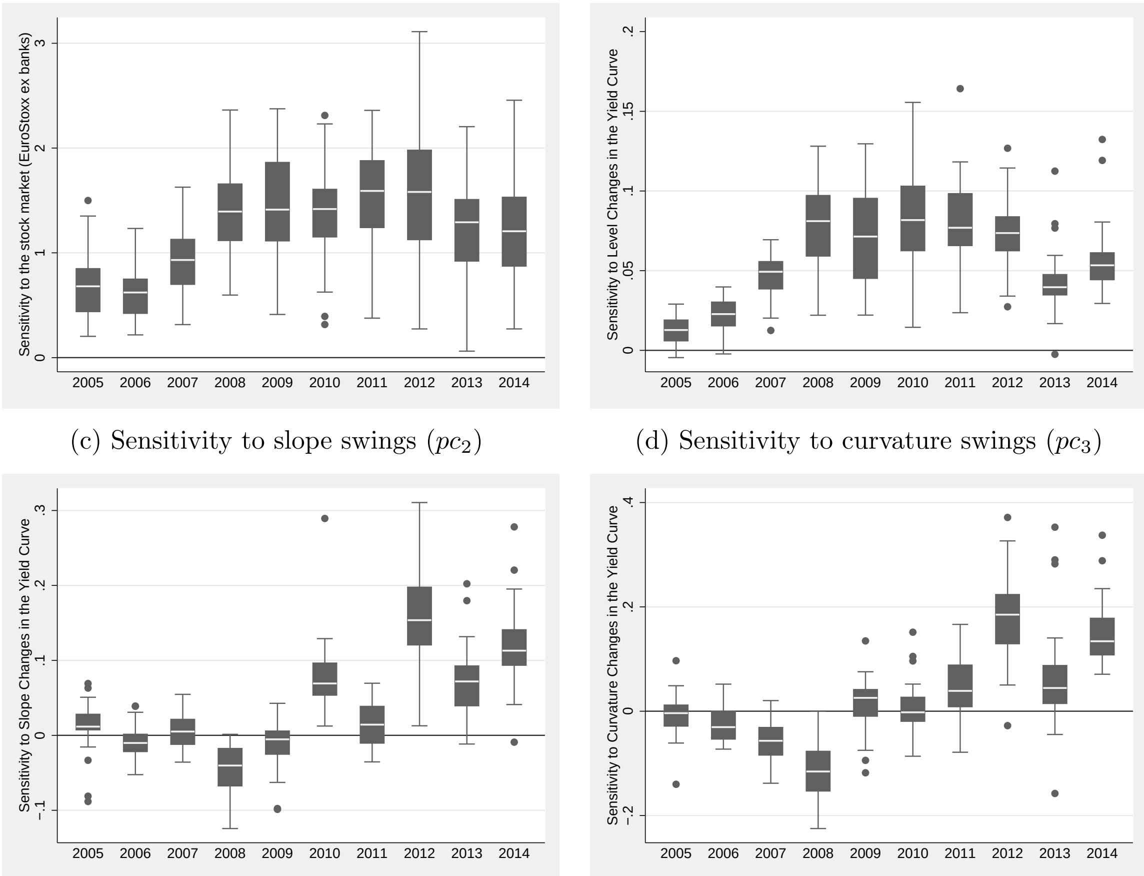
risk factor fails in capturing the market risk for some Cyprian and Greek banks (see coefficients in Table 7 (full period) and Table 8 (subperiods)).

Interest rate risk exposure is measured via the interest rate beta coefficient in Equation 1 describing the percentage change in a bank's stock return associated with a change in the corresponding interest rate risk factor, i.e., principal component of changes in the euro area yield curve. A bank-specific overview of the estimated exposures is summarized in Table 7 (full period) and Table 8 (subperiods). Almost all the assessed conditional correlations of banks' stock price returns with interest rate risk factors, and, hence, the SSM banks' interest rate risk exposures, are statistically significant.

Box plots showing the interest rate risk exposure across all SSM banks covering the period 1/2005 to 12/2014 are presented in Figure 4, illustrating that banks' interest rate risk exposure changes considerably over time. SSM banks are positively exposed to level increases. Further, on average, banks' share prices react positively to slope increases as well as to increases in the curvature combining decreases in mid-term rates and increases in short-term and long-term rates. The positive relation between share price increases and rising interest rates is also supported by Ballester et al. (2009) for Spanish banks and our results on SSM banks' average daily interest rate risk exposure over the period 1/2005 to 12/2014, provided in Table 7 and Table 8. In particular, the tables suggests that banks domiciled in the European core countries (i.e., Germany, France, Austria) are more sensitive to European market conditions than banks in the countries located closer to or at the periphery.

As depicted in Figure 4, after the financial crisis 2007 to 2009, the interest rate risk exposure of the SSM banks has been increasing. This observation is in line with the evidence presented by Begenau, Piazzesi, and Schneider (2015), who, though using a different estimation procedure, document that big banks increased their interest rate risk exposure after the financial crisis. Of particular interest is that the exposure to slope and curvature swings in the yield curve has dramatically increased between 2010 and 2014. As these exposures were almost negligible in 2005 to 2007, this might be an explanation why previous studies have partly neglected the slope and always disregarded the sensitivity to curvature movements. Further, it is noteworthy that almost all banks exhibit the same sign during the examined period, i.e., the results hold true for (almost) all banks and are not driven by few outliers (see Figure 4a to Figure 4d). Given that result, we proceed in Section 3 with an analysis of banks' accounting data and regulatory disclosure in order to understand what bank-level characteristics can explain the above-mentioned heterogeneity.

Figure 4: SSM banks' exposure to the market risk factor as well to level, slope and curvature swings in the euro area yield curve



(a) Sensitivity to the market risk factor (r_m)

(b) Sensitivity to level swings (pc_1)

(c) Sensitivity to slope swings (pc_2)

(d) Sensitivity to curvature swings (pc_3)

This figure presents the variation in the market risk factor and in the interest rate risk exposure to swings in the euro area yield curve observed among the SSM banks. Figure 4a shows a positive relation between banks' share prices and the market risk factor. Figure 4b shows that banks' share prices are positively associated with the first principal component which goes along with rate increases. Accordingly, interest rate increases lead to hikes in share prices. Figure 4c reveals that banks have been barely sensitive to slope changes in the years 2005 to 2009. However, a positive sensitivity can be observed for the years 2010 to 2014. The sensitivity to curvature is depicted in Figure 4d. It turns out that the sensitivity is slightly negative in the years 2005 to 2009 but becomes positive for 2010 to 2014. The dots visualize outliers. The time period covers 1/2005 to 12/2014.

3 Explaining SSM banks' interest rate risk exposure

While banks' overall interest rate risk exposures have been assessed in Section 2 based on market data, the sources which make a particular bank more vulnerable to interest rate risk can be explained by accounting data, such as banks' balance sheet structure or their off-balance sheet items. In this step of the analysis, we connect the SSM banks' interest rate risk sensitivities for level, slope and curvature swings with individual bank-level characteristics that could explain the variation in those interest rate parameters in the cross section and over time. As level shifts account for more than 75% of interest rate risk variability (see Section 2.2), they are clearly the most relevant risk factor to be examined. Besides analyzing the sources of banks' interest rate risk exposure that could potentially serve as "red flags" for regulators and other stakeholders, this step also constitutes a validation procedure of the results obtained in the initial stage, as the latter are input variables in this stage of our analysis.

3.1 Bank characteristics and overview results

This section explains which relation of bank characteristics and banks' interest rate risk exposure we expect to come forth based on economic sense and on findings in the literature. To investigate which particular positions on both the asset and the liability side might expose a bank to interest rate risk, we reconstruct a representative balance sheet from the available data on banks' financial positions (see Table 10 in Appendix B). The details of each position, as defined by the SNL Financial database, are provided in Table 11 and Table 12. Among the available data, we preselect the positions which are either rate-sensitive due to the instruments they contain, or which have been reported to be potential indicators of interest rate risk exposure in earlier studies on this topic.

The selected balance sheet positions include total financial assets, broken down into net customer loans and securities on the asset side, as well as deposits (with term deposits as a subset), debt (with senior and subordinated debt as its components), and derivatives on the liability side (see Table 11 and Table 12). The Core Tier capital ratio is included as a measure of banks' solvency. We also consider the gap between customer-related assets and liabilities by including net customer loans minus deposits to total assets. All balance sheet positions are normalized by total assets or, respectively, by the sum of total liabilities (and equity) in order to make them comparable across the sample.

The return on average assets (ROAA), calculated as net income divided by banks' average assets, controls for variation in the realized profitability across the banks,[16] and it is further broken down to the net interest income relative to operating revenue and the net fee income relative to risk-weighted assets (RWA). Finally, the relation of loan loss reserves to gross customer loans is included to control for banks' credit risk, and the logarithm of banks' total assets accounts for size effects in their interest rate risk exposure.

Table 3 summarizes the expected directional impact of the bank characteristics on banks' interest rate risk and provides also an overview of factors which prove to have a significant impact in our analysis. The regression model used is described in Section 3.2; more detailed results are given in Section 3.3 where we discuss the relevant variables for each interest rate risk factors separately. For facilitating the interpretation, it should be noted that we measure interest rate risk by the reaction of banks' equity on changes in the first, second and third principal component of the yield curve. Given the interpretations of the principal components (see Section 2.2), increases in the level, slope and the curvature go along with a higher interest rate sensitivity (see Figure 4b to Figure 4d as

[16] The inclusion of ROAA in the analysis is motivated by the findings of Hao and Zhang (2007), who find that firms' profitability affects their stock price sensitivity to market wide information (market betas). In this context, banks' overall profitability might also have an impact on their sensitivity to swings in the term structure.

well as Table 7 and Table 8). Accordingly, increases in all three types of interest rate movements can be interpreted in the same way, as they make banks more vulnerable, i.e., more sensitive, to interest rate risk.

Table 3: Bank characteristics which determine banks' interest rate risk exposure

Bank characteristic	Expected relation	Empirical results w.r.t. Level	Slope	Curvature
Total financial assets to total assets	+	∼	∼	∼
Securities to total assets	+	∼	∼	+
Net customer loans to total assets	+	+	+	+
Core Tier capital ratio	−	+	−°	+
Deposits to total liabilities (and equity)	−	−	∼	∼
Term deposits to deposits	−	∼	−	−
Total debt to total liabilities (and equity)	−	−	∼	−
Subordinated debt to total liab. (and equity)	+/−	+	∼	∼
Senior debt to total liabilities (and equity)	−	−	∼	−
Derivative liabilities to total liab. (and equity)	+/−	+°	∼	+
Net interest income to operating revenue	+/−	−	∼	∼
Net fee income to risk-weighted assets (RWA)	−	∼	−	−
Return on average assets (ROAA)	+/−	−	+°	∼
Net customer loans minus deposits to total assets	+	∼	+	+
Loan loss reserves to gross customer loans	−	−	∼	+
Size	+	+	+	+

The symbols +, - and +/- indicate a positive, negative and inconclusive/ambigeous relation of the bank characteristics on interest rate risk. The symbol ∼ stands for inconclusive empirical results, whereas ° indicates empirical results that are only significant during the first half of the period (subperiod: 2005 to 2009).

As regards the variables on the asset side, we expect a positive relation of *financial assets* on banks' balance sheets and their interest rate risk exposure, because the value and return on non-financial assets (e.g., real-estate investments) do not immediately depend on the level and shape of the term structure. Even more clearly, banks which have a relatively high fraction of *securities* on the balance sheet should be more exposed to interest rate risk from a present value perspective, as the economic value of securities can generally be inferred from market prices, whereas banks whose balance sheet consists to a high degree of *customer loans* granted (which usually do not reprice on a high frequency) should be more exposed to interest rate risk from an earnings perspective. The latter effect would be in line with prior evidence by Fraser et al. (2002), Au Yong et al. (2007) and Ballester et al. (2009).

Banks' leverage as measured by the *Core Tier capital ratio* is expected to be negatively related with their interest rate risk exposure, because equity on the balance sheet should serve as a cushion to adverse developments such as sudden interest rate changes and make a bank safer. This expectation is in line with empirical evidence by Fraser et al. (2002), Saporoschenko (2002) and Au Yong et al. (2007).

As regards banks' liability side, we expect a negative relation between *deposits* and banks' interest rate risk exposure, which has also been identified in the literature (Fraser et al. (2002), Saporoschenko (2002) Ballester et al. (2009) and English et al. (2014)). The interest paid on both *demand deposits* and *term deposits*, which we consider as a specific variable, depends to a much lesser degree on changes in the yield curve than the interest paid, e.g., on the money market.

The association between *total debt* and banks' interest rate risk is more difficult to grasp. Generally, medium and long-term debt financing – as opposed to the short-term money market – should reduce banks' exposure to yield curve changes because, assuming that these instruments have fixed coupons, future interest payable does not depend on the future term structure. This is particularly true for *senior debt* and less so for *subordinated debt*. The latter, due to its junior status, has a downside risk that resembles equity, and therefore, we expect it to be positively related to banks' interest rate risk. In contrast, the association of senior debt and banks' sensitivity to term structure changes is expected to be negative.

Derivative liabilities, instead, may be positively or negatively related to banks' interest rate risk exposure, depending on their use for hedging or speculation. Unfortunately, this information cannot be retrieved from accounting data. English et al. (2014) provide comprehensive evidence regarding their impact on banks' sensitivity to interest rate changes, but we leave it as an empirical question to identify a positive or negative relation.

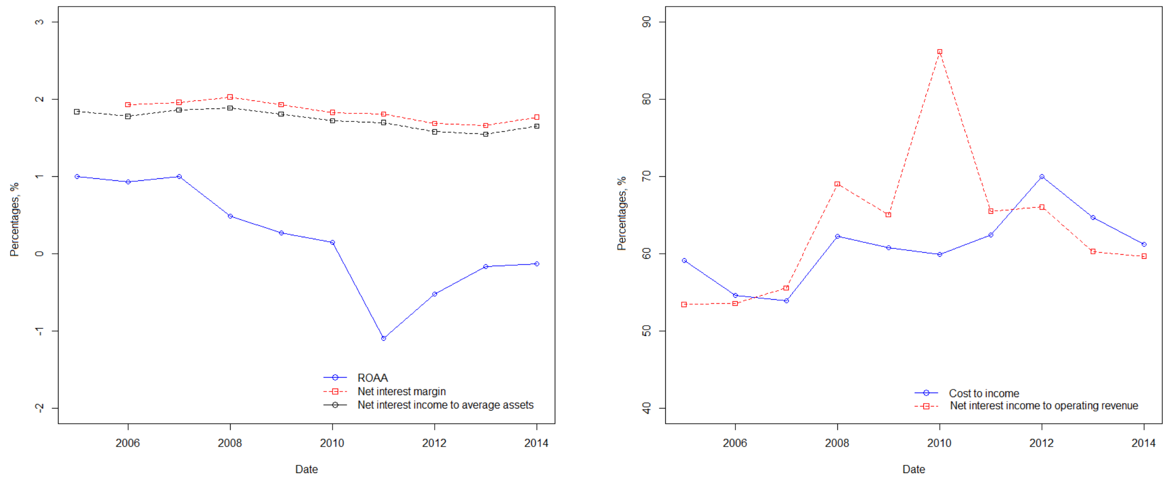
Net interest income to operating revenue measures banks' reliance on interest income and, thus, approximates their income structure at different points in time. This does not allow us to derive any clear expectation on its relation to interest rate risk. *Changes in net fee income, normalized by risk-weighted assets*, indicate banks' involvement in "non-interest" business lines, such as credit card servicing, non-deposit product sales, trust and mortgage banking (see FDIC (2015)). In line with Fraser et al. (2002), we expect it to be negatively related to banks' interest rate risk exposure.

A closer examination of the earnings metrics is shown in Figure 5 where the development in average ROAA and in net interest income across the SSM banks, as compared to other profitability measures, is provided. This reveals that, during 2005 to 2014, the listed SSM banks, on average, experienced either a small return (2005 to 2010 and 2013 to 2014) or losses (2011 to 2012) as indicated by their ROAA. In line with Wright and Houpt (1996), the figure shows that big banks sustain stable net interest margins as well as a stable ratio of net interest income to average assets. These margins may be a sign that banks engage in maturity transformation, which implies higher interest rate risk and, hence, a higher sensitivity to interest rate movements, but they may also be considered as a cushion against events (such as changes in the term structure) that adversely affect banks' income. Therefore, the expected relation of the ROAA and banks' sensitivity to interest rate risk is unclear. An increase in net interest income to operating revenue observed in 2010 might indicate that the SSM banks incurred a sharp decrease in income linked to other businesses as the European sovereign debt crisis unfolded. More detailed statistics on SSM banks' profitability measures can be found in Table 9 in the Appendix B.

Figure 5: SSM banks' profitability

(a) Profitability indicators: ROAA, net interest margin, net interest income to average assets

(b) Profitability indicators: cost to income, net interest income to operating revenue



The figure presents key profitability ratios of the considered 36 SSM banks during 2005 and 2014. The ratios are calculated as averages over the respective bank-level indicators observed in the sample for a given year. The net interest margin is calculated as net interest income divided by interest earning assets. Data source: SNL Financial.

Further, we consider *loans minus deposits* as a liquidity indicator that measures the gap between customer-related assets and liabilities.[17] As this imbalance between banks' assets and liabilities may not only imply liquidity risk but also interest rate risk, we expect a positive relation of this variable to banks' sensitivities.

The *loan loss reserves to gross customer loans* ratio reflects an overall credit quality of banks' credit portfolio (see Bolt, Haan, Hoeberichts, van Oordt, and Swank (2012)). If credit risk and interest rate risk are negatively related, we should expect a negative sign for this variable.

Finally, size, defined as the logarithm of banks' total assets, accounts for the differences in banks' policies, lending and borrowing practices as well as other circumstances, which are linked to this indicator. For example, large banks are more prone to the moral hazard problem and might, thus, accept larger interest rate risk. Ballester et al. (2009) and Saporoschenko (2002) have empirically detected this positive relation, and we also expect to identify it in our study.

The data on SSM banks' balance sheets, income statements, asset quality and regulatory capital reporting is obtained from SNL Financial. The time period of this second part of the analysis covers - like the first part - 2005 to 2014. To ensure consistency

[17]In the empirical literature, banks' liquidity is also measured as loans to deposits. However, as net customer loans minus deposits are normalized to total assets and, thus, comparable across banks, the initial specification does not make a difference in the analysis.

in the measurement across the sample, we use only the observations reported based on IFRS accounting standards.[18] Since comprehensive quarterly (or more frequent) reporting is not available for some SSM banks in the sample, the data is collected on an annual basis.

The above-mentioned indicators are collected for the 36 SSM banks in our sample. As some bank-level data is missing for some years, the resulting panel is unbalanced. The outlined variables are then matched to SSM banks' interest rate risk exposures to level, slope and curvature swings in the euro area yield curve, estimated in the first step of our analysis (see Section 2). Each bank's interest rate risk exposure to swings in the yield curve in a given year is calculated as the average of daily exposures to a particular interest rate risk factor observed during that year.

3.2 Methodology

In line with Ballester et al. (2009), we use a country-level fixed effects (FE) panel data framework. This approach allows us to eliminate a potential bias related to the time-invariant country-specific conditions, which might have, among many others, an impact on banks' behavior, their balance sheet composition and income structure. Furthermore, we include time fixed effects on a yearly level, which capture any systematic changes in interest rate risk exposure that might happen throughout the entire sample over time. Essentially, the econometric model is, thus, identified by the within-country variations in exposure in a specific year.

The basic linear model used in the analysis is

$$\beta^{(i)}_{\mathrm{IR,t}} = X_{i,t}^{\top} b + Y^{\top}\theta + \epsilon_{i,t}, \tag{2}$$

where $\beta^{(i)}_{\mathrm{IR,t}}$ corresponds to bank i's sensitivity to a particular interest rate risk factor (i.e., to level, slope or curvature swings in the euro area yield curve) at time t;[19] $X_{i,t}$ refers to the matrix of bank-specific characteristics; Y is the matrix of time- and country-fixed effects;[20] $\epsilon_{i,t}$ are independently, identically distributed error terms.

We run separate regressions for SSM banks' sensitivities to level $\beta^{(i)}_{pc_1,t}$, slope $\beta^{(i)}_{pc_2,t}$, and curvature swings $\beta^{(i)}_{pc_3,t}$ in the euro area yield curve. For example, while searching for factors explaining SSM banks' exposure to level swings in the term structure, the following panel is estimated

$$\beta^{(i)}_{pc_1,t} = X_{i,t}^{\top} b + Y^{\top}\theta + \epsilon_{i,t}, \tag{3}$$

[18]For instance, IKB Deutsche Industriebank AG is excluded from the analysis during 2013 and 2014, because it switched to German GAAP.

[19]Even in the presence of measurement error in the dependent variable, the zero conditional mean assumption is not violated and the subsequent estimates are unbiased.

[20]Bank-level fixed effects are not considered as the inclusion of 36 group dummies corresponding to 36 banks substantially reduces between-group variation. Furthermore, controlling for both country-specific and bank-level fixed effects means that, in cases where there is only one SSM bank located in a particular country, fixed effects for such a bank would be controlled for twice: first on a country level, and the second time on a bank level.

where explanatory variables are the same as in the general Equation 2. The same procedure is applied when analyzing banks' exposure to slope and curvature swings in the yield curve.

As pointed out in Section 2.3, particularly some Cyprian and Greek banks were strongly affected by the crisis and decoupled from the general market movements. Accordingly, for these banks, a material part of the risk needs to be explained by idiosyncratic risk. Thus, in order to ensure the robustness of our results, we excluded six additional banks during crisis years from the analysis. However, the results in Table 3 were similar in magnitude and significance.

A variety of model specifications allows us to ensure the robustness of our results across several dimensions. First, we consider two different regression settings, in which we control for different bank-specific characteristics as explained in this section. Second, we estimate both models for the full period (2005-2014) as well as for the pre- and post-crisis subperiods (2005-2009 and 2010-2014). Third, since the accounting data for year t is released only at the end of the year, it is possible that during year t investors condition their expectations regarding SSM banks' interest rate risk exposure on the previous year's financial and regulatory reporting. Thus, we also run the above-outlined models on the averages of the independent variables over two subsequent years as a robustness check, i.e., matrix $X_{i,t}$ in Equation 2 is replaced by the averages $\widehat{X}_{i,t} = \left(X_{i,t} + X_{i,t-1}\right)/2$.

3.3 Detailed results

3.3.1 Exposure to level swings

Table 4 presents the results of bank-specific factors that account for variation in SSM banks' interest rate risk exposure to level swings in the euro area yield curve in the cross section and over time. As described in Section 3.2, the results are presented for two different regression settings, which differ in terms of the explanatory variables included ((1a–1c) vs (2a–2c)). Further, we consider the full period as well as the pre- and the post-crisis subperiods (2005-2009 and 2010-2014). Please note that the sensitivity was considerably larger from 2010 to 2014, hence results from this subperiod are particularly interesting.

Table 4: Explaining SSM banks' sensitivity to level changes

	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Regressors	Full period	2005 – 2009	2010 – 2014	Full period	2005 – 2009	2010 – 2014
Total financial assets to total assets	0.047	0.066	0.047			
	(0.75)	(0.71)	(0.73)			
Securities to total assets				0.024	-0.062	0.003
				(0.62)	(-0.99)	(0.05)
Net customer loans to total assets				**0.088***	-0.049	0.090
				(2.03)	(-0.84)	(1.32)
Core Tier capital ratio	**0.114****	0.208	**0.170*****	**0.103****	0.153	**0.101***
	(2.48)	(1.38)	**(3.67)**	**(2.25)**	(1.16)	**(1.79)**
Deposits to total liabilities (and equity)				**-0.119*****	-0.027	**-0.155****
				(-3.78)	(-0.70)	**(-2.50)**
Term deposits to deposits				0.020	0.026	0.000
				(0.99)	(0.67)	(0.02)
Total debt to total liabilities (and equity)	-0.048	0.013	**-0.076***			
	(-1.62)	(0.31)	**(-1.87)**			
Subordinated debt to total liabilities (and equity)				**0.377****	0.309	0.198
				(2.41)	(1.56)	(0.78)
Senior debt to total liabilities (and equity)				**-0.110*****	0.010	**-0.177*****
				(-3.22)	(0.19)	**(-2.88)**
Derivative liabilities to total liabilities (and equity)	0.008	-0.020	0.045	0.082	**0.215****	0.075
	(0.19)	(-0.49)	(0.74)	(1.27)	**(2.48)**	(0.82)
Net interest income to operating revenue	**-0.011*****	0.009	**-0.009*****	-0.003	-0.001	-0.007
	(-6.34)	(0.59)	**(-5.29)**	(-0.31)	(-0.03)	(-0.62)
Net fee income to RWA	0.062	0.015	-0.035	0.097	0.625	-0.414
	(0.20)	(0.03)	(-0.11)	(0.26)	(1.30)	(-0.98)
ROAA	**-0.461****	**-1.469****	**-0.428****	**-0.348****	**-1.942*****	-0.224
	(-2.59)	**(-2.38)**	**(-2.62)**	**(-2.09)**	**(-4.58)**	(-1.39)
Net customer loans minus deposits to total assets	0.050	-0.008	0.056			
	(1.66)	(-0.19)	(1.58)			
Loan loss reserves to gross customer loans	**-0.180*****	-0.163	**-0.241*****	**-0.169*****	-0.189	**-0.202****
	(-2.79)	(-0.41)	**(-2.81)**	**(-3.01)**	(-0.54)	**(-2.55)**
Size	**0.008*****	**0.008*****	**0.007*****	**0.005****	0.002	**0.007****
	(4.91)	**(3.28)**	**(3.39)**	**(2.04)**	(0.76)	**(2.34)**
Observations	275	119	156	241	105	136
R^2	0.61	0.70	0.58	0.66	0.78	0.61

The dependent variable is banks' interest rate risk exposure to level changes in the euro area yield curve. RWA refers to banks' risk-weighted assets. Core Tier capital ratio is defined as a ratio of a bank's core equity capital to risk-weighted assets. Banks' size is calculated as a logarithm of total assets. The details of the items included in other positions are provided in Table 11 and Table 12. The data is collected from the SNL Financial database on an annual basis. Time period: 2005 to 2014. In each case the regression is run while controlling for time- and country-fixed effects. Standard errors are clustered at bank level; t-statistics are shown in brackets. The symbols *, ** and *** indicate significance at the 10%, 5% and 1% levels.

In order to interpret the estimated coefficients correctly, please notice that the dependent variable ($\beta^{(i)}_{pc_1,t}$) has almost exclusively positive values (see Figure 4b, Table 7 and Table 8), which represents the positive relation of increases in the interest rate level (the first principal component takes positive values with interest rate increases (see Figure 2)) and banks' share prices. Thus, a positive coefficient for the explanatory variables implies that the positive sensitivity to level changes in the yield curve is even more pronounced.

Regression results are mostly in line with the expectations explained in Section 3.2: While coefficients for total financial assets and securities are insignificant, the ratio of net customer loans to total assets is positively related to banks' sensitivity to level changes, which corresponds with the expected effect on earnings volatility. The negative relation of deposits to total liabilities (and equity) is also in line with our expectation. They indicate lower sensitivity to changes in the yield curve level, are economically reasonable as the payable deposit rate is usually lower than the market rate and only a small portion of a rate shock is passed onto customers. Given that in particular the second half of the sample period was characterized by rate cuts and deposit gathering – meaning that the difference between the market rate and the deposit rate became smaller or even reversed – the effect is significantly stronger from 2010 onwards. Please notice that the impact of term deposits is insignificant instead.

Although total debt to total liabilities (and equity) is only marginally significant in model (1c), the breakdown of debt into subordinated and senior debt reveals that especially banks with a higher amount of subordinated debt, i.e., debt with the lowest seniority, are more sensitive to changes in the level of the yield curve: a 1 percentage point increase in the subordinated debt normalized to total liabilities (and equity) is related to a corresponding 0.4 percentage points increase in banks' exposure to level swings in the yield curve. A possible explanation for this observation is that subordinated debt, due to its junior status, has a downside risk that resembles equity and is, thus, particularly sensitive to level changes in the term structure of interest rates. In this context, a parallel rise in the euro area bond yields leads to mark-to-market losses in its value on banks' balance sheets. Instead, the relationship between senior debt and banks' exposure to level changes in the yield curve goes in the opposite direction: coefficients point towards a small and partly significant risk-reducing role of senior debt. Both findings are in line with our expectations.

The significantly negative coefficients for the return on assets (ROAA) shown in Table 4 model (1) and during the first half of the sample period in model (2) indicate that less profitable banks are more exposed to changes in the level of the term structure. On the one hand, rising long-term interest rates that correspond to changes in the yield curve level translate into immediate capital losses on the long-term assets; on the other hand, banks that are more profitable are more resilient in absorbing these potential losses. In contrast, higher ROAA, which to some extent serves as a cushion against adverse market scenarios, is linked to lower sensitivity to level swings in the yield curve. The same rationale applies for the risk-reducing function of the net interest income to operating revenue: Banks which rely more heavily on interest income as an earnings source are less exposed to level changes in the yield curve, possibly because they apply effective hedging strategies.

Further, our regression results hint towards a negative relation of credit risk and interest rate risk: Banks with higher ratios of loan loss reserves to gross customer loans are, on average, less exposed towards interest rate risk. The positive and significant coefficients for bank size point to the higher interest rate risk exposure of larger banks, which is in line with potential moral hazard problems.

One empirical finding that does not correspond with our expectations is represented by the positive coefficients for the Core Tier capital ratio. This indicates that banks with less capital and, hence, a lower risk-bearing capacity are also less exposed to level changes in the yield curve, but it is not in line with the contrary effect that has been identified in the literature (Fraser et al. (2002), Saporoschenko (2002) and Au Yong et al. (2007)).

While SSM banks' financial reporting is disclosed only at the end of the year, it might be the case that, up to the release, investors condition their decisions and expectations based on the information contained in the previous year's financial statements, adjusted for any news, disclosures or analyst reports that come up in the course of the current year. To account for this, we re-estimate the same models on the averages (see Section 3.2). The results are provided in Table 13 in Appendix B.

Regressions on the averages support the initial conclusions. There is a significantly negative association between banks' return on average assets (ROAA) and banks' exposure to level swings in the yield curve. Moreover, banks' sensitivity to level changes in the yield curve increases with their size, with the amount of subordinated debt they hold, and with their net customer loans, normalized by total assets or respectively by total liabilities (and equity). Further, there is a significantly negative relation between banks' net interest income, normalized by the operating revenue, and their sensitivity to changes in the level of the yield curve. On the one hand, banks whose interest income constitutes a major part of their operating revenues, are more vulnerable to unexpected changes in the yield curve level (see English et al. (2014)). On the other hand, heavier reliance on interest income might make these banks hedge their level exposure, which has a big loss potential, as opposed to banks with a non-interest income focus. Finally, it should be noted that deposits, scaled by total liabilities (and equity), as well as loan loss reserves show significantly negative coefficients, which points towards the limited pass-through of level swings in the yield curve to deposit rates and to a negative relation of credit risk and interest rate risk.

3.3.2 Exposure to slope swings

As explained in Section 2.2, more than 75% of all interest rate variability can be attributed to level shifts. Hence, the factors that explain banks' sensitivity to changes in the level of the yield curve should be considered as *primary* bank-specific factors for interest rate risk exposure. We have analyzed these drivers in Section 3.3.1. However, even if a bank is insensitive to level swings - say, due to corresponding hedges - it may still have exposure to non-parallel changes of the yield curve. This sensitivity and the associated *secondary* bank-specific factors are analyzed in this section.

Hence, please note that it is less obvious that the bank-specific factors which drive banks' exposure to slope swings are represented in financial reports and that the market incorporates them when pricing banks' equity. Moreover, uncertainty in the type of the slope change is present, as an increase in the slope parameter could be triggered either by increased short-term rates or by decreased long-term rates.

In order to investigate which bank-level indicators can explain SSM banks' interest rate risk exposure to slope swings in the yield curve, we run separate regressions of banks' estimated exposures to changes in the slope of the yield curve on the same set of explanatory variables as described in Section 3.2. The results are provided in Table 5.

Table 5: Explaining SSM banks' sensitivity to slope swings

	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Regressors	Full period	2005 – 2009	2010 – 2014	Full period	2005 – 2009	2010 – 2014
Total financial assets to total assets	0.105	-0.024	0.112			
	(0.66)	(-0.23)	(0.34)			
Securities to total assets				0.116	0.012	0.105
				(1.16)	(0.10)	(0.52)
Net customer loans to total assets				**0.182****	-0.054	**0.282***
				(2.09)	(-0.44)	**(1.74)**
Core Tier capital ratio	-0.014	**-0.597*****	0.059	0.051	**-0.394***	0.042
	(-0.12)	**(-3.26)**	(0.48)	(0.40)	**(-1.99)**	(0.32)
Deposits to total liabilities (and equity)				-0.054	0.140	-0.153
				(-0.62)	(1.62)	(-0.98)
Term deposits to deposits				**-0.059***	**-0.073***	-0.013
				(-1.82)	**(-1.72)**	(-0.37)
Total debt to total liabilities (and equity)	-0.046	0.055	-0.127			
	(-0.80)	(0.91)	(-1.38)			
Subordinated debt to total liabilities (and equity)				0.227	0.343	0.321
				(0.69)	(1.13)	(0.42)
Senior debt to total liabilities (and equity)				-0.110	0.097	-0.214
				(-1.09)	(1.00)	(-1.27)
Derivative liabilities to total liabilities (and equity)	0.065	0.025	0.104	0.094	0.041	0.129
	(1.11)	(0.52)	(0.86)	(0.98)	(0.29)	(0.83)
Net interest income to operating revenue	-0.004	-0.005	-0.004	-0.020	0.010	-0.039
	(-0.86)	(-0.16)	(-0.73)	(-0.86)	(0.40)	(-1.37)
Net fee income to RWA	-0.852	-0.324	-1.715	**-2.208*****	**-1.569****	**-2.799*****
	(-1.16)	(-0.50)	(-1.66)	**(-3.05)**	**(-2.49)**	**(-2.76)**
ROAA	-0.064	**1.891*****	-0.124	-0.029	**2.426*****	0.005
	(-0.14)	**(2.91)**	(-0.27)	(-0.06)	**(4.03)**	(0.01)
Net customer loans minus deposits to total assets	0.057	-0.041	**0.121***			
	(1.20)	(-0.84)	**(1.79)**			
Loan loss reserves to gross customer loans	0.104	0.187	-0.168	0.091	0.065	-0.116
	(0.52)	(0.41)	(-0.47)	(0.53)	(0.15)	(-0.48)
Size	**0.005****	-0.004	**0.012****	**0.008*****	0.000	**0.016*****
	(2.19)	(-1.32)	**(2.46)**	**(2.74)**	(0.05)	**(3.51)**
Observations	275	119	156	241	105	136
R^2	0.76	0.54	0.59	0.76	0.58	0.55

The dependent variable is banks' interest rate risk exposure to slope changes in the euro area yield curve. RWA refers to banks' risk-weighted assets. Core Tier capital ratio is defined as a ratio of a bank's core equity capital to risk-weighted assets. Banks' size is calculated as a logarithm of total assets. The details of the items included in other positions are provided in Table 11 and Table 12. All the data is collected from the SNL Financial database. Time period: 2005 to 2014. In each case the regression is run while controlling for time- and country-fixed effects. Standard errors are clustered at bank level; t-statistics are shown in brackets. The symbols *, ** and *** indicate significance at the 10%, 5% and 1% levels.

The majority of banks has on average a positive exposure to slope swings representing steepening yield curves (see Table 7). However, as Figure 4a and Table 8 show, sensitivities are near zero and partly negative during the first half of the sample period (2005-2009), while sensitivities to slope changes from 2010 onwards are significantly positive. Hence, a positive coefficient in Table 5 means – in particular during the second half of the sample period – that increasing values of independent variables (i.e., regressors) go along with higher values of the dependent variable ($\beta^{(i)}_{pc_2,t}$) and, thus, expose the bank more strongly to slope swings. In contrast, a negative coefficient pulls $\beta^{(i)}_{pc_2,t}$ closer to zero and, thus, reduces the sensitivity to slope swings.

Again, results are generally in line with our expectations as explained in Section 3.1. Coefficients for banks' net customer loans to total assets are significantly positive (in particular from 2010 onwards), which indicates – in line with the findings regarding level changes in the yield curve – that banks with a focus in the lending business are more exposed to interest rate risk.[21] The regression models are also consistent with the observation that larger banks are exposed to more interest rate risk in the second half of the sample period. Furthermore, banks with high levels of net fee income, scaled by RWA, are less exposed to slope changes in the yield curve.

Models (1b) and (2b) in Table 5 show that during the first half of the sample period (2005–2009), several other dependencies of banks' balance sheet structure and their sensitivity to slope swings seem to work in the same direction as the effects explained in Section 3.3.1 above. Banks' profitability, as measured by ROAA, is positively associated with exposure to shifts in the slope of the yield curve, and a positive coefficient for the Core Tier capital ratio confirms the notion that banks with higher core Tier capital ratios, i.e., higher loss absorbing capacity, will more likely take additional interest rate risk. Again, please note that the vast majority of banks' interest rate risk exposure can be explained by their sensitivity to level shifts in the term structure, meaning that these effects should only be regarded as *secondary* relative to the results explained in Section 3.3.1.

As for level swings in yield curves, regressions on the averages yield similar results, except for the fact that coefficients for customer loans to total assets are lower in magnitude and significance (compare Table 14 in Appendix B). Additionally, estimates for the impact of subordinated debt to total liabilities (and equity) as well as net interest income to operating revenue on banks' exposure to slope swings are in line with our findings regarding exposure to level swings, as shown in Section 3.3.1.

3.3.3 Exposure to curvature swings

To investigate the determinants of SSM banks' interest rate risk exposure to curvature swings in the yield curve, we implement the same models as in Section 3.3.1 and Section 3.3.2, but with curvature exposure ($\beta^{(i)}_{pc_3,t}$) as the dependent variable. The general disclaimer that exposure to slope and curvature swings in the term structure (as well as their bank-specific factors) should only be regarded as *secondary* relative to banks' *primary* sensitivity to level swings applies to this section, too. Estimated coefficients are

[21]This is also in line with the weakly significant positive coefficient for net customer loans minus deposits.

shown in Table 6.

Table 6: Explaining SSM banks' sensitivity to curvature swings

	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Regressors	Full period	2005 – 2009	2010 – 2014	Full period	2005 – 2009	2010 – 2014
Total financial assets to total assets	0.103	0.153	0.180			
	(0.73)	(0.86)	(1.20)			
Securities to total assets				**0.221***	0.116	**0.339****
				(2.02)	(0.83)	**(2.09)**
Net customer loans to total assets				**0.392*****	0.194	**0.495*****
				(3.30)	(1.39)	**(2.83)**
Core Tier capital ratio	**0.558*****	-0.080	**0.682*****	**0.556****	-0.052	**0.647****
	(3.02)	(-0.25)	**(2.84)**	**(2.55)**	(-0.17)	**(2.37)**
Deposits to total liabilities (and equity)				-0.149	0.041	-0.143
				(-1.48)	(0.33)	(-1.01)
Term deposits to deposits				**-0.093*****	-0.019	-0.073
				(-2.77)	(-0.36)	(-1.53)
Total debt to total liabilities (and equity)	**-0.193****	-0.072	**-0.258****			
	(-2.48)	(-0.79)	**(-2.20)**			
Subordinated debt to total liabilities (and equity)				-0.411	-0.084	-0.097
				(-1.21)	(-0.23)	(-0.15)
Senior debt to total liabilities (and equity)				**-0.290****	-0.084	**-0.301***
				(-2.34)	(-0.58)	**(-1.79)**
Derivative liabilities to total liabilities (and equity)	**0.217****	**0.133**	**0.269***	0.194	0.071	0.271
	(2.40)	(1.54)	**(1.70)**	(1.50)	(0.37)	(1.00)
Net interest income to operating revenue	0.003	0.033	-0.000	0.046	0.045	0.007
	(0.59)	(1.22)	(-0.02)	(1.25)	(1.19)	(0.12)
Net fee income to RWA	**-1.995***	-1.295	**-1.948***	**-4.244*****	**-4.161*****	**-3.958*****
	(-2.02)	(-0.99)	**(-1.80)**	**(-4.01)**	**(-4.55)**	**(-3.45)**
ROAA	0.428	0.984	0.376	0.426	1.813	0.348
	(0.86)	(0.70)	(0.56)	(0.74)	(1.30)	(0.50)
Net customer loans minus deposits to total assets	**0.135****	0.071	**0.169****			
	(2.20)	(0.89)	**(2.14)**			
Loan loss reserves to gross customer loans	**0.418***	-0.259	0.304	0.344	-0.694	0.261
	(1.73)	(-0.35)	(1.06)	(1.50)	(-1.03)	(1.04)
Size	0.003	0.002	0.003	**0.010*****	**0.009****	**0.010***
	(0.94)	(0.34)	(0.56)	**(2.86)**	**(2.29)**	**(1.81)**
Observations	275	119	156	241	105	136
R^2	0.78	0.68	0.66	0.79	0.71	0.66

The dependent variable corresponds to banks' interest rate risk exposure to curvature changes in the euro area yield curve ($\beta^{(i)}_{pc_3,t}$). RWA refers to banks' risk-weighted assets. Core Tier capital ratio is defined as a ratio of a bank's core equity capital to risk-weighted assets (RWA). Banks' size is calculated as a logarithm of total assets. The details of the items included in other positions are provided in Table 11 and Table 12. All the data is collected on an annual basis from the SNL Financial database. Time period: 2005 to 2014. In each case the regression is run while controlling for time- and country-fixed effects. Standard errors are clustered at bank level; t-statistics are shown in brackets. The symbols *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Again, notice that while the majority of banks has on average a positive exposure to curvature swings (see Table 7), sensitivities are near zero and partly negative during the first half of the sample period (2005–2009), while sensitivities to slope changes from 2010 onwards are significantly positive (see Figure 4a and Table 8). Hence, a positive coefficient in Table 6 means in particular during the second half of the sample period that increasing values of independent variables (i.e., regressors) go along with higher values of the dependent variable ($\beta^{(i)}_{pc_3,t}$) and, thus, expose the bank more strongly to curvature swings. In contrast, a negative coefficient pulls $\beta^{(i)}_{pc_3,t}$ closer to zero and, thus, reduces the sensitivity to curvature swings.

In the following, we compare the coefficient estimates for curvature exposure shown in Table 6 with those regarding level exposure (Section 3.3.1) and slope exposure (Section 3.3.2) and do not detect any inconsistencies. Accordingly, the results are generally in line with our expected relations as explained in Section 3.1. The positive relation of bank size and net customer loans (scaled by total assets) with banks' sensitivity towards curvature changes in the yield curve is in line with both previous analyses (i.e., level and slope). The findings that better capitalized banks and banks with less senior debt to total liabilities (and equity) exhibit significantly higher sensitivities to curvature swings are consistent with the findings for sensitivities to level shifts in the yield curve. The significantly negative coefficient for net fee income to RWA and the significantly positive coefficient for net customer loans minus deposits mirror the results for slope sensitivities. Derivative liabilities seem to be used for speculating, as there is a positive relation in the first half of the period for level swings and a positive relation to curvature swings for the full period. In this regard, it is noteworthy that more complex product like derivatives seems to be rather linked to more complex curvature swings than to usual level or slope changes.

Additionally, the estimates indicate a positive relation of banks' securities to total assets and negative relation of banks' term deposits to total deposits as well as to their total debt scaled by total liabilities, but given that sensitivity towards curvature swings accounts for only a small portion of banks' sensitivity to interest rate changes, these factors should not be seen as *primary* for banks' overall interest rate risk. As in the previous cases, regressions on the averages corroborate most results, as can be seen from Table 15 in Appendix B.

4 Conclusions

In this paper, we investigate the interest rate risk exposure of listed European banks, which fall under the Single Supervisory Mechanism (SSM) in the euro area. The analysis indicates that banks' stock prices react to various types of movements in the yield curve. Moreover, banks' sensitivity to level, slope and curvature swings in the yield curve varies over time.

On average, banks' stock prices exhibit a positive sensitivity to level, slope and curvature increases. More precisely, out of 36 banks, all exhibit a significantly positive coefficient to level changes, which indicates that their share prices tend to increase if interest rate levels rise, 35 banks have a positive coefficient to slope changes (i.e., a steepening yield curve), and 31 banks show a positive coefficient to curvature changes. This is consistent with Ballester et al. (2009), who show that Spanish banks experienced a positive interest rate risk sensitivity in the period between 1994 and 2006. This suggests that euro area banks may, at least during a low interest rate environment, be exposed in the opposite direction to interest rate shocks than US banks (English et al. (2014)).

At the onset of the financial crisis, interest rate risk exposure to changes in the euro area yield curve increased for almost all banks in the sample. In the subsequent years, banks maintained a high level of interest rate risk sensitivity regarding level swings, while the sensitivity to slope and curvature swings increased in particular from end-2012/early-2013, when the ECB began to take non-standard monetary policy measures with its active balance sheet expansion.

Considering curvature swings in the yield curve is one further contribution of our work. For our data set which covers several crises, curvature swings amount to more than 8% of total variation of the yield curve; this is more than usually attributed to this type of interest rate movement. Further, regulators have increased the requirements on the selection of interest rate scenarios for banks' internal risk measurements systems and want banks to consider changes in tilts as well (BCBS (2016a, pp. 44-47)). Both aspects emphasize the importance of considering curvature movements which proves to play a significant role and which constitute one of our most interesting findings.

A third contribution is our analysis on the bank-specific factors that influence their interest rate risk exposure. Our empirical analysis indicates that the market price of equity of banks with larger balance sheets, higher capital ratios, higher parts of customer loans and lower parts of deposits is more sensitive to interest rate swings. Knowledge about these factors which make a bank more vulnerable to interest rate risk may inform supervisory decisions and market analysts' assessment of bank stock.

References

Akella, S., & Greenbaum, S. (1992). Innovations in Interest Rates, Duration Transformation, and Bank Stock Returns. *Journal of Money, Credit and Banking*, *24*(1), 27-42.

Au Yong, H., Faff, R., & Chalmers, K. (2007). Derivative activities and Asia-Pacific banks' interest rate and exchange rate exposures. *Journal of International Financial Markets, Institutions and Money*, *19*(1), 16-32.

Ballester, L., Ferrer, R., Gonzales, C., & Soto, G. (2009). Determinants of Interest Rate Exposure of Spanish Banking Industry. *UCLM Working Paper*.

Bauwens, L., Laurent, S., & Rombouts, J. (2006). Multivariate GARCH models: a survey. *Journal of Applied Economics*, *21*(1), 79-109.

BCBS. (2016a). *Interest rate risk in the banking book: Standards.* Bank for International Settlements.

BCBS. (2016b). *Minimum capital requirements for market risk.* Bank for International Settlements.

Begenau, J., Piazzesi, M., & Schneider, M. (2015). Banks' risk exposures. *NBER Working Paper*.

Beirne, J., Caporale, M., & Spagnolo, N. (2009). Market, interest rate and exchange risk effects on financial stock returns: A GARCH-M approach. *Quantitative and Qualitative Analyisis in Social Sciences*, *3*(2), 44-68.

Benink, H., & Wolff, C. (2000). Survey data and the interest rate sensitivity of US bank stock returns. *Economic Notes by Banca Monte dei Paschi di Siena SpA*, *29*(2-2000), 201-213.

BIS. (2005). Zero-coupon yield curves: technical documentation. *BIS Papers No 25*.

Bollerslev, T., & Wooldridge, J. (1992). Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. *Econometric Reviews*, *11*(2), 143-172.

Bolt, W., Haan, L. de, Hoeberichts, M., van Oordt, M., & Swank, J. (2012). Bank profitability during recessions. *Journal of Banking and Finance*, *36*(9), 2552-2564.

Czaja, M., & Scholz, H. (2006). Sensitivity of Stock Returns to Changes in the Term Structure of Interest Rates - Evidence from the German Market. In K.-H. Waldmann & U. M. Stocker (Eds.), *Operations Research Proceedings 2006* (p. 305-310). Springer.

Czaja, M., Scholz, H., & Wilkens, M. (2009). Interest rate risk of German financial institutions: The impact of level, slope, and curvature of the term structure. *Review of Quantitative Finance and Accounting*, *1*(33), 1-26.

Czaja, M., Scholz, H., & Wilkens, M. (2010). Interest Rate Risk Rewards in Stock Returns of Financial Corporations: Evidence from Germany. *European Financial Management*, *16*(1), 124-154.

Drakos, K. (2001). Interest Rate Risk and Bank Common Stock Returns: Evidence from the Greek Banking Sector. *Working Paper, London Guildhall University*.

ECB. (2014a). Guide to banking supervision.

ECB. (2014b). *The list of significant supervised entities and the list of less significant institutions.* European Central Bank Documentation.

ECB. (2015). Technical notes on Eurozone yield calibration. *European Central Bank Technical Documentation*.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate autoregressive conditional heteroskedasticity models,. *Journal of Business & Economic Statistics*, *20*(3), 339-350.

English, W., Van den Heuvel, S., & Zakrajšek, E. (2014). Interest Rate Risk and Bank Equity Valuations. *Working Paper, Wharton School, University of Pennsylvania*.

Entrop, O., Memmel, C., Wilkens, M., & Zeisler, A. (2008). Analyzing the interest rate risk of banks using time series of accounting-based data: evidence from Germany. *Bundesbank Discussion Paper 01/2008*.

Esposito, L., Nobili, A., & Ropele, T. (2015). The management of interest rate risk during the crisis: Evidence from Italian banks. *Journal of Banking and Finance*, *59*, 486-504.

Fama, E., & French, K. (1974). The cross-section of expected stock returns. *The Journal of Finance*, *47*(2), 427-465.

FDIC. (2015). RMS Manual of examination policies: sensitivity to market risk.

Fernandez, C., & Steel, M. (1998). On Bayesian modelling of fat tails and skewness. *Journal of American Statistical Association*, *93*(441), 359-371.

Ferrer, R., Bolos, V., & Benitez, R. (2016). Interest rate changes and stock returns: a European multi-country study with wavelets. *International Review of Economics & Finance*, *44*, 1-12.

Fioruci, J., Ehlers, R., & Filho, M. (2014). Bayesian multivariate GARCH models with dynamic correlations and asymmetric error distributions. *Journal of Applied Statistics*, *41*(2), 320-331.

Flannery, M., & James, C. (1984). The effect of interest rate changes on the common stock returns of financial institutions. *The Journal of Finance*, *39*(4), 1141-1153.

Fraser, D., Madura, J., & Weigand, D. (2002). Sources of bank interest rate risk. *The Financial Review*, *37*(3), 351-367.

Hamilton, J. (1994). *Time Series Analysis*. Princeton University Press, Princeton.

Hao, S., & Zhang, G. (2007). Relative Firm Profitability and Stock Price Sensitivity to Aggregate Information. *Working Paper*.

Hasan, I., Kalotychou, E., Staikouras, S., & Zhao, G. (2013). Financial intermediaries and their risk exposure to level and slope. *Working Paper*.

Kwan, S. (1991). Re-examination of interest rate sensitivity of commercial bank stock returns using a random coefficient model. *Journal of Financial Services Research*, *5*(1), 61-76.

Landier, A., Sraer, D., & Thesmar, D. (2015). Banks' Exposure to Interest Rate Risk and the Transmission of Monetary Policy. *SSRN Working Paper*.

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, *47*(1), 13-37.

Litterman, R., & Scheinkman, J. (1991). Common Factors Affecting Bond Returns. *The Journal of Fixed Income*, *1*(1), 54-61.

Madigan, D., & York, J. (1995). Bayesian graphical models for discrete data. *International Statistical Review*, *63*(2), 215-232.

Mirza, N., & Dauphine, P. (2010). Size, Value and Asset Quality Premium in European

Banking Stocks. *Paris Dauphine Publications*.

Nelson, C. R., & Siegel, A. F. (1987). Parsimonious modeling of yield curves. *The Journal of Business*, *60*(4), 473-489.

Phoa, W. (2000). Yield Curve Risk Factors: Domestic And Global Contexts. In L. Borodovsky & L. Marc (Eds.), *Professional's Handbook of Financial Risk Management, First Edition* (p. 155-174). Butterworth-Heinemann, Oxford.

Reichert, A., & Shyu, Y. (2003). Derivative activities and the risk of international banks: a market index and VaR approach. *International Review of Financial Analysis*, *12*(5), 489-511.

Saporoschenko, A. (2002). The sensitivity of Japanese bank stock returns to economic factors - An examination of asset/liability differences and main bank status. *Global Finance Journal*, *13*, 253-270.

Saunders, A., & Yourougou, P. (1990). Are banks special? The separation of banking from commerce and interest rate risk. *Journal of Economics and Business*, *42*(2), 171-182.

Schuermann, T., & Stiroh, K. (2006). Visible and hidden risk factors for banks. *Working Paper, Federal Reserve Bank of New York*.

Sharpe, W. (1964). Capital asset prices: a theory of market equilibrium under conditions of risk. *The Journal of Finance*, *19*(3), 425-442.

Stone, B. (1974). Systematic interest rate risk in a two index model of returns. *Journal of Financial and Quantitative Analysis*, *9*, 709-721.

Svensson, L. E. (1994). Estimating and interpreting forward interest rates: Sweden 1992-1994. *Centre for Economic Policy Research: Discussion Paper*.

Van den Heuvel, S. (2014). Interest rate risk at banks: an economist perspective. *Working Paper, Federal Reserve Bank of Boston*.

Virbickaite, A., Concepcion, A., & Galeano, P. (2015). Bayesian inference methods for univariate and multivariate GARCH models: a survey. *Journal of Economic Surveys*, *29*(1), 76-96.

Wright, D., & Houpt, J. (1996). An analysis of commercial bank exposure to interest rate risk. *Federal Reserve Bulletin*, *82*(2), 115-128.

A Bayesian DCC M-GARCH model and estimation

A.1 The Bayesian DCC M-GARCH model

We consider the quasi return vector

$$y_t = [r_t, r_{mt}, pc_{1t}, pc_{2t}, pc_{3t}]^\top \sim N(\mu; H_t) \tag{4}$$

where r_t is the time series of a bank's stock log returns; r_{mt} is a time series of market log returns; pc_{1t}, pc_{2t}, pc_{3t} are time series of interest rate risk factors, i.e., the first three principal components that capture the changes in the euro area yield curve shape. μ denotes the mean of the multivariate time series $y_t = (y_{t1}, \ldots, y_{kt})^\top$ with $k = 5$ and H_t is the conditional variance-covariance matrix of y_t where $H_t^{1/2}$ is an $k \times k$ positive definite matrix. Hence, the centered random variable $y_t^* = (y_t - \mu)$ can be expressed as

$$y_t^* = H_t^{1/2} \epsilon_t, \tag{5}$$

where the error terms ϵ_t are independently, identically distributed with mean $\mathbb{E}(\epsilon_t) = 0$ and variance $\mathbb{V}(\epsilon_t) = I_k$ equal to the identity matrix of order k.

In the Bayesian DCC M-GARCH setting, the conditional variance-covariance matrix H_t is decomposed in a conditional standard deviation matrix D_t and a correlation matrix R_t as[22]

$$H_t = D_t R_t D_t. \tag{6}$$

Here $D_t = \mathrm{diag}\left(\mathrm{h}_{11,\mathrm{t}}^{1/2} \ldots \mathrm{h}_{\mathrm{kk,t}}^{1/2}\right)$ where $h_{ii,t}^{1/2}$ corresponds to the standard deviation of factor i in the quasi return vector (see Equation Equation 4). Moreover, each conditional variance $h_{ii,t}$ is modelled as a univariate GARCH $(1, 1)$ process

$$h_{ii,t} = \omega_i + \alpha_i (y_{i,t-1}^*)^2 + \beta_i h_{ii,t-1} \tag{7}$$

with $\omega_i > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$ and $\alpha_i + \beta_i < 1$, $i = \{1, \ldots, k\}$.

The matrix R_t in Equation 6 is symmetric, positive definite, and its elements are time-dependent conditional correlations $\rho_{ij,t}$, for all $i, j = \{1, \ldots k\}$ with $\rho_{ij,t} = 1$ when $i = j$. Thus, conditional covariance $h_{ij,t}$ between factors i and j in the quasi return vector can be expressed as

$$h_{ij,t} = \rho_{ij,t} \sqrt{h_{ii,t} h_{jj,t}}. \tag{8}$$

Following Engle (2002) we decompose the conditional correlation matrix R_t as

$$R_t = \mathrm{diag}(\mathrm{Q_t})^{-1/2} \mathrm{Q_t} \mathrm{diag}(\mathrm{Q_t})^{-1/2} \tag{9}$$

[22] In the literature, different specifications of the conditional covariance matrix H_t have been studied. Here, we focus on the conditional correlation model, which allows us to separately evaluate the individual conditional variance and the conditional correlation matrices. See Bollerslev and Wooldridge (1992) for further details.

where Q_t is a $k \times k$ symmetric positive definite matrix defined as

$$Q_t = (1 - \alpha - \beta) R + \alpha u_{t-1}^{\top} u_{t-1} + \beta Q_{t-1} \tag{10}$$

and diag($\mathrm{Q_t}$) denotes the diagonal matrix with entries equal to the the diagonal elements of the matrix Q_t. In the above equation, $u_t = D_t^{-1} y_t^* = D_t^{-1} H_t^{1/2} \epsilon_t$ are the standardized innovations of the centered quasi return vector y_t^*, which can be obtained from the GARCH (1,1) process in Equation 7. Moreover, R is the unconditional covariance matrix of u_t and the conditions $\alpha > 0$, $\beta > 0$ and $\alpha + \beta < 1$ hold.[23] Thus, the conditional covariances in Equation 8 can also be expressed as $h_{ij,t} = q_{ij,t} \sqrt{h_{ii,t} h_{jj,t}} / \sqrt{q_{ii,t} q_{jj,t}}$.

In the conventional DCC M-GARCH approach, the usual assumption is that return series follow the normal distribution. However, since in practice the unconditional distribution of stock log returns tend to expose fatter tails than implied by the models with normally distributed errors, we use the Bayesian DCC M-GARCH method - an improved version of the DCC M-GARCH model - which allows us to relax the distributional assumption in a given setting and leaves it to the Bayesian inference procedure. The Bayesian inference enters the estimation process in the part where all the sub-model parameters are estimated (i.e., α_i and β_i in the Equation 7 of conditional variance and α and β in Equation 10 of the conditional covariance). An outline of the Bayesian estimation procedure under the given setting is provided in Appendix A.2. More details may be found in the original article by Fioruci et al. (2014).

A.2 Bayesian inference procedure

The Bayesian inference procedure regarding the distributions of banks' log returns and interest rate risk factors is conducted in line with the approach suggested by Fioruci et al. (2014). We start from the setting as described in Section 2.1.2, where conditional variances and covariances are modeled with DCC M-GARCH methods based on the observed interest rate risk factors (i.e., changes in the level, slope and curvature of the euro area yield curve) and SSM banks' stock log returns (see Equation 1).

A.2.1 General estimation framework

The Bayesian DCC M-GARCH model is estimated using a maximum likelihood function. Given observations $(y_1^* \dots y_n^*)$ of the centered quasi return vector y_t^* (see Appendix A.1), a conditional likelihood function related to the model $y_t^* = H_t^{1/2} \epsilon_t$ (see Equation 5) is expressed as

$$\begin{aligned} l(\theta) &= l(\theta | y_1^*, \dots, y_n^*) = \textstyle\prod_{t=1}^{n} |H_t|^{-1/2} p_\epsilon \left(H_t^{-1/2} y_t^* \right) \\ &= \textstyle\prod_{t=1}^{n} \left[\prod_{t=1}^{k} h_{ii,t}^{-1/2} \right] |R_t|^{-1/2} p_\epsilon \left((D_t R_t D_t)^{-1/2} y_t^* \right), \end{aligned} \tag{11}$$

[23]Note, when $\alpha = \beta = 0$, meaning that the matrix Q_t does not depend on the past correlations, Equation 10 cuts to $Q_t = R$, and we are back to the constant conditional correlation framework.

where p_ϵ denotes the joint density function for ϵ_t and the set of model parameters is summarized in the vector

$$\theta = (\omega_1, \alpha_1, \beta_1, \ldots, \omega_k, \alpha_k, \beta_k, \rho_{12}, \ldots, \rho_{k-1,k})$$

which needs to be estimated.[24] The rest of the variables are the same as defined in Appendix A.1.

If the series of banks' equity log returns and interest rate risk factors were normally distributed, the usual procedure would be to estimate the conditional likelihood function in Equation 11 by choosing the joint density p_ϵ of the error terms as multivariate normal, which is the case in a conventional DCC M-GARCH method. However, since the time series used in the analysis deviate from normality (see Section 2.2) and to take into account the distributional implications of these asymmetries, we follow Fioruci et al. (2014), who develop a Bayesian approach to estimate DCC M-GARCH models with skewed and heavy tailed errors.

Formally, the approach proceeds in two steps. First, a DCC M-GARCH model (see the set-up in Appendix A.1) is estimated based on the different distributional assumptions using the conditional maximum likelihood function specified in Equation 11. The suggested distributions for the error terms are the multivariate normal, the multivariate t and the multivariate exponential power distributions, also known as generalized error distribution (GED), which can accommodate skewed and heavy-tailed errors (see the description below). Each time the DCC M-GARCH model is assessed, we get a set of parameters which characterize conditional variances and covariances (i.e., parameter values for ω_k, α_k, β_k, α and β, as denoted in Section 2.1.2), as well as parameters that describe the distribution itself (i.e., skewness, kurtosis). Second, the different model specifications corresponding to differing distributions of the error terms are then compared according to a deviance information criterion (DIC).[25] The DCC M-GARCH model with the lowest DIC is selected to calibrate conditional variances and covariances between each bank's log returns and interest rate risk factors.

A.2.2 Introducing asymmetries into the multivariate distributions

The following section describes how skewness is introduced into the distributions which are tested in this paper. The Bayesian estimation procedure and distributional assumptions in the DCC M-GARCH method used in the paper are based on the approach suggested by Fioruci et al. (2014). The main idea on which the method is based is to take any symmetric continuous distribution (multivariate normal, t or GED) and change the scale on both sides of the mode so as to transform this distribution into a skewed one. In

[24] Recall that ω_k, α_k and β_k are the parameters in a GARCH (1,1) model for the conditional variance of factor k (see Equation 7 in Appendix A.1); $\rho_{k-1,k}$ is the conditional correlation between two factors considered in the model.

[25] A deviance information criterion is a single number which is used as a measure of the relative quality of a model. It consists of two components: one component assesses a goodness of fit, another component penalizes for an additional model complexity. The lower the DIC value is, the better the model is considered to be.

this way, skewness in the error distributions is introduced via a shape parameter $\gamma > 0$, which accounts for the allocation of probability mass at both sides of the mode and thus captures the degree of asymmetry in the distribution. When $\gamma = 1$, the distribution is symmetric, $\gamma > 1$ indicates the right marginal skewness, $\gamma < 1$ captures the left marginal skewness.

Following Bauwens, Laurent, and Rombouts (2006) and Fioruci et al. (2014) a skewed multivariate density function can be constructed from a given symmetric multivariate density $f(\cdot)$ as[26]

$$s\left(x|\gamma\right) = 2^k \left(\prod_{i=1}^{k} \frac{\gamma_i}{1+\gamma_i^2}\right) f\left(x^*\right), \tag{12}$$

where $x^* = (x_1^*, \dots, x_k^*)$ is a vector such that $x_i^* = x_i/\gamma_i$ if $x_i \geq 0$, and $x_i^* = x_i\gamma_i$ if $x_i < 0$, $i = \{1, \dots, k\}$. As noted above, $\gamma_i > 1$ corresponds to the right marginal skewness, whereas $\gamma_i < 1$ refers to the left marginal skewness. Based on this methodology, the distributions considered during the Bayesian estimation procedure in this paper narrow down to the following cases.

Case 1: Multivariate t-distribution
Within the DCC M-GARCH model an excess of unconditional kurtosis in the data can be taken into account by assuming the error terms $\epsilon_t = (\epsilon_{1t}, \dots, \epsilon_{kt})$ in Equation 5 to be (standard) multivariate Student t-distributed, i.e.,

$$p\left(\epsilon_t\right) = \frac{\Gamma\left(\frac{\nu+k}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\left[\pi\left(\nu-2\right)\right]^{k/2}} \left[1 + \frac{\epsilon_t^\top \epsilon_t}{\nu-2}\right]^{-\frac{\nu+k}{2}} \tag{13}$$

where $\Gamma(\cdot)$ is the Gamma function; $E\left(\epsilon_t\right) = 0$ and $\mathrm{Var}\left(\epsilon_t\right) = \mathrm{I_k}$; $\nu > 2$, so as to ensure that H_t (see Appendix A.1) is positive definite and can thus be interpreted as a conditional covariance matrix.

Given the multivariate t-distribution with ν degrees of freedom and given the skewness parameters $\gamma_1, \dots, \gamma_k$, the skewed multivariate density corresponding to t-distribution can be rewritten as [27]

$$s\left(\epsilon_t|\gamma\right) = 2^k \left(\prod_{i=1}^{k} \frac{\gamma_i\sigma_{\gamma_i}}{1+\gamma_i^2}\right) \frac{\Gamma\left(\frac{\nu+k}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\left[\pi\left(\nu-2\right)\right]^{k/2}} \left[1 + \frac{\epsilon_t^{*\top} \epsilon_t^*}{\nu-2}\right]^{-\frac{\nu+k}{2}} \tag{14}$$

where $\epsilon_{it}^* = \left(\epsilon_{it}\sigma_{\gamma_i} - \mu_{\gamma_i}\right)/\gamma_i$ if $\epsilon_{it} \geq -\mu_{\gamma_i}/\sigma_{\gamma_i}$ and $\epsilon_{it}^* = \left(\epsilon_{it}\sigma_{\gamma_i} - \mu_{\gamma_i}\right)/\gamma_i$ if $x_i < -\mu_{\gamma_i}/\sigma_{\gamma_i}$. Mean μ_{γ_i} and variance $\sigma_{\gamma_i}^2$ for each margin are calculated as[28]

$$\mu_\gamma = \frac{\Gamma\left(\left(\nu-1\right)/2\right)\sqrt{\nu-2}\left(\gamma - 1/\gamma\right)}{\sqrt{\pi}\Gamma\left(\nu/2\right)}, \tag{15}$$

[26]Note, when $k = 1$, Equation 12 simplifies to the univariate skew density.
[27]Here, the density function for multivariate t-distribution given in Equation 13 is plugged into Equation 12, while taking into account the fact that the elements x_i^* have been standardized.
[28]See Fioruci et al. (2014) for further details.

$$\sigma_\gamma^2 = \left(\gamma^2 + 1/\gamma^2\right) - \mu_\gamma^2 - 1. \tag{16}$$

The resulting expression in Equation 14 is then a standardized multivariate skew Student t density function that is able to accommodate heavier tails than a multivariate skew normal distribution. Note that Equation 14 reduces to the standardized symmetric multivariate Student t density, when $\gamma_i = 1$ for all $i = \{1, \ldots, k\}$. If a skewed multivariate t-distribution is selected based on the DIC criteria, Equation 14 is then used in the conditional likelihood function (see Equation 11) to calibrate conditional variances and covariances.

Case 2: Multivariate normal distribution
With $\nu \to \infty$, the multivariate Student t-distribution converges to the multivariate standard normal distribution. Thus, by choosing the function $f(x^*)$ in Equation 12 as a standard multivariate normal density, we obtain a standardized multivariate skew normal density.

Case 3: Multivariate GED
Another heavy-tailed multivariate distribution, which is considered during the Bayesian inference procedure, is the multivariate exponential power distribution, also referred to as the multivariate GED distribution. The probability density function related to the univariate GED distribution with the tail parameter $\delta > 0$ is given as

$$p\left(x|\delta\right) = \left[\frac{\Gamma\left(3/\delta\right)}{\Gamma\left(1/\delta\right)}\right]^{1/2} \frac{1}{2\Gamma\left(\left(\delta+1\right)/\delta\right)} \exp\left(-\left[\frac{\Gamma\left(3/\delta\right)}{\Gamma\left(1/\delta\right)}x^2\right]^{\delta/2}\right). \tag{17}$$

Kurtosis equals $\Gamma\left(1/\delta\right)\Gamma\left(5/\delta\right)\Gamma\left(1/\delta\right)^2 - 3$, thus values $\delta < 2$ produce leptokurtic distributions (fat tails), whereas $\delta > 2$ leads to thinner tails than those captured by the normal distribution. When $\delta = 2$, a standard normal distribution is obtained.

In contrast to the previous cases, marginal distributions and the corresponding moments are difficult to obtain analytically. Therefore, Fioruci et al. (2014) start with the joint distribution of k independent random variables, so that the marginal density is described by the equation above with the tail parameter δ. In the multivariate case, the joint density of the standardized GED $(0,\ I_k,\ \delta)$ distribution with $\mathbb{E}(X) = 0$ and $\mathrm{Var(X)} = \mathrm{I_k}$ is given by

$$p\left(x|\delta\right) = \left[\frac{\Gamma\left(3/\delta\right)}{\Gamma\left(1/\delta\right)}\right]^{1/2} \frac{1}{2\Gamma\left(\left(\delta+1\right)/\delta\right)} \exp\left(-\left[\frac{\Gamma\left(3/\delta\right)}{\Gamma\left(1/\delta\right)}\right]\sum_{i=1}^{k}|x_i|^\delta\right). \tag{18}$$

Asymmetry can be introduced in the same way as for the multivariate Student t and normal distributions above. In particular, in line with Equation 12, the density of the standardized skew multivariate GED can be expressed as

$$s\left(x|\gamma\right) = 2^k\left(\prod_{t=1}^{k}\frac{\gamma_i\sigma_{\gamma_i}}{1+\gamma_i^2}\right)\left[\frac{\Gamma\left(3/\delta\right)}{\Gamma\left(1/\delta\right)}\right]^{1/2} \frac{\exp\left(-\left[\Gamma\left(3/\delta\right)/\Gamma\left(1/\delta\right)\right]^{\delta/2}\sum_{i=1}^{k}|x_i^*|^\delta\right)}{\left(2/\delta\right)^k\left[\Gamma\left(1/\delta\right)\right]^k} \tag{19}$$

where $x_i^* = (x_i^* \sigma_{\gamma_i} - \mu_{\gamma_i}) / \gamma_i$ if $x_i \geq -\mu_{\gamma_i}/\sigma_{\gamma_i}$, and $x_i^* = (x_i^* \sigma_{\gamma_i} - \mu_{\gamma_i}) / \gamma_i$ if $x_i < -\mu_{\gamma_i}/\sigma_{\gamma_i}$.

A.2.3 Prior distributions assigned to the parameters

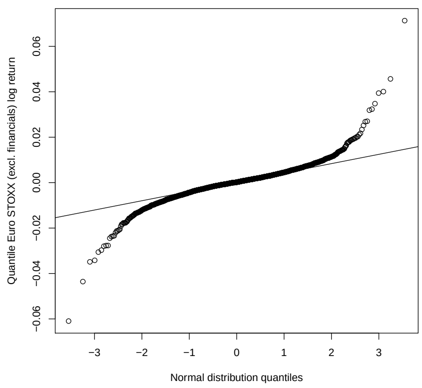
During the initial stage of the Bayesian inference procedure, a prior distribution is assigned to each parameter outlined above. By default, these are initially independent, truncated normal distributions on the domains of each parameter, i.e., for the parameters of the GARCH (1,1) model of the conditional variance Equation 7 we assume $\omega_i \sim N(\mu_{\omega_i}, \sigma^2_{\omega_i}) \, I_{\{\omega_i>0\}}$, $\alpha_i \sim N(\mu_{\alpha_i}, \sigma^2_{\alpha_i}) \, I_{\{0<\alpha_i<1\}}$ and $\beta_i \sim N(\mu_{\beta_i}, \sigma^2_{\beta_i}) \, I_{\{0<\beta_i<1\}}$, for $i = \{1, \ldots, k\}$. Moreover, depending on the initially assumed distribution of error terms (i.e., multivariate normal, Student t, or GED), a prior distribution corresponding to the tail parameter is assigned as $\nu \sim N(\mu_\nu, \sigma_{\nu^2}) \, I_{\{\nu>2\}}$ or $\delta \sim N(\mu_\delta, \sigma_{\delta^2}) \, I_{\{\delta>2\}}$. Finally, the parameters in Equation 10 are assigned a prior distribution $\alpha \sim N(\mu_\alpha, \sigma^2_\alpha) \, I_{\{0<\alpha<1\}}$ and $\beta \sim N(\mu_\beta, \sigma^2_\beta) \, I_{\{0<\beta<1\}}$. Values of the hyperparameters are fixed and in our analysis chosen as $\mu_{\omega_i} = \mu_{\alpha_i} = \mu_{\beta_i} = \mu_\nu = \mu_\delta = \mu_\alpha = \mu_\beta = 0$ and $\sigma^2_{\omega_i} = \sigma^2_{\alpha_i} = \sigma^2_{\beta_i} = \sigma^2_\nu = \sigma^2_\delta = \sigma^2_\alpha = \sigma^2_\beta = 100$. Following Fernandez and Steel (1998) and Fioruci et al. (2014) we choose the prior distribution for each skewness parameter γ_i as Gamma(a, b) where a and b are such that $E[\gamma_i] = 1$ implying that $b = (\Gamma(a + 1/2)/\Gamma(a))^2$. In line with the mentioned references, we choose $a = 1/2$ such that $\mathrm{Var}(\gamma_\mathrm{i}) \approx 0.57$.

Using Bayes' theorem, the joint posterior density $\pi(\theta|y^*)$ is proportional to the likelihood function $l(\theta)$ (see Equation 11) multiplied by the joint prior density of the parameters θ. The posterior distribution, however, is analytically intractable. Therefore, following Fioruci et al. (2014) samples of the distribution $\pi(\theta|y^*)$ are obtained by applying Markov chain Monte Carlo (MCMC) sampling where the Metropolis-Hastings algorithm is implemented to update all parameters as a block (see Madigan and York (1995)).

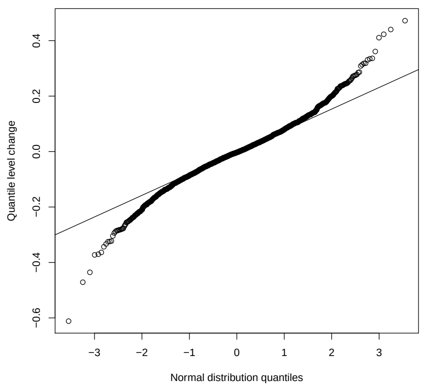
B Descriptive statistics and robustness checks

Figure 6: Normal QQ plots: Interest rate risk factors

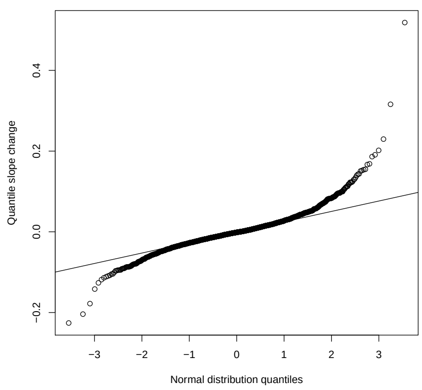
(a) Normal QQ plot: r_m



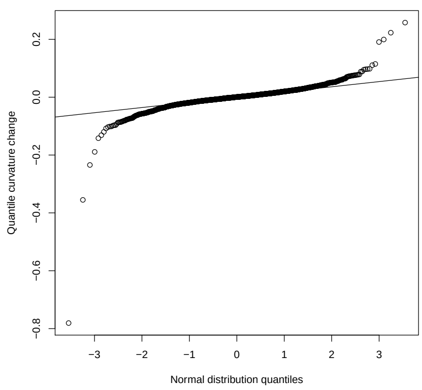
(b) Normal QQ plot: pc_1



(c) Normal QQ plot: pc_2



(d) Normal QQ plot: pc_3



The figures above present tests for evidence whether the market risk factor and the interest rate risk factors used in the analysis are normally distributed. The parameter r_m represents log returns of the EURO STOXX 50 excluding financials index, whereas pc_1, pc_2, and pc_3 represent the first three principal components of changes in the euro area yield curve (see Section 2.1.1). Sample quantiles are plotted against theoretical quantiles of the normal distribution. The time period for which the data has been collected is 1/2005 to 12/2014. The plot indicates that the distribution of log returns of the market risk factors as well as the changes in the yield curve slope, level and curvature parameters deviates from normality.

Table 7: Banks' interest rate risk exposure to level, slope and curvature swings in the yield curve (Full period)

SSM bank	Country	Market	Level (pc_1)	Slope (pc_2)	Curvature (pc_3)
Erste Group Bank AG	AT	1.4482	0.0638	0.0394	-0.0020
Dexia SA	BE	0.6294	0.0785	0.0110	0.0067
KBC Group NV	BE	1.0548	0.0681	0.0302	0.0337
Hellenic Bank	CY	0.3148	0.0347	-0.0196	0.0108
Aareal Bank AG	DE	1.5679	0.0560	0.0106	-0.0027
Commerzbank AG	DE	1.5948	0.0687	0.0336	0.0433
Deutsche Bank AG	DE	1.6206	0.0591	0.0241	0.0075
IKB Deutsche Industriebank AG	DE	0.7389	0.0372	0.0220	0.0260
Bankinter SA	ES	1.2277	0.0558	0.0485	0.0404
BBVA SA	ES	1.5946	0.0605	0.0419	0.0131
Banco de Sabadell SA	ES	0.9722	0.0374	0.0345	0.0141
Banco Popular Español SA	ES	1.1518	0.0505	0.0404	0.0085
Banco Santander SA	ES	1.9087	0.0634	0.0381	0.0144
BNP Paribas SA	FR	0.9409	0.0661	0.0461	0.0240
Crédit Agricole SA	FR	1.5017	0.0708	0.0352	0.0139
Société Générale SA	FR	1.2077	0.0703	0.0399	0.0074
Alpha Bank AE	GR	0.9052	0.0718	0.0808	0.0922
Eurobank Ergasias SA	GR	0.7427	0.0831	0.0621	0.1014
National Bank of Greece SA	GR	0.4717	0.0322	0.0321	0.0214
Piraeus Bank SA	GR	1.0715	0.0701	0.0614	0.0788
Allied Irish Banks. Plc	IE	0.9274	0.0650	0.0220	0.0099
Bank of Ireland	IE	1.3481	0.0668	0.0123	-0.0263
Banca Carige SpA	IT	0.9594	0.0425	0.0183	-0.0025
Banca Monte dei Paschi di Siena SpA	IT	1.3843	0.0588	0.0700	0.0135
Banca Popolare dell'Emilia Romagna SC	IT	1.4150	0.0377	0.0566	0.0476
Banca Popolare di Milano Scarl	IT	1.7740	0.0548	0.0371	-0.0065
Banca Popolare di Sondrio SCpA	IT	0.9868	0.0306	0.0469	0.0417
Banco Popolare Societá Cooperativa	IT	1.4601	0.0612	0.0797	0.0081
Credito Emiliano SpA	IT	1.2837	0.0510	0.0194	0.0075
Credito Valtellinese Societá Cooperativa	IT	0.7276	0.0364	0.0551	0.0256
Intesa Sanpaolo SpA	IT	1.6105	0.0656	0.0620	0.0434
Mediobanca SpA	IT	1.3215	0.0532	0.0389	0.0223
UniCredit SpA	IT	1.2544	0.0746	0.0667	0.0411
Unione di Banche Italiane SCpA	IT	1.4050	0.0523	0.0567	0.0283
Banco BPI SA	PT	0.9625	0.0477	0.0386	0.0331
Banco Comercial Português SA	PT	1.4039	0.0428	0.0249	0.0492

The table above provides SSM banks' average daily exposure to changes in the respective risk factors during 1/2005 to 12/2014. "Market" corresponds to banks' exposure to market risk (known as "market beta"), "Level", "Slope"and "Curvature" denote banks' exposure to swings in the level, slope and curvature of the euro area yield curve (see Section 2.1.1 for details). All the exposures are given as a percentage change in a bank's stock price associated with a 1 percentage point change in the corresponding interest rate risk factor.

Table 8: Banks' interest rate risk exposure to level, slope and curvature swings in the yield curve (sub-periods)

		2005-2009				2010-2014			
SSM bank	Country	Market	Level	Slope	Curvature	Market	Level	Slope	Curvature
Erste Group Bank AG	AT	1.3704	0.0680	-0.0128	-0.0810	1.5258	0.0596	0.0914	0.0768
Dexia SA	BE	0.5413	0.0579	-0.0354	-0.0522	0.7172	0.0990	0.0573	0.0654
KBC Group NV	BE	0.9755	0.0625	-0.0186	-0.0382	1.1338	0.0736	0.0788	0.1053
Hellenic Bank	CY	0.3689	0.0382	-0.0517	-0.0258	0.2608	0.0311	0.0123	0.0473
Aareal Bank AG	DE	1.4306	0.0562	-0.0270	-0.0740	1.7046	0.0559	0.0481	0.0682
Commerzbank AG	DE	1.5126	0.0695	-0.0117	-0.0230	1.6767	0.0679	0.0787	0.1093
Deutsche Bank AG	DE	1.5553	0.0565	-0.0085	-0.0418	1.6856	0.0616	0.0567	0.0567
IKB Deutsche Industriebank AG	DE	0.9169	0.0369	-0.0161	-0.0336	0.5615	0.0375	0.0599	0.0854
Bankinter SA	ES	1.0588	0.0482	0.0054	-0.0346	1.3959	0.0635	0.0915	0.1152
BBVA SA	ES	1.4302	0.0545	-0.0083	-0.0520	1.7584	0.0665	0.0919	0.0780
Banco de Sabadell SA	ES	0.8613	0.0336	-0.0051	-0.0338	1.0826	0.0411	0.0739	0.0619
Banco Popular Español SA	ES	1.0650	0.0440	0.0006	-0.0481	1.2383	0.0570	0.0800	0.0649
Banco Santander SA	ES	1.7504	0.0567	-0.0031	-0.0445	2.0664	0.0700	0.0791	0.0731
BNP Paribas SA	FR	0.8599	0.0577	-0.0002	-0.0543	1.0216	0.0744	0.0921	0.1020
Crédit Agricole SA	FR	1.3326	0.0651	-0.0300	-0.0768	1.6701	0.0765	0.1001	0.1043
Société Générale SA	FR	1.0507	0.0563	-0.0039	-0.0646	1.3642	0.0842	0.0836	0.0790
Alpha Bank AE	GR	0.7581	0.0514	0.0145	-0.0205	1.0517	0.0920	0.1468	0.2045
Eurobank Ergasias SA	GR	0.7698	0.0645	-0.0198	-0.0353	0.7157	0.1017	0.1435	0.2376
National Bank of Greece SA	GR	0.4703	0.0187	0.0070	-0.0106	0.4731	0.0457	0.0571	0.0532
Piraeus Bank SA	GR	0.9090	0.0513	-0.0068	-0.0340	1.2333	0.0888	0.1293	0.1912
Bank of Ireland	IE	1.2669	0.0589	-0.0396	-0.1021	1.4289	0.0748	0.0639	0.0492
Allied Irish Banks. Plc	IE	0.9230	0.0537	-0.0494	-0.0829	0.9319	0.0764	0.0931	0.1024
Banca Carige SpA	IT	0.7938	0.0332	-0.0086	-0.0425	1.1243	0.0518	0.0450	0.0374
Banca Monte dei Paschi di Siena SpA	IT	1.0671	0.0369	0.0090	-0.0388	1.7002	0.0806	0.1307	0.0656
Banca Popolare di Milano Scarl	IT	1.4434	0.0388	-0.0407	-0.0854	2.1033	0.0707	0.1145	0.0721
Banco Popolare Societá Cooperativa	IT	1.1889	0.0486	0.0299	-0.0286	1.7302	0.0739	0.1293	0.0446
Banca Popolare dell'Emilia Romagna SC	IT	0.6195	0.0188	-0.0034	-0.0023	2.2073	0.0565	0.1163	0.0973
Banca Popolare di Sondrio SCpA	IT	0.4988	0.0160	0.0013	0.0226	1.4728	0.0451	0.0923	0.0607
Credito Emiliano SpA	IT	1.0813	0.0378	-0.0145	-0.0369	1.4853	0.0643	0.0531	0.0518
Credito Valtellinese Societá Cooperativa	IT	0.6001	0.0272	0.0194	-0.0099	0.8546	0.0456	0.0907	0.0609
Intesa Sanpaolo SpA	IT	1.2818	0.0485	0.0064	-0.0083	1.9378	0.0826	0.1173	0.0949
Mediobanca SpA	IT	0.9883	0.0376	-0.0139	-0.0198	1.6535	0.0687	0.0915	0.0643
UniCredit SpA	IT	1.0961	0.0589	0.0027	-0.0263	1.4121	0.0902	0.1304	0.1083
Unione di Banche Italiane SCpA	IT	1.0156	0.0382	0.0064	-0.0123	1.7929	0.0664	0.1068	0.0687
Banco BPI SA	PT	0.7268	0.0337	-0.0053	-0.0242	1.1973	0.0616	0.0823	0.0902
Banco Comercial Português SA	PT	0.9811	0.0335	-0.0100	-0.0129	1.8250	0.0522	0.0596	0.1110

The table above provides SSM banks' average daily exposure to changes in the respective risk factors during 1/2005 to 12/2014. "Market" corresponds to banks' exposure to market risk (known as "market beta"), "Level", "Slope"and "Curvature" denote banks' exposure to swings in the level, slope and curvature of the euro area yield curve (see Section 2.1.1 for details). All the exposures are given as a percentage change in a bank's stock price associated with a 1 percentage point change in the corresponding interest rate risk factor.

Table 9: SSM banks' profitability measures

Date	ROAA	ROAE	NIM	NII to average assets	NII to operating revenue	Cost-to-income ratio
2005	1.00%	NA	NA	1.84%	53.42%	59.09%
2006	0.93%	16.29%	1.93%	1.78%	53.52%	54.61%
2007	1.00%	16.35%	1.96%	1.86%	55.54%	53.90%
2008	0.49%	7.05%	2.03%	1.89%	69.05%	62.27%
2009	0.27%	3.20%	1.93%	1.81%	65.02%	60.79%
2010	0.15%	0.79%	1.83%	1.72%	86.21%	59.93%
2011	-1.10%	-21.94%	1.81%	1.70%	65.50%	62.42%
2012	-0.52%	-14.70%	1.69%	1.58%	66.04%	70.00%
2013	-0.17%	-3.40%	1.66%	1.55%	60.28%	64.70%
2014	-0.13%	-2.56%	1.77%	1.65%	59.67%	61.21%

The table above provides the descriptive statistics on key profitability measures of the analyzed SSM banks over the period 2005 to 2014. The sample includes 36 listed SSM banks in the euro area. The data is collected from SNL Financial. ROAA is the return on average assets; ROAE is the return on average equity; NIM is the net interest margin; NII stands for the net interest income. All indicators have been calculated as the arithmetic averages over the bank sample in a given year. NA indicates that no data for the corresponding position is available in the database.

Table 10: A representative balance sheet

Assets	**Liabilities**
Cash and cash equivalents	**Total equity**
of which: Cash and balances with central banks	Deposits
of which: Net loans to banks	of which: Deposits from banks
Net loans to customers	of which: Term deposits from banks
of which: Gross loans to customers	of which: Deposits from customers
of which: Reserve on loans to customers	of which: Term deposits from customers
Securities	Total debt
Total financial assets	of which: Subordinated debt
Equity accounted investments	of which: Senior debt
Other investments	Securities sold, not yet purchased
Unit-linked investments	Other financial liabilities
Insurance assets	Derivative liabilities
Non-current assets HFS & discontinued operations	**Total financial liabilities**
Tangible and intangible assets	**Unit-linked insurance and investment contracts**
Tax assets	**Insurance liabilities**
Total other assets	**Non-current liabilities HFS & discontinued operations**
	Tax liabilities
	Non-current asset retirement obligations
	Other provisions
	Total other liabilities
Total assets	**Total liabilities (and equity)**

The table above shows SSM banks' representative balance sheet reconstructed from the data available in the SNL Financial database. The bold positions sum up to the balance sheet sum. The following positions are assumed to be interest rate risk-sensitive on the asset side: net loans to customers and securities, which combine into financial assets. From the liability side, deposits, term deposits, total debt (with subordinated debt and senior debt as sub-components) and total financial liabilities with all sub-components are rate-sensitive. The details of each position are reported in Table 11 and Table 12.

Table 11: Assets: Explanations

Assets	Explanations
Cash and balances with central banks	Any cash and balances held with central banks
Net loans to banks	Gross loans to banks minus reserves on these loans
Cash and cash equivalents	Comprises cash and balance with central banks and net loans to banks
Gross loans to customers	All the loans issued to customers
Reserve on loans to customers	Reserves hold for the issued loans to customers
Net loans to customers	Gross loans to customers minus reserves on loans to customers
Securities	All securities in the trading, available for sale, held to maturity and other securities categories, and does not include segregated securities or securities pledged as collateral for broker-dealers and asset managers
Total financial assets	Financial assets including derivatives, cash and cash equivalents
Equity accounted investments	Investments in unconsolidated joint ventures and partnerships
Other investments	Investments as reported by the company that are not otherwise classified above
Unit-linked investments	Separate accounts are established by life insurance companies, to be distinguished from other funds used primarily for pension plans and variable life products
Insurance assets	Total insurance assets including net contractual rights under an insurance contract and a cedent net contractual right under a reinsurance contract. Excludes insurance assets where the customer bears the risk
Non-current assets HFS & discontinued operations	Assets for which the carrying amount will be recovered principally through a sale transaction (hold for sale) rather than through continuing use
Tangible and intangible assets	Comprises total intangible assets, fixed assets, net investment properties and equipment under operating leases
Tax assets	Comprises current tax assets (taxes already paid, but which exceed the amount due) and deferred tax assets (granted tax relief)
Total other assets	Any other assets

The table above presents the definitions of the balance sheet positions on the asset side (see Table 10). The definitions are in accordance with the SNL Financial database, which serves as the main data source for the analysis conducted in Section 3.

Table 12: Liabilities: Explanations

Liabilities	Explanations
Total equity	Comprises equity attributable to parent company and minority interests
Term deposits from banks	Amount of received term deposits from banks
Deposits from banks	Amount of received deposits from banks
Term deposits from customers	Amount of received term deposits from customers
Deposits from customers	Amount of received deposits from customers
Deposits	Comprises deposits from banks and from customers
Subordinated debt	Debt in which the creditor's claims to the assets of the company are subordinated to those of other creditors. In the event of liquidation, dissolution, bankruptcy, or reorganization, such debts are junior to present or future obligations (e.g., payables, deposits, and senior debt). Subordinated debt is usually not collateralized by any specific asset, but only pledged by the full faith and credit of the company
Senior debt	Principal amounts outstanding on loans, notes payable, bonds, securities sold under repurchase agreements, mortgage-backed bonds, short-term borrowings, mortgage notes and other notes payable, capitalized lease obligations, and other debt instruments not classified as subordinated debt
Total debt	Comprises subordinated and senior debt
Securities Sold, not yet Purchased	Securities sold short, to be purchased at a later date
Other financial liabilities	Any other financial liabilities
Derivative liabilities	Total negative replacement values of hedging and non-hedging derivatives. A derivative is a financial instrument with all of the following three characteristics: its value changes in response to the change in an underlying variable; it requires no initial net investment or an initial net investment that is smaller than would be required for other contracts that would be expected to have a similar response to changes in market factors; it is settled at a future date. For European insurers, this also includes liabilities held at fair value through profit and loss
Total financial liabilities	Comprises deposits, total debt, securities sold, not yet purchased, other financial liabilities and derivative liabilities
Unit-linked insurance and investment contracts	Separate accounts are established by life insurance companies, to be distinguished from other funds used primarily for pension plans and variable life products
Insurance liabilities	Net contractual obligations under insurance contracts
Non-current liabilities HFS & discontinued operations	Liabilities included in a disposal group held for sale
Tax liabilities	Comprises current tax liabilities and deferred tax liabilities (obligations to pay more income tax because of a transaction that took place during the current period)
Non-current asset retirement obligations	Non-current portion of the cumulative value of asset retirement obligations in accordance with FAS 143
Other provisions	Any other provisions
Total other liabilities	Any other liabilities

The table above presents the definitions of the balance sheet positions on the liability side (see Table 10). The definitions are in accordance with the SNL Financial database, which serves as the main data source for the analysis conducted in Section 3.

Table 13: Explaining SSM banks' sensitivity to level changes: regression on the averages

	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Regressors	Full period	2005-2009	2010-2014	Full period	2005-2009	2009-2014
Total financial assets to total assets	0.071	0.113	0.050			
	(0.97)	(1.02)	(0.59)			
Securities to total assets				0.095*	0.020	0.036
				(1.87)	(0.20)	(0.45)
Net customer loans to total assets				0.105*	-0.077	0.100
				(1.95)	(-0.90)	(1.47)
Core Tier capital ratio	0.115	0.107	0.231***	0.121*	0.084	0.135**
	(1.58)	(0.46)	(5.84)	(1.91)	(0.38)	(2.57)
Deposits to total liabilities (and equity)				-0.070*	0.036	-0.130*
				(-1.91)	(0.69)	(-1.91)
Term deposits to deposits				0.009	-0.014	0.004
				(0.40)	(-0.39)	(0.24)
Total debt to total liabilities (and equity)	-0.042	0.009	-0.058*			
	(-1.38)	(0.17)	(-1.73)			
Subordinated debt to total liabilities (and equity)				0.621***	0.144	0.645***
				(4.00)	(0.85)	(3.11)
Senior debt to total liabilities (and equity)				-0.061	0.099	-0.152**
				(-1.52)	(1.42)	(-2.24)
Derivative liabilities to total liabilities (and equity)	-0.048	0.055	-0.005	0.119	0.274***	0.173
	(-1.25)	(-1.34)	(-0.09)	(1.36)	(3.02)	(1.37)
Net interest income to operating revenue	-0.022***	-0.005	-0.019***	-0.026**	-0.017	-0.022
	(-7.64)	(-0.24)	(-6.58)	(-2.16)	(-0.87)	(-1.24)
Net fee income to RWA	0.060	0.215	-0.168	0.550	1.079	-0.047
	(0.18)	(0.27)	(-0.52)	(1.55)	(1.45)	(-0.08)
ROAA	-0.563***	-1.670*	-0.582***	-0.503**	-2.755***	-0.320*
	(-3.01)	(-1.80)	(-4.08)	(-2.56)	(-4.50)	(-1.77)
Net customer loans minus deposits to total assets	0.054**	0.002	0.057**			
	(2.10)	(0.04)	(2.04)			
Loan loss reserves to gross customer loans	-0.234***	0.205	-2.268***	0.212***	0.260	-0.243**
	(-3.07)	(0.41)	(-2.74)	(-3.25)	(0.50)	(-2.72)
Size	0.010***	0.008**	0.009***	0.004**	0.001	0.004
	(5.93)	(2.87)	(4.14)	(2.28)	(0.35)	(1.22)
Observations	235	82	153	204	73	131
R^2	0.60	0.70	0.60	0.66	0.81	0.63

The dependent variable corresponds to banks' interest rate risk exposure to level changes in the euro area yield curve. RWA refers to risk-weighted assets. Core Tier capital ratio is defined as a ratio of a bank's core equity capital to risk-weighted assets. Banks' size is calculated as a logarithm of total assets. The details of the items included in other positions are provided in Table 11 and Table 12. All the data is collected on an annual basis from the SNL Financial database. Time period: 2005 to 2014. In each case the regression is run while controlling for time- and country-fixed effects. Standard errors are clustered at bank level; t-statistics are shown in brackets. The symbols *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Table 14: Explaining SSM banks' sensitivity to slope swings: regression on the averages

	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Regressors	Full period	2005-2009	2010-2014	Full period	2005-2009	2010-2014
Total financial assets to total assets	0.038	-0.052	0.060			
	(0.17)	(-0.41)	(0.15)			
Securities to total assets				0.063	-0.150	0.093
				(0.42)	(-0.84)	(0.43)
Net customer loans to total assets				0.196	-0.145	0.270
				(1.46)	(-0.81)	(1.37)
Core Tier capital ratio	0.171	**-0.668****	0.183	0.253*	**-0.591****	0.194
	(1.25)	**(-2.35)**	(0.96)	(1.63)	(-2.33)	(0.98)
Deposits to total liabilities (and equity)				-0.095	0.056	-0.138
				(-1.03)	(0.52)	(-0.88)
Term deposits to deposits				-0.036	-0.047	-0.006
				(-1.20)	(-0.74)	(-0.16)
Total debt to total liabilities (and equity)	-0.101	0.002	-0.140			
	(-1.49)	(0.03)	(-1.41)			
Subordinated debt to total liabilities (and equity)				**0.669****	0.062	**1.066***
				(2.25)	(0.12)	**(1.91)**
Senior debt to total liabilities (and equity)				–0.192	0.012	-0.245
				(-1.65)	(0.10)	(-1.34)
Derivative liabilities to total liabilities (and equity)	0.094	-0.006	0.079	**0.261***	0.001	0.260
	(1.34)	(-0.10)	(0.68)	(1.76)	(0.01)	(1.18)
Net interest income to operating revenue	**-0.014****	0.019	**-0.016***	-0.025	0.065	-0.063
	(-2.27)	(0.44)	**(-1.83)**	(-1.13)	(1.39)	(-1.56)
Net fee income to RWA	-1.274	0.231	**-1.986***	**-3.054****	-1.341	**-3.682****
	(-1.43)	(0.30)	**(-1.70)**	**(-2.75)**	(-1.46)	**(-2.35)**
ROAA	**-0.705***	**2.240***	**-0.583***	-0.669	**3.153*****	-0.412
	(-1.74)	**(2.02)**	**(-1.74)**	(-1.56)	**(2.79)**	(-1.08)
Net customer loans minus deposits to total assets	**0.096***	0.005	**0.135***			
	(1.81)	(0.09)	**(2.00)**			
Loan loss reserves to gross customer loans	-0.058	-0.496	-0.248	-0.036	-0.927	-0.160
	(-0.22)	(-0.92)	(-0.64)	(-0.18)	(-1.52)	(-0.61)
Size	**0.007*****	-0.001	**0.013****	**0.006**	0.003	**0.013*****
	(2.77)	(-0.30)	**(2.71)**	**(1.75)**	(0.62)	**(3.04)**
Observations	235	82	153	204	73	131
R^2	0.76	0.52	0.59	0.75	0.53	0.57

The dependent variable states for banks' interest rate risk exposure to slope changes in the Euro area yield curve. RWA refers to risk-weighted assets. Core Tier capital ratio is defined as a ratio of a bank's core equity capital to risk-weighted assets. Size is calculated as a logarithm of banks' total assets. The details of the items included in other positions are provided in Table 11 and Table 12. All the data is collected on an annual basis from the SNL Financial database. Time period: 2005 to 2014. In each case the regression is run while controlling for time- and country-fixed effects. Standard errors are clustered at bank level; *t*-statistics are shown in brackets. The symbols *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Table 15: Explaining SSM banks' sensitivity to curvature swings: regressions on the averages

	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Regressors	Full period	2005-2009	2010-2014	Full period	2005-2009	2010-2014
Total financial assets to total assets	0.058	0.037	0.139			
	(0.42)	(0.20)	(0.71)			
Securities to total assets				0.106	-0.183	0.242
				(0.93)	(-0.82)	(1.60)
Net customer loans to total assets				**0.409*** **	0.189	**0.365***
				(3.15)	(0.90)	**(2.04)**
Core Tier capital ratio	**0.951*** **	0.187	**1.092*** **	**0.959*** **	-0.127	**1.064*** **
	(5.93)	(0.31)	**(5.80)**	**(6.20)**	(-0.25)	**(5.72)**
Deposits to total liabilities (and equity)				**-0.329*** **	**-0.214***	-0.222
				(-2.82)	**(-1.88)**	(-1.53)
Term deposits to deposits				**-0.070** **	0.101	**-0.111** **
				(-2.07)	(1.57)	(-2.19)
Total debt to total liabilities (and equity)	**-0.248** **	-0.218	**-0.245** **			
	(-2.37)	(-1.50)	**(-2.12)**			
Subordinated debt to total liabilities (and equity)				0.095	-0.703	**0.864** **
				(0.31)	(-1.38)	**(2.05)**
Senior debt to total liabilities (and equity)				**-0.518*** **	**-0.411*** **	**-0.392** **
				(-3.32)	**(-2.95)**	**(-2.14)**
Derivative liabilities to total liabilities (and equity)	**0.224***	0.117	**0.268***	0.151	-0.093	0.218
	(1.94)	(0.70)	(1.71)	(0.71)	(-0.27)	(0.55)
Net interest income to operating revenue	0.015	0.029	0.012	0.038	0.062	-0.048
	(1.52)	(0.71)	(0.73)	(0.93)	(1.20)	(-0.67)
Net fee income to RWA	-1.771	-1.858	-1.375	**-5.482*** **	**-4.981*** **	**-4.929*** **
	(-1.48)	(-0.98)	(-0.97)	**(-3.62)**	**(-3.87)**	**(-3.28)**
ROAA	-0.181	0.863	-0.306	0.041	2.742	-0.053
	(-0.47)	(0.41)	(-0.67)	(0.10)	(1.47)	(-0.11)
Net customer loans minus deposits to total assets	**0.167***	0.157	0.166			
	(1.82)	(1.17)	(1.66)			
Loan loss reserves to gross customer loans	0.299	-1.222	0.336	0.250	**-2.246** **	0.428
	(1.34)	(-1.40)	(1.42)	(1.18)	**(-2.58)**	(1.66)
Size	0.005	**0.010***	0.002	**0.010** **	**0.018*** **	0.007
	(1.67)	**(1.70)**	(0.32)	**(2.16)**	**(2.80)**	(0.98)
Observations	235	82	153	204	73	131
R^2	0.79	0.70	0.67	0.80	0.73	0.69

The dependent variable corresponds to banks' interest rate risk exposure to curvature changes in the euro area yield curve. RWA refers to banks' risk-weighted assets. Core Tier capital ratio is defined as a ratio of a bank's core equity capital to risk-weighted assets (RWA). Banks' size is calculated as a logarithm of total assets. The details of the items included in other positions are provided in Table 11 and Table 12. All the data is collected on an annual basis from the SNL Financial database. Time period: 2005 to 2014. In each case the regression is run while controlling for time- and country-fixed effects. Standard errors are clustered at bank level; *t*-statistics are shown in brackets. The symbols *, ** and *** indicate significance at the 10%, 5% and 1% levels.