Essays on Systemic Risk and Bank Profitability

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This thesis consists of the following works:

Döring, Benjamin, Thomas Hartmann-Wendels, and Claudio Wewel (2016).
Systemic risk measures and their viability for banking supervision.
Working Paper.

Döring, Benjamin, Thomas Hartmann-Wendels, and Claudio Wewel (2016a).
Systemic importance, default risk, and profitability in the European banking system.
Working Paper.

Döring, Benjamin (2016).
Risk-adjusted bank performance and income diversification.
Working Paper.

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“*We feel that fundamentally Wall Street is sound, and that for people who can afford to pay for them outright, good stocks are cheap at these prices.*”

– Goodbody and Company market-letter quoted in The New York Times (Friday, October 25, 1929)

“*Life’s biggest tragedy is that we get old too soon and wise too late.*”

– Benjamin Franklin

1 Introduction

The U.S. housing bubble, with house prices peaking in 2006, was primarily initiated by lax mortgage lending standards of U.S. banks. As interest rates increased, however, fewer and fewer debtors were able to service their outstanding loans, which contributed to a sudden rise of the default rates of U.S. subprime mortgages in mid 2007. The following credit crunch, forcing banks to write down several hundred billion dollars in bad loans, has caused the most severe financial crisis since the Great Depression (Brunnermeier, 2009). However, the unprecedented International Financial Crisis of 2007 to 2009 would not have reached such a global and disastrous scale without the bankruptcy of the investment bank Lehman Brothers in September 2008.

Before then, large and interconnected financial institutions were generally considered as "too-big-too-fail", "too-interconnected-too-fail" or just "systemically important" because their default would easily trigger banking system turmoil with contagious effects spreading from one bank to the other. Therefore, bondholders and managers of those banks perceived their investments to be backed by implicit government bailout guaranties in the case of failure. This strategy worked for investors of Bear Stearns and Northern Rock. Both banks were rescued by their governments after experiencing significant losses in the aftermath of the U.S. credit crunch. In the case of Lehman Brothers, though, the U.S. Department of the Treasury and the Federal Reserve Bank were not willing to provide rescue funds guaranteed by the taxpayers to offset its liquidity shortage resulting from heavy subprime mortgage losses in early 2008 (Brunnermeier, 2009).

One explanation for this proceeding was the strategy to break the vicious cycle between large banks' "too-big-too-fail" status and their corresponding government bailout guarantees. Nonetheless, the decision resulted in a loss of confidence of financial market participants and a disruption of the interbank lending market, which led to a severe liquidity crisis that globally prompted governments and central banks to intervene and bailout financial institutions. Thus, the Lehman bankruptcy can be best described as the trigger of a systemic event that significantly aggravated the U.S. credit crunch. Generally, such an event can be regarded as the materialization of the banking system's underlying level of systemic risk, whereas systemic risk is tantamount to the risk of the occurrence of a severe banking crisis with spillover effects to the real economy (FSB, IMF, BIS, 2009).

As a response to the International Financial Crisis and the ripple effects of the default of the investment bank Lehman Brothers, the Group of Twenty agreed on the implementation of a whole bunch of new regulatory rules commonly summarized as Basel III with the purpose of, besides improving microprudential supervision, fostering the resilience of the banking system by introducing macroprudential measures such as counter-cyclical capital buffers and capital surcharges for systemically important banks. The adequate application of such macroprudential measures, however, necessitates the precise measurement of a banking system's level of systemic risk and a comprehensive understanding of the particularities of systemically important banks.

Notwithstanding the ongoing efforts of politicians, regulators, and supervisors to improve the stability of the global banking system and hence the reduction of systemic risk, European banks, especially those in the euro area, are still suffering from the long-term consequences of the International Financial Crisis and the subsequent European Sovereign Debt Crisis. Today, however, the insufficient profitability patterns of a lot of banks and the unsustainable business models of some of the largest European banks are in the spotlight and a growing concern for aggregate banking system stability (see, e.g., European Central Bank, May 2014, Financial Stability Review).

Unfortunately, especially the monetary policy of the European Central Bank (ECB) targeted at stimulating economic growth in the euro area with interest rates at or close to zero has become a growing drag on banks' profitability patterns. It is more and more difficult for banks to achieve profits from maturity transformation because the yield curve flattened over the last couple of years. Moreover, at current market rates, banks are unable to profitably invest the excess supply of deposits into liquid and more or less risk-free financial assets. The fact that financial institutions are facing ever increasing costs from regulation and an enhanced competition from Fintechs is not particularly helpful either.

Given the European economic environment, one recurring expert suggestion to boost banks' business model profitability and sustainability is the increased diversification into non-interest income generating activities such as fees and commissions. The question that remains, however, is whether the diversification into non-interest income is a generally valid option for the average bank.

This thesis consists out of three essays on systemic risk, systemic importance, and bank profitability. To be more precise, the essays address the following three main questions. How should we evaluate the viability of systemic risk measures? Do systemically important banks (SIBs) exhibit default risk and return characteristics that are distinctively different from non-SIBs? How can banks adjust their business models in order to achieve sufficiently high but sustainable risk-adjusted profitability patterns in the post-crisis area?

The first essay (Döring et al., 2016, Systemic risk measures and their viability for banking supervision) contributes to the literature by proposing a criteria-based framework to assess the viability of systemic risk measures as a monitoring tool for banking supervision and investigates the bank characteristics that determine the banking system's overall level of systemic risk. We empirically evaluate and compare the *Marginal Expected Shortfall* (MES) (Acharya et al., 2010), the *SRISK* measure (Acharya et al., 2012; Brownlees and Engle, 2015), and the *Conditional Value at Risk* (CoVaR) (Adrian and Brunnermeier, 2016) on the basis of a representative sample of listed European institutions covering the period from July 2005 to June 2013. The three measures have had the highest impact on research and regulation over the past years and are applied by the U.S. Department of the Treasury and the European Systemic Risk Board.

We assess the monitoring qualities of the former systemic risk measures (SRMs) by focusing on their forecasting capabilities for a set of major aggregated bank-specific and macroeconomic state variables. We find that all of them are informative for the prediction of the future state of the banking system; however, the measures vary significantly in their predictive power for the state of the real economy. In fact, only the MES and the SRISK measure are able to significantly explain future variations in the macroeconomic state variables. Furthermore, we find that the system-wide market-to-book and loan-to-deposit ratios act as fundamental drivers of systemic risk.

The results have paramount implications. First, the market-to-book ratio itself may be used as a simple and efficient proxy for the systemic tension in the banking system. Second, the systemic relevance of the loan-to-deposit ratio underlines the critical role of funding liquidity and supports recently proposed regulatory initiatives that curb aggregate liquidity risks, i.e., the Basel III Liquidity Coverage Ratio and Net Stable Funding Ratio. Third, the inclusion of balance sheet data is beneficial for systemic risk measurement, which becomes obvious in a comparison between SRMs based on both balance sheet data and stock market information and SRMs based solely on stock market information.

The second essay (Döring et al., 2016a, Systemic importance, default risk, and profitability in the European banking system) examines the relation between banks' systemic importance and their default risk and return characteristics on a broad sample of listed European banks. To be more specific, we analyze whether systemically important banks (SIBs) exhibit default risk and return patterns that are distinctively different from those of non-systemically important banks (non-SIBs). We apply the SRISK (Acharya et al., 2012; Brownlees and Engle, 2015) as the measure of systemic importance.

By grouping banks into quintiles according to their systemic importance we show that SIBs' default risk and return characteristics feature above average pro-cyclicality with respect to economic conditions. We do not find evidence that non-SIBs exhibit such patterns. These insights are particularly important for the design of macroprudential stress-testing procedures because supervisors need to separately account for SIBs' and non-SIBs' sensitivities to macroeconomic shocks. Our finding on the increased procyclicality of SIBs' financial stability patterns also indicates the usefulness of the Basel III leverage ratio for the regulation of SIBs since the former measure acts much more countercyclical than current regulations on risk-weighted assets (Brei and Gambacorta, 2015).

Furthermore, systemic importance coincides with significantly weaker return patterns. That is, SIBs feature annual returns that are around 5% lower than those of non-SIBs. In contrast, the 20% least systemically important banks exhibit returns that are approximately 2% higher when compared to more systemically important banks. Institutions' systemic nature, however, cannot be associated with higher levels of default risk, challenging the notion that systemically important banks take excessive risks as a result of perceived bailout guarantees. In fact, SIBs exhibit levels of ameliorating default risk over time.

The third essay (Döring, 2016, Risk-adjusted bank performance and income diversification) contributes to the academic literature by analyzing the effects of income diversification on banks' profitability patterns for a broad sample of listed and unlisted euro area banks covering the period from 2007 to 2014. We measure bank profitability employing the ratio return on risk-weighted assets (RoRWA) and proxy a bank's income diversification by calculating the shares of non-interest income, fee income, trading income, and other non-interest income in total operating income.

We apply the two-step system GMM (generalized method of moments) regression technique for estimation purposes developed by Arellano and Bover (1995) and Blundell and Bond (1998) in order to account for the possibility of reverse causalities between banks' risk-adjusted profitability patterns and their non-interest income shares. The system GMM estimator is further capable of controlling for unobserved heterogeneity across our sample banks by first differencing the employed regression variables.

Our empirical analysis shows that the diversification into non-interest income activities such as fees, commissions, and trading substantially increases a bank's profitability, supporting the existence of economies of scope. However, we also find that a diversification into other non-interest revenue streams is disadvantageous for the average bank. Yet, the significance of the relations between the fee and trading income shares and bank performance depends to a large extent on bank type and bank size. That is to say, especially investment banks and banks with a stock exchange listing profit from the economies of scope resulting from fee generating activities, whereas smaller banks are the only ones that are able to significantly increase their RoRWAs by diversifying into trading activities.

2 Systemic risk measures and their viability for banking supervision

2.1 Introduction

How should we monitor systemic risk? In the aftermath of the Lehman bankruptcy that triggered an unprecedented international financial crisis this question has become of vital interest to regulators and researchers. Over the last years, a large number of approaches to measure both – systemic importance (at the institutional level) and systemic risk (at the banking system level) – have been proposed.

The Bank for International Settlements (2013), for example, identifies systemically important financial institutions (SIFIs) by various balance and off-balance sheet characteristics such as size, interconnectedness, and substitutability. Moreover, academia has recommended a whole bunch of approaches with a strand of literature based on asset prices applying standard risk measures such as the *Conditional Value at Risk* (Adrian and Brunnermeier, 2016) and the *Marginal Expected Shortfall* (Acharya et al., 2010), extreme value theory (De Jonghe, 2010; Zhou, 2010), principal components analysis (Billio et al., 2012; Kritzman et al., 2011), and credit default models and default probabilities (Suh, 2012; Gray and Jobst, 2010; Huang et al., 2009; Segoviano and Goodhart, 2009; Lehar, 2005). Another strand of literature applies network analysis to investigate systemic risk arising from interbank relationships (e.g., Halaj and Kok Sorensen, 2013; Drehmann and Tarashev, 2013; Allen et al., 2010). Furthermore, supervisors and academia suggest the use of simple market indicators such as Libor-OIS and credit default swap spreads for the monitoring of systemic risk. For an extensive survey on the literature on systemic risk measurement we refer to Bisias et al. (2012).

Despite the multitude of approaches, research on the measures' capability to effectively capture and predict the dynamics of systemic risk and its potential consequences is scarce. For macroprudential policymaking and supervision, however, the assessment of the measures' adequacy as a monitoring tool is crucial. But how can we determine whether systemic risk measures (SRMs) are viable as a monitoring tool or not?

While it is difficult to assess SRMs at the institutional level because an individual bank's rank with respect to its systemic importance is predominantly determined by the applied measure, evaluating SRMs at the banking system level is more expedient. According to the definition of the International Monetary Fund, aggregate systemic risk is *the risk of excessive losses within all or parts of the financial system with imminent* *negative spillover effects to the real economy* (FSB, IMF, BIS, 2009). Recent research supports this definition. E.g., Reinhart and Rogoff (2009) show that systemic financial crises often have substantial adverse effects on the overall state of the economy, such as drops in asset prices, output, and employment levels. Therefore, expedient SRMs should be capable of pre-identifying banking system distress as well as downturns in the real economy in order to gauge the overall level of systemic risk.

This paper contributes to the literature on the analysis of SRMs and underlying aggregate systemic risk by proposing a criteria-based framework that can be applied to assess the viability of SRMs as a monitoring tool for banking supervision. We make use of our assessment framework and empirically evaluate and compare the *Marginal Expected Shortfall* (MES), the related *SRISK* measure (Acharya et al., 2012; Brownlees and Engle, 2015), and the *Conditional Value at Risk* (CoVaR). Over the past years, these measures have had the highest impact on research and regulations. They are applied by the U.S. Treasury Department and the European Systemic Risk Board.

To be more specific, we compute time series of cross-sectional averages for the bank-level series of MES, SRISK, and CoVaR in order to evaluate the measures' capability of capturing the level of systemic risk by focusing on their predictive power for a set of major aggregated bank-specific and macroeconomic state variables. We investigate the directionalities and dependencies between the SRMs and the latter variables employing vector autoregressions. This approach allows us to simultaneously examine the aggregate bank characteristics that determine the banking system's overall level of systemic risk, which is vital in order to achieve macroeconomic stability (Arnold et al., 2012). We apply the measures to a broad sample of European publicly listed banks analyzing the level of systemic risk in the European banking system in the period between July 2005 and June 2013. The latter provides a unique setting for the evaluation of SRMs, as European institutions were affected by both the Subprime Crisis including the subsequent International Financial Crisis of 2007–2009 and the European Sovereign Debt Crisis.

Our main results are as follows. We find that all three SRMs generally possess substantial predictive power for bank-specific state variables, including those that directly proxy for the banking system's capital strength and crisis resilience. For instance, an increase in the value of the measures coincides with an increase in the future level of system-wide leverage and a decrease of aggregate equity values. The forecasting capabilities of MES and SRISK for macroeconomic state variables, particularly for aggregate production and employment, are superior to those of CoVaR, however. In fact, CoVaR's capability of capturing the future state of the real economy is rather poor. Thus, given the dependencies between the SRMs and bank-specific and macroeconomic state variables, only the dynamics of MES and SRISK are informative for the identification of true systemic events. A sharp increase of the latter coincides with a deterioration of the state of the banking system and a decrease in macroeconomic activity. A sharp increase in CoVaR, on the contrary, does not precisely distinguish between banking system turmoil with no macroeconomic effects and systemic banking crises that cause downturns in the real economy.

Our analysis additionally reveals that the ratio of market valued equity to book valued equity (MTB) and the ratio of total loans to total customer deposits (LTD), both calculated as the aggregate of institutions within the predefined banking system, act as *fundamental drivers* of systemic risk. Both ratios significantly determine the future dynamics of MES, SRISK, and CoVaR at the banking system level. I.e., lower levels of the MTB ratio (higher levels of the LTD ratio) are associated with higher levels of future systemic risk.

The results have paramount implications. First, the MTB ratio, capturing the market's view about banks' aggregate risk of financial distress by itself, may be used as a simple early warning indicator for the banking system's systemic tension. The latter indicated a significant deterioration in the value of European banks as early as in 2007, pointing at the risk of a systemic banking crisis. Moreover, since it is well-documented in literature that lower MTB values of equity can be mainly attributed to lower earnings expectations, higher earnings uncertainty, and elevated debt burdens (Chen and Zhang, 1998; Fama and French, 1995), our findings indicate that banks' earnings volatility contributes to systemic risk. Thus, supervisors might incentivize institutions to establish more sustainable business models with higher earnings certainty such as to reduce their vulnerability in times of crises, thereby reducing institutions' aggregate systemic footprint.

Second, the significance of the aggregate LTD ratio demonstrates that an effective regulation of funding liquidity risk is vital to lower the overall level of systemic risk. Therefore, our empirical findings stress the importance of the new Basel III guidelines concerning limits on institutions' liquidity mismatch and the strengthening of the institutions' ability to survive periods of stress without market funding, namely the Net Stable Funding Ratio and the Liquidity Coverage Ratio.

Finally, our results reveal that the inclusion of balance sheet data is beneficial for systemic risk measurement. This becomes particularly visible in a comparison between SRMs based on both balance sheet and stock market information and SRMs based exclusively on stock market information.

Our paper is most closely related to the work of Rodriguez-Moreno and Peña (2013), who evaluate the performance of SRMs at the banking system level based on their correlation with an index of systemic events and policy actions. In contrast, we establish a criteria-based approach that explicitly considers the consequences of changes in the SRMs' level of systemic risk for a set of aggregated bank-specific and macroeconomic state variables. Our approach does not require the identification of systemic events that may be prone to selection biases. Moreover, we are – to the best of our knowledge – the first to identify aggregate bank characteristics that drive the overall level of systemic risk.

We contribute to a growing body of literature on the MES, SRISK, and CoVaR measures, which can be systemized as follows. The first strand implements MES, SRISK (e.g., Engle et al., 2014; Idier et al., 2014; Acharya and Steffen, 2013) or CoVaR (e.g., Weiß et al., 2014; Brunnermeier et al., 2012; López-Espinosa et al., 2012) and identifies determinants of systemic importance at the institutional level. These studies find, among others, that balance sheet characteristics such as banks' non-interest income, short-term wholesale funding or regulatory standards substantially drive an institution's systemic importance.

Another strand of literature compares or extends these measures. Jiang (2012) analyzes the tail dependence structure of MES and CoVaR. Benoit et al. (2013) rank US financial institutions according to MES, SRISK, and CoVaR and find that the risk measures can be proxied by market risk and liabilities. Löffler and Raupach (2013) estimate the robustness of MES and CoVaR. Girardi and Ergün (2013) propose the use of bivariate GARCH estimates to measure CoVaR and Cao (2013) extends the CoVaR measure from one bank being in financial distress to a set of one or more banks being in distress.

The remainder of this paper is structured as follows. Section 2.2 describes the sample selection and Section 2.3 defines the SRMs. In Section 2.4 we introduce our assessment framework as well as the employed aggregated bank-specific and macroeconomic variables. Section 2.5 presents and discusses our results and Section 2.6 concludes.

2.2 Sample selection

Our empirical analysis focuses on the European banking system. We concentrate on the member states of the European Union to ensure sufficient homogeneous banking regulation across our sample excluding countries from Eastern Europe. However, we additionally include Switzerland due to its comparable regulatory standards and the country's individual banking sector's importance within the European banking system.[1] Our sample covers the period from July 2005 to June 2013 including the International Financial Crisis

[1] All member states of the European Union and Switzerland implemented the Basel II Directives 2006/48/EC and 2006/49/EC and are introducing the new Basel III criteria.

from 2007 to 2009 and the subsequent European Sovereign Debt Crisis.

Beyond location, we select banks according to the following two main criteria: free float market capitalization and total assets. By restricting our sample to free float publicly listed institutions, we ensure that all sample banks are actively traded and that institutions' share prices adequately reflect their financial state and health. Thus, as a starting point we identify all banks that are included in the STOXX Europe TMI Banks Index in at least one quarter within the sample period and select those that fit our geographical restrictions.[2] This procedure ensures that our sample of banks adequately reflects the aggregate of traded stocks of banks in Western Europe leaving us with 126 banks.[3]

In the next step, all preselected banks are ranked with respect to their size in total assets. Based on the Single Supervisory Mechanism (SSM) approved by the European Commission, the European Central Bank started supervising euro area based banks with total assets exceeding €30bn in November 2014 (Council Regulation 1024/2013/EU). Restricting our sample to institutions that fulfill the latter criterion for at least one quarter within the sample period, we ensure that our sample only includes institutions with relevant systemic exposure to the European banking system. Furthermore, we apply a penny stock sanction excluding banks in case their stock is traded at a price of lower than €1 for 22 consecutive trading days. To ensure that our sample does not suffer from any survivorship biases, we do not exclude banks that are delisted from the STOXX Europe TMI Banks Index.

The resulting sample contains 84 banks from 15 countries including Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. As a result of bankruptcies, mergers and acquisitions, and new listings the number of sample banks varies over time with a maximum of 78 and a minimum of 51 banks per sample quarter.

For our predefined selection of banks, we obtain all stock price information and quarterly balance sheet data from Datastream. Table 2.1 displays the names and different characteristics of the banks in our sample and Table 2.2 provides a summary of the latter. The institutions' mean total assets over the sample period range from €13.8bn to

[2] The individual banks are admitted into the index based on their free float market capitalization and cover roughly 95% of the free float market capitalization of all banks headquartered in Western Europe. The index composition is updated on a quarterly basis (STOXX Limited, 2013, STOXX Index Methodology Guide, `http://www.stoxx.com/indices/rulebooks.html`).

[3] To our preselection of banks we furthermore add the ING Groep. STOXX classifies the ING Groep as an insurance company. However, a substantial part of ING's revenue comes from banking related activities. In addition, the bank is classified as a global systemically important bank by the Financial Stability Board.

Institution	Country	ISIN	Total assets	Rank	Leverage	Rank	Market-to-book	Rank	Profitability	Rank
ABN AMRO Holding N.V.	Netherlands	NL0000301109	794,905	15	14.25	67	3.39	83	0.5712	27
Ageas N.V.	Belgium	BE0974264930	420,419	23	23.48	45	1.36	52	-3.2078	84
Agricultural Bank of Greece S.A.	Greece	GRS414003004	25,216	80	30.99	34	14.39	84	-1.2763	81
Alliance & Leicester PLC	United Kingdom	GB0000386143	90,321	48	52.37	18	1.27	45	0.3100	46
Allied Irish Banks PLC	Ireland	IE0000197834	148,411	38	71.99	12	1.51	60	-0.9409	80
Alpha Bank A.E.	Greece	GRS015013006	56,845	60	34.71	29	1.18	38	-0.0445	71
Banca Antonveneta S.p.A.	Italy	IT0003270102	44,553	67	6.19	83	2.59	81	0.2621	48
Banca Carige S.p.A.	Italy	IT0003211601	33,588	71	13.62	68	1.09	29	0.4959	31
Banca Civica S.A.	Spain	ES0148873005	74,048	55	87.40	8	0.30	5	0.1397	62
Banca Lombarda	Italy	IT0000062197	40,222	68	7.52	81	2.04	79	0.7362	15
Banca Monte dei Paschi di Siena S.p.A.	Italy	IT0001334587	196,445	33	37.52	28	0.82	17	-0.0375	70
Banca Nazionale del Lavoro S.p.A.	Italy	IT0001254884	88,283	49	10.59	75	1.75	74	0.5646	29
Banca Popolare dell'Emilia Romagna	Italy	IT0000066123	52,307	61	21.96	50	0.89	21	0.4140	39
Banca Popolare di Milano	Italy	IT0000064482	45,742	66	25.63	40	0.72	12	0.1460	61
Banca Popolare di Sondrio	Italy	IT0000784196	21,916	82	11.42	72	1.42	57	0.5391	30
Banca Popolare Italiana S.C.A.R.L.	Italy	IT0000064300	46,138	64	7.86	80	1.79	76	-0.1701	72
Banche Popolari Unite S.C.A.R.L.	Italy	IT0003487029	109,530	43	22.88	47	0.73	13	0.2368	52
Banco Bilbao Vizcaya Argentaria S.A.	Spain	ES0113211835	507,807	19	13.08	69	1.64	68	0.8504	9
Banco Comercial Portugues S.A.	Portugal	PTBCP0AM0007	87,428	52	30.47	35	1.30	47	0.2058	56
Banco de Sabadell S.A.	Spain	ES0113860A34	88,060	50	16.79	63	1.26	43	0.6536	20
Banco Espanol de Credito S.A.	Spain	ES0113440038	104,562	45	22.78	48	1.38	53	0.4690	33
Banco Espirito Santo S.A.	Portugal	PTBES0AM0007	70,588	56	18.94	54	0.98	25	0.4895	32
Banco Pastor S.A.	Spain	ES0113790085	26,549	77	19.90	53	1.32	49	0.4449	36
Banco Popolare Societa CooperativaAz.	Italy	IT0004231566	108,159	44	32.35	33	0.68	10	0.1641	59
Banco Popular Espanol S.A.	Spain	ES0113790226	114,220	41	17.00	61	1.44	58	0.6177	23
Banco Portugues de Investimento S.A.	Portugal	PTBPI0AM0004	39,802	70	28.11	36	1.70	71	0.4643	34
Banco Santander S.A.	Spain	ES0113900J37	1,025,916	10	15.78	65	1.17	37	0.6863	18
Bank Austria Creditanstalt AG	Austria	AT0000995006	206,010	32	11.21	74	1.46	59	0.9729	4
Bank of Greece	Greece	GRS004013009	84,172	54	194.01	6	0.50	6	0.2962	47
Bank of Ireland	Ireland	IE0030606259	169,136	37	60.52	15	1.08	28	0.1949	58
Bankia S.A.	Spain	ES0113307021	287,902	27	210.26	4	-0.44	1	-2.0169	83
Bankinter	Spain	ES0113679I37	50,617	62	18.55	55	1.56	65	0.4312	37
Banque Cantonale Vaudoise	Switzerland	CH0015251710	25,552	78	10.16	77	1.74	72	1.0558	3
Banque Nationale de Belgique S.A.	Belgium	BE0003008019	100,203	46	80.73	9	0.15	3	0.7001	17
Barclays PLC	United Kingdom	GB0031348658	1,633,656	5	46.37	23	1.11	31	0.3259	45
Basler Kantonalbank	Switzerland	CH0009236461	22,432	81	44.05	25	0.28	4	0.7228	16
Bayerische Hypo- und Vereinsbank AG	Germany	DE0008022005	457,780	21	17.43	59	1.42	56	0.1281	63
BNP Paribas S.A.	France	FR0000131104	1,743,205	1	33.25	32	0.95	24	0.3738	41
Bradford & Bingley PLC	United Kingdom	GB0002228152	64,273	58	120.48	7	0.88	20	0.1270	64
Caisse Regionale de Credit Agricole Mutuel de Paris	France	FR0000045528	29,870	74	50.64	21	0.58	7	0.9527	5
Caixabank S.A.	Spain	ES0140609019	111,228	42	11.86	71	0.79	16	2.5606	2
Capitalia S.p.A.	Italy	IT0003121495	138,590	39	9.03	79	1.74	73	0.7673	12

Table 2.1 – Bank characteristics and descriptives (continued on the next page)

Institution	Country	ISIN	Total assets	Rank	Leverage	Rank	Market-to-book	Rank	Profitability	Rank
Commercial Bank of Greece	Greece	GRS006013007	25,549	79	20.63	52	2.72	82	-1.7566	82
Commerzbank AG	Germany	DE000CBK1001	663,395	16	75.76	10	0.65	8	0.0746	67
Crédit Agricole S.A.	France	FR0000045072	1,465,511	6	66.49	13	0.75	14	0.1258	65
Credit Suisse Group AG	Switzerland	CH0012138530	805,461	13	23.01	46	1.54	64	0.3263	44
Credito Emiliano S.p.A. CredemAz.	Italy	IT0003121677	27,395	76	17.17	60	1.22	40	0.5992	25
Credito Valtellinese S.C.A.R.L. Az.	Italy	IT0000064516	21,571	83	27.99	37	0.66	9	0.2063	55
Danske Bank	Denmark	DK0010274414	415,945	24	33.83	30	1.04	27	0.2476	50
Depfa Bank	Germany	IE0072559994	223,521	30	44.54	24	1.86	77	0.2268	53
Deutsche Bank AG	Germany	DE0005140008	1,722,101	2	53.30	17	0.94	23	0.2040	57
Deutsche Postbank AG	Germany	DE0008001009	196,433	34	33.52	31	1.24	41	0.1484	60
Dexia S.A.	Belgium	BE0003796134	523,914	18	506.42	1	0.93	22	-0.2472	73
Erste Group Bank AG	Austria	AT0000652011	194,229	35	20.65	51	1.34	50	0.3545	42
Eurobank Ergasias S.A.	Greece	GRS323003004	67,235	57	64.02	14	1.24	42	-0.4100	75
GAM Holding AG	Switzerland	CH0102659627	13,786	84	3.12	84	1.68	70	13.8219	1
HBOS PLC	United Kingdom	GB0030587504	805,950	12	51.84	19	1.76	75	-0.3134	74
HSBC Holdings	United Kingdom	GB0005405286	1,644,162	4	13.06	70	1.42	55	0.6277	21
IKB Deutsche Industriebank AG	Germany	DE0008063306	40,094	69	73.66	11	0.86	18	-0.5720	77
ING Groep N.V.	Netherlands	NL0000303600	1,220,294	7	40.27	26	1.15	33	0.3428	43
Intesa Sanpaolo S.p.A.	Italy	IT0000072626	542,920	17	301.56	3	0.87	19	0.4532	35
Investec PLCShs	United Kingdom	GB00B17BBQ50	45,940	65	18.47	57	1.59	66	0.8766	8
Irish Bank Resolution Corporation Ltd	Ireland	IE00B06H8J93	87,850	51	329.59	2	1.19	39	0.8093	11
Julius Bär	Switzerland	CH0102484968	32,597	72	7.02	82	1.65	69	0.7451	13
Jyske Bank	Denmark	DK0010307958	28,094	75	15.85	64	1.40	54	0.6222	22
KBC Groep N.V.	Belgium	BE0003565737	318,055	25	26.93	39	1.11	30	0.2164	54
Lloyds Banking Group	United Kingdom	GB0008706128	798,099	14	24.21	42	1.53	63	0.3948	40
Mediobanca - Banca di Credito Finanziario S.p.A.	Italy	IT0000062957	64,004	59	10.51	76	1.26	44	0.9519	6
National Bank of Greece S.A.	Greece	GRS003003019	93,762	47	24.01	44	1.17	36	-0.7827	79
Natixis Banques Populaires	France	FR0000120685	425,956	22	50.14	22	0.69	11	0.0777	66
Nordea Bank AB	Sweden	SE0000427361	485,820	20	18.53	56	1.35	51	0.5956	26
Northern Rock PLC	United Kingdom	GB0001452795	123,666	40	195.77	5	0.11	2	-0.5364	76
Piraeus Bank S.A.	Greece	GRS014003008	46,352	63	51.79	20	1.16	34	-0.7509	78
Pohjola Bank PLC	Finland	FI0009003222	32,148	73	16.83	62	1.16	35	0.6632	19
Raiffeisen Bank International AG	Austria	AT0000606306	86,980	53	15.23	66	1.52	62	0.9156	7
Royal Bank of Scotland Group PLC	United Kingdom	GB00B7T77214	1,689,769	3	56.99	16	1.15	32	0.0660	69
Sanpaolo IMI S.p.A. Az.	Italy	IT0001269361	279,409	28	11.26	73	2.17	80	0.7428	14
Skandinaviska Enskilda Banken AB	Sweden	SE0000148884	236,951	29	22.75	49	1.29	46	0.4223	38
Société Générale S.A.	France	FR0000130809	1,054,032	9	38.11	27	1.04	26	0.2606	49
Standard Chartered PLC	United Kingdom	GB0004082847	299,863	26	9.52	78	1.59	67	0.8342	10
Svenska Handelsbanken AB	Sweden	SE0000193120	220,029	31	17.59	58	1.51	61	0.6166	24
Swedbank AB	Sweden	SE0000242455	175,054	36	24.05	43	1.31	48	0.5677	28
UBS AG	Switzerland	CH0024899483	1,212,246	8	24.99	41	1.99	78	0.0746	68
UniCredit S.p.A.	Italy	IT0004781412	850,254	11	27.05	38	0.79	15	0.2388	51

Table 2.1 – Bank characteristics and descriptives

The table exhibits figures averaged across the entire time series of quarterly bank characteristics for each of the 84 sample banks. The time series of observations cover the period from July 2005 to June 2013. *Total assets* is the book value of total assets expressed in EUR m. *Leverage* is the ratio of market valued total assets (book valued total debt + market valued equity) divided by market valued equity and *market-to-book* is the ratio of market valued equity divided by book valued equity. *Profitability* is defined as the ratio of net income over total assets expressed in percentage terms. All data are obtained from Datastream.

Statistics	Total assets	Leverage	Market-to-book	Profitability
mean	343,964	49.07	1.40	0.41
std dev	466,554	76.42	1.54	1.65
min	13,786	3.12	-0.44	-3.21
$q = 0.25$	46,298	16.55	0.92	0.13
$q = 0.50$	110,379	24.13	1.25	0.35
$q = 0.75$	433,912	50.27	1.53	0.62
max	1,743,205	506.42	14.39	13.82

Table 2.2 – Summary of bank characteristics and descriptives
The table provides a summary of Table 2.1. *Total assets* is the book value of total assets expressed in EUR m. The time series of observations cover the period from July 2005 to June 2013. *Leverage* is the ratio of market valued total assets (book valued total debt + market valued equity) divided by market valued equity and *market-to-book* is the ratio of market valued equity divided by book valued equity. *Profitability* is defined as the ratio of net income over total assets expressed in percentage terms. All data are obtained from Datastream.

€1,743bn. The median-sized bank has around €110bn in total assets. Our sample banks are leveraged (market leverage) between 3.12 and 506.42 with a median leverage of 24.13 across the sample period. The banks' mean market-to-book ratio of equity ranges from -0.44 to 14.39 across the sample period with a sample median of 1.25.[4] The institutions' mean profitability (return on assets) over the sample period ranges from 13.82% to -3.21% with a sample median of 0.35%.

2.3 Systemic risk measures

This section briefly defines the systemic risk measures (SRMs) implemented in this paper and elaborates on their econometric implementation.

2.3.1 Marginal Expected Shortfall

The *Marginal Expected Shortfall* (MES) proposed by Acharya et al. (2010) measures the expected return (loss) of bank i's stock given that the banking system's overall return is in its tail. More intuitively, the MES can be interpreted as the "participation rate" of bank i within a financial crisis. Following Acharya et al. (2010), Brownlees and Engle (2015) introduce a time-dependent dynamic extension of the MES that is defined as bank

[4] After its IPO in July 2011, Bankia S.A. requested a bailout of €19bn in May 2012 and was partially nationalized by the Spanish government. As a consequence, the bank reported on average a negative balance for its book value of equity over the sample period.

i's expected cumulative h-day stock return – i.e., over time interval $[t, t+h]$ – with the condition that the banking system's cumulative h-day return is falling below a predefined threshold C, indicating distress in the banking system:

$$\mathrm{MES}_t^{i,h}(C) = -\mathbb{E}\left[R_{i;[t,t+h]} \middle| R_{sys;[t,t+h]} \leq C\right], \tag{2.1}$$

with $R_{i;[t,t+h]}$ denoting bank i's cumulative stock return over h days:

$$R_{i;[t,t+h]} = \exp\left(\sum_{\tau=1}^{h} r_{i,t+\tau}\right) - 1. \tag{2.2}$$

$r_{i,t}$ represents the one-day returns of bank i's stock. The h-day banking system return $R_{sys;[t,t+h]}$ is defined analogously. Note that for the ease of interpretation, we switch the sign for the risk measure. Thus, an increase in the measure indicates an increase in the level of systemic risk.

2.3.2 SRISK

Based on the MES, Acharya et al. (2012) directly model a bank's expected undercapitalization during a financial crisis. The proposed systemic risk measure, *SRISK*, therefore incorporates financial market data as well as balance sheet data. A bank's capital shortfall or its undercapitalization, respectively, is defined as the amount of capital that a bank would have to raise during a financial crisis in order to prevent bankruptcy. Hence, a bank's expected time-varying capital shortfall over the time interval $[t, t+h]$ given the event of a financial crisis or severe distress in the banking system is calculated as follows:

$$\mathrm{SRISK}_t^{i,h}(C,k) = \mathbb{E}\left[\text{capital shortfall}_{i;[t,t+h]} \middle| \text{crisis}\right]. \tag{2.3a}$$

Applying the going concern loss absorbing capacity concept, Equation (2.3a) can be rearranged:

$$\mathrm{SRISK}_t^{i,h}(C,k) = \mathbb{E}\left[\{k \times (\text{debt} + \text{equity}) - \text{equity}\}_{i;[t,t+h]} \middle| \text{crisis}\right], \tag{2.3b}$$

In order to prevent bankruptcy, institution i's equity cushion needs to be larger than a fraction k of the (market valued) total assets. Within the Basel III framework, parameter k can be considered to represent the absolute Tier I capital ratio of 3%, which is consistent with the Basel III maximum Leverage Ratio of 33.3 that must be satisfied even during a crisis. In that case, k can be interpreted as a Basel Capital Adequacy Ratio equivalent on market valued total assets instead of risk-weighted assets. The market value of total assets is determined using current debt balance sheet data – assuming that the levels of debt remain relatively constant over the observed time interval $[t, t+h]$ – and the market value of equity. The market value of equity within a future financial crisis can be expressed as a function of MES:

$$\mathrm{SRISK}_t^{i,h}(C,k) = k \times \mathrm{debt}_{i,t} - (1-k)\left(1 - \mathrm{MES}_t^{i,h}(C)\right) \times \mathrm{equity}_{i,t}. \tag{2.3c}$$

The higher a bank's SRISK, the higher its capital shortfall during a crisis period. A negative SRISK indicates that a bank's equity cushion is sufficiently large in order to avoid bankruptcy.

2.3.3 Conditional Value at Risk

The bottom-up measure *Conditional Value at Risk* (CoVaR) proposed by Adrian and Brunnermeier (2016) explicitly allows the calculation of a bank's contribution to systemic risk in the banking system measuring the value at risk return of the banking system conditional on institution i being in severe financial distress. In analogy to the MES and SRISK measures we define a multi-period CoVaR measure that is in line with the CoVaR extension of Girardi and Ergün (2013). The "distress CoVaR" $\mathrm{CoVaR}_t^{sys|i\leq \mathrm{VaR},h}$ is defined as the banking system's h-day value at risk return, conditional on bank i's h-day stock return being *at* or *below* bank i's h-day value at risk:

$$\mathbb{P}\left(R_{sys;[t,t+h]} \leq \mathrm{CoVaR}_t^{sys|i\leq \mathrm{VaR},h}(q) \middle| R_{i;[t,t+h]} \leq \mathrm{VaR}_{t,q}^{i,h}\right) = q, \tag{2.4a}$$

with $\mathrm{VaR}_{t,q}^{i,h}$ denoting bank i's h-day value at risk return. Parameter q indicates the confidence level.[5] The median state CoVaR is given by conditioning on the one standard deviation band around institution i's median h-day return:

$$\mathbb{P}\left(R_{sys;[t,t+h]} \leq \mathrm{CoVaR}_t^{sys|i=\mathrm{median},h}(q) \middle| \left|R_{i;[t,t+h]} - \nu_{i,t}^h\right| \leq \sigma_{i,t}^h\right) = q, \tag{2.4b}$$

[5] Whereas Adrian and Brunnermeier (2016) estimate CoVaR using a quantile regression approach, we employ a bivariate conditionally heteroskedastic model to account for the time-varying dependence structure between banks and the banking system, which enables the measure to better capture the tail events of distress (Girardi and Ergün, 2013). Furthermore, we are able to evaluate all three SRMs within a common statistical setup that improves the comparability and interpretability of our key results.

where $\sigma_{i,t}^{h}$ and $\nu_{i,t}^{h}$ indicate the standard deviation and the median return of institution i's h-day cumulative stock return. Thus, institution i's marginal systemic risk contribution to overall systemic risk in the banking system is defined as the difference between the system's CoVaR conditional on bank i being in financial distress and the system's CoVaR conditional on bank i being in its median state:

$$\Delta\text{CoVaR}_t^{i,h}(q) = -\left[\text{CoVaR}_t^{sys|i\leq\text{VaR},h}(q) - \text{CoVaR}_t^{sys|i=\text{median},h}(q)\right]. \tag{2.4c}$$

Note that again we switch the sign of ΔCoVaR in order to facilitate the comparison of the three different risk measures MES, SRISK, and ΔCoVaR.

2.3.4 Implementation

We follow Brownlees and Engle (2015) and calculate weekly series of SRMs for each of the 84 sample banks by modeling the bivariate return dynamics of bank i and the banking system employing a conditionally heteroskedastic model and estimate the return distributions of $R_{i;[t,t+h]}$ and $R_{sys;[t,t+h]}$ by applying Monte Carlo simulation techniques. We set the crisis regime threshold $C = -25\%$, the leverage ratio parameter $k = 3\%$, the VaR confidence level $q = 5\%$, and the length of the SRMs' forward looking period $h = 60$ days (a quarter of a year).[6] For a detailed exposition of the implementation methodology we refer to Appendix 2.A.

Finally, we compute time series of cross-sectional averages for the bank-level series of MES, SRISK, and ΔCoVaR in order to evaluate the measures' ability to gauge the overall systemic tension in the banking system and to examine the determinants of the banking system's aggregate level of systemic risk. We call these averaged measures *avg*MES, *avg*SRISK, and *avg*ΔCoVaR.

2.4 Evaluation methodology

Evaluating the viability of SRMs as a tool for macroprudential supervision necessitates the development of a framework that can be readily applied to assess the SRMs' ability of capturing the overall level of systemic risk in a banking system. In the following, we

[6] To calibrate the threshold level C, we observed the performance of the STOXX Europe TMI Banks Index during the most severe periods of the International Financial Crisis and the European Sovereign Debt Crisis. In both periods the index dropped on average by around 25% within a three month time window.

motivate our assessment criteria and provide an outline of the empirical data (i.e., the choice of variables) that our empirical analysis requires.

2.4.1 Assessment criteria

By definition SRMs are designed to measure the systemic importance of individual banks and/or the level of systemic risk in a predefined system. Since we are solely interested in the SRMs' macro perspective, the evaluation of the latter, in particular, requires a concept of what systemic risk is. Generally, systemic risk can be regarded as *the risk or danger of the occurrence of a systemic event*, whereas the systemic event is tantamount to the materialization of systemic risk. In recent years, policy-making institutions have defined the term *systemic risk* in numerous ways. However, most of the definitions feature adverse effects of systemic events on the banking system and the macroeconomy. The International Monetary Fund (FSB, IMF, BIS, 2009) provides a useful working definition of systemic risk:

> *Systemic risk is the risk of excessive losses within all or parts of the financial system with imminent negative spillover effects to the real economy.*

The above definition is twofold and features the two main preconditions that we will use as foundations for our assessment criteria that we derive in the following.

According to the IMF, systemic risk first materializes as banking system turmoil. The materialization of systemic risk in return implies that an indicator of systemic risk (or an SRM, respectively) should sharply increase before the onset of such an event. Moreover, an SRM should – to some extent – be capable of predicting the consequences of systemic risk materialization. Thus, we can formulate the following assessment criterion:

Criterion 1 *SRMs should possess predictive power for the state of the banking system.*

In addition to the distress that systemic events cause to the banking system, the IMF definition features imminent spillover effects to the real economy that could potentially result in an economic recession. Such spillovers from the banking system to the real economy typically manifest themselves in substantial drops in output and employment (Reinhart and Rogoff, 2009). Hence, increases in systemic risk (as indicated by SRMs) should have predictive power for such spillover effects:

Criterion 2 *SRMs should possess predictive power for macroeconomic state variables.*

The latter assessment criteria are crucial, because forward looking measures that possess predictive power for the state of the banking system and the real economy are able to capture current systemic risk exposures. Consequentially, such measures may act as early warning indicators at the banking system level.

Measures fulfilling both criteria have to be negatively correlated with the general state of the banking system as well as the state of the real economy. Thus, a sharp increase in systemic risk (as indicated by the SRMs) would indicate a deterioration of the future state of the banking system and a decrease in macroeconomic activity. In contrast, SRMs that are uncorrelated with the state of the banking system and/or the real economy are incapable of effectively distinguishing between financial turmoil in the banking system with no macroeconomic effects, macroeconomic cycles with little effect on the banking system, and true systemic events.

However, our empirical evaluation of the SRMs' ability to measure systemic risk according to the above definition and criteria requires a comprehensive measurement of the state of the banking system, especially the banking system's level of financial distress, and it's corresponding macroeconomic activity.

2.4.2 Selection of state variables

We assess the SRMs' predictive power employing a set of aggregated bank-specific and macroeconomic variables, which we discuss briefly in the following.

Bank-specific variables

We measure the banking system's aggregate default risk applying the variables leverage and Z-score. We define *leverage* as the ratio of market valued total assets over market valued equity. Market valued total assets is calculated as the sum of total book valued debt and market valued equity. The system-wide ratio of leverage therefore reflects institutions' aggregate capital strength and crisis resilience. The *Z-score* gives the number of standard deviations that an institution's return on assets needs to decline in order to trigger its bankruptcy, given its current capital asset ratio (Hannan and Hanweck, 1988; Boyd and Runkle, 1993). A lower Z-score at the banking system level therefore implies a higher propensity to systemic default. We calculate the measure as $(roa_t + car_t)/\sigma\,(roa)$, where roa denotes the return on assets, car the capital asset ratio, and $\sigma\,(roa)$ the return on assets' standard deviation over the sample period.

Furthermore, we capture the market's view about institutions' aggregate risk of financial distress employing the variable *market-to-book* (MTB). MTB is defined as market valued equity divided by book valued equity. The ratio is primarily driven by future earnings expectations, earnings uncertainty, and current debt burdens (Chen and Zhang, 1998; Fama and French, 1995). A low MTB ratio at the banking system level should thus coincide with high levels of systemic risk.

To additionally account for the banking system's underlying profitability, credit risk, and liquidity risk, we include the following bank-specific control variables. *Profitability* is the ratio of net income over total assets. The variable proxies the financial institutions' ability to generate profits efficiently throughout the business cycle. We employ the ratio of *nonperforming loans* (NPL) over total gross loans to control for the quality of the financial institutions' on-balance-sheet credit exposures. A rise in NPL not only reduces current profits, but might also impede future credit lending due to an increase in risk aversion and binding regulatory capital constraints.

Lastly, we define *loan-to-deposit* (LTD) as total loans over total customer deposits and apply the latter to proxy for liquidity risk. A ratio of greater than *one* indicates that institutions are relying on (short-term) wholesale funding in addition to customer deposits in order to refinance loans. The resulting liquidity mismatch increases an institution's dependence on capital-market-based funding. At the banking system level, a high LTD ratio may easily lead to an acute shortage of funding liquidity in times of crises.

For each of the previously outlined bank-specific variables we compute quarterly aggregate time series at the banking system level by consolidating the balance sheet data and market data (market valued equity) across all 84 sample banks.[7]

Macroeconomic variables

To be consistent with macroeconomic forecasting literature, we measure the state of the European Union's real economy and its economic activity employing the variables production and real GDP.

Production represents the total industrial production excluding the construction sector. By predominantly measuring current output levels, the macroeconomic variable thus serves as an ideal measure for economic activity. As a classic indicator of the economy's overall state, *real GDP* is defined as nominal GDP deflated by the GDP deflator. In contrast to production, a country's gross domestic product not only captures the market value of final goods but also the value of services produced within the economy. Thus, due to its definition that is much broader than production, we expect real GDP adjustments to be sluggish.

[7] We collect aggregate harmonized time series data for NPL and the LTD ratio referring to the EU27 from the Worldbank and the EBF/EBA, respectively. Given the ratios' sensitivity to accounting standards, this approach minimizes the effects of differences in accounting definitions and thus allows meaningful comparisons across time and countries.

Label	**Description**	**Sampling frequency**	**Data source**
Bank-specific variables			
Leverage*	market valued total assets / market valued equity, where market valued total assets = book valued total debt + market valued equity	quarterly	Datastream
Z-score*	$roa_t + car_t/\mathrm{sd}\,(roa)$, where sd = standard deviation of the sample period, car = capital asset ratio, and roa = return on equity	quarterly	Datastream
Market-to-book*	market valued equity / book valued equity	quarterly	Datastream
Profitability*	net income / book valued total assets (in %)	quarterly	Datastream
Nonperforming loans	nonperforming loans / total gross loans (EU27, in %)	annual	Worldbank
Loan-to-deposit	total loans / total customer deposit (EU27, in %)	quarterly/annual	EBA/EBF
Macroeconomic variables			
Production	EU Industrial Production Index excluding construction (EU27)	monthly	Datastream
Real GDP	real quarterly gross domestic product (EU27, in EUR bn)	quarterly	Datastream
Inflation	Harmonized Index of Consumer Prices (HICP) (EU27, in %)	monthly	Datastream
Unemployment	unemployment rate (EU28, in %)	monthly	Datastream
House prices	EU House Price Index (EU evolving)	quarterly	Datastream
Credit private	domestic credit to private sector (EU27, in % of GDP)	annual	Worldbank

Table 2.3 – Description of bank-specific and macroeconomic variables
The table shows the label, description, sampling frequency, and data source of the bank-specific and macroeconomic variables used in the regression analysis. The time series of observations cover the period from July 2005 to June 2013. * The bank-specific variables leverage, Z-score, market-to-book, and profitability represent quarterly time series for the aggregate of all 84 sample banks. We compute quarterly time series at the banking system level for the latter by consolidating the balance sheet data and market data (market valued equity) across all sample banks.

We furthermore include a set of macroeconomic control variables. *Inflation* measures the steady increase in the general price level over time and acts as a proxy for a stable economy. Generally, a moderate inflation target is regarded as positive (Mundell, 1963; Tobin, 1965). Higher inflation rates typically coincide with economic boosts and may display signs of overheating. Contrary to that, low economic activity typically results in low inflation rates. *Unemployment* reflects the structural health of the economy. Lower levels of economic activity are associated with higher levels of unemployment, which became visible in the recent financial crises. In addition, unemployment rates are indicative for the propensity of future consumption spending.

Moreover, we use *house prices* to proxy for the state of the economy in two ways. First, the index simply measures the households' wealth. Second, real estate is an important source of collateral that serves as a cushion for the losses from distressed debt. Finally, measured as a proportion of GDP, *credit private* is the total amount of domestic credit held by the private sector. We employ credit private to control for economic sustainability.

Table 2.3 provides a summary of all aggregated bank-specific and macroeconomic variables used in our subsequent analysis including their description, sampling frequency, and data source.

2.5 Empirical evidence

This section divides into three subsections. We commence with the investigation of the SRMs' predictive power for the state of the banking system and the real economy in Section 2.5.1. Section 2.5.2 then investigates the determinants of the banking system's overall level of systemic risk and Section 2.5.3 closes with critical remarks on SRMs.

2.5.1 SRMs' predictive power

To be viable for the identification of systemic events and to be used as a tool for macro-prudential supervision, SRMs should possess predictive power for the state of the banking system and the real economy. Based on prominent working definitions of systemic risk, we formulated these prerequisites as assessment criteria.

First of all, however, in order to develop an understanding about our explanatory variables' dynamics during the International Financial Crisis and European Sovereign Debt Crisis, Figures 2.1 and 2.2 display the time series of the bank-specific and the macroeconomic state variables that we apply in our regression analysis within the period from July 2005 to June 2013.

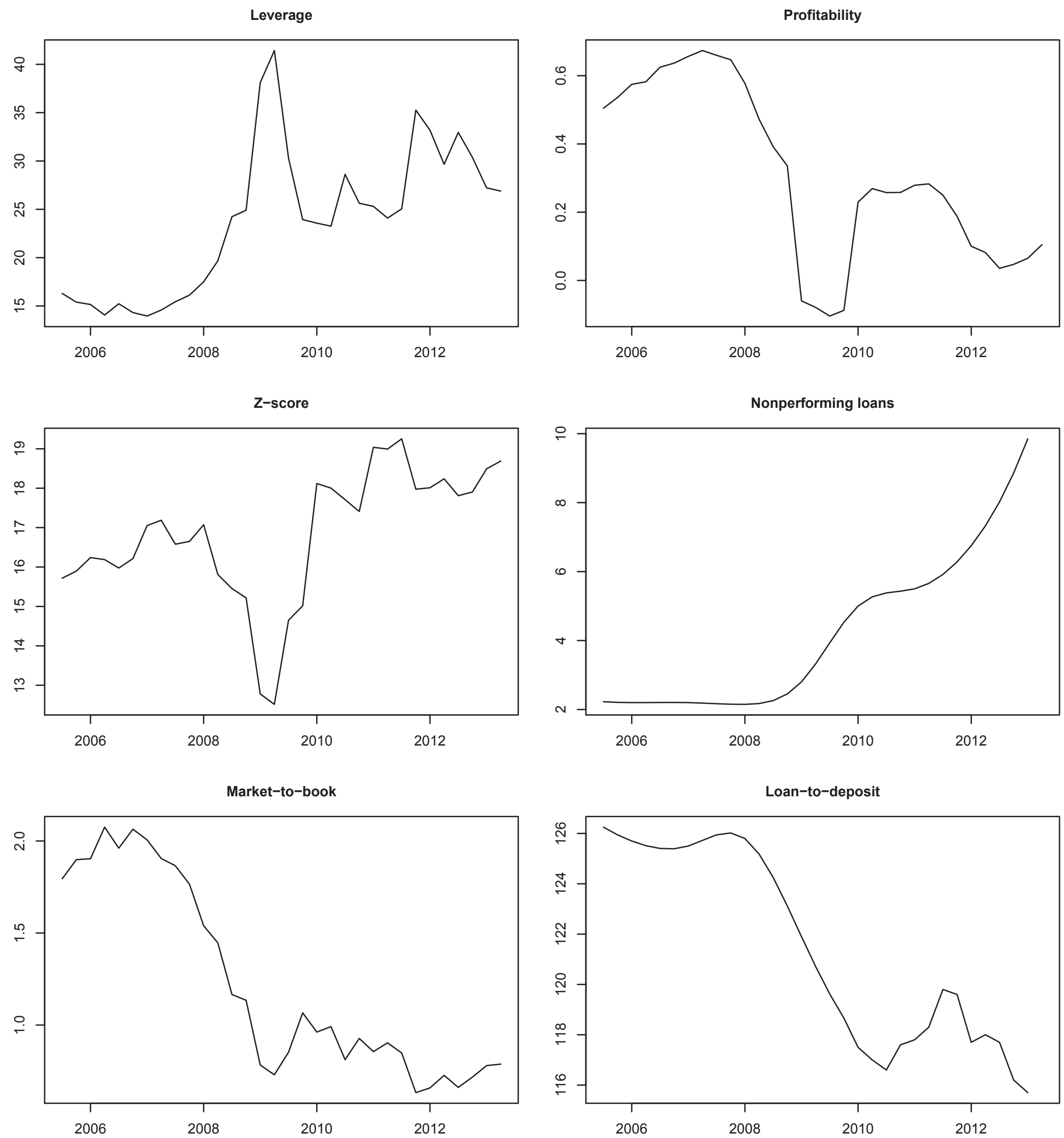

Figure 2.1 – Time evolution of bank-specific variables
The figure presents quarterly time series for the aggregate of all 84 sample banks, except for nonperforming loans and the loan-to-deposit ratio, which refer to the European Union (EU27). The time series of observations cover the period from July 2005 to June 2013. For a detailed description of the bank-specific variables we refer to Table 2.3. Data on nonperforming loans is obtained from the Worldbank's database and data on the loan-to-deposit ratio is obtained from the European Banking Authority and the European Banking Federation. All remaining data is from Datastream.

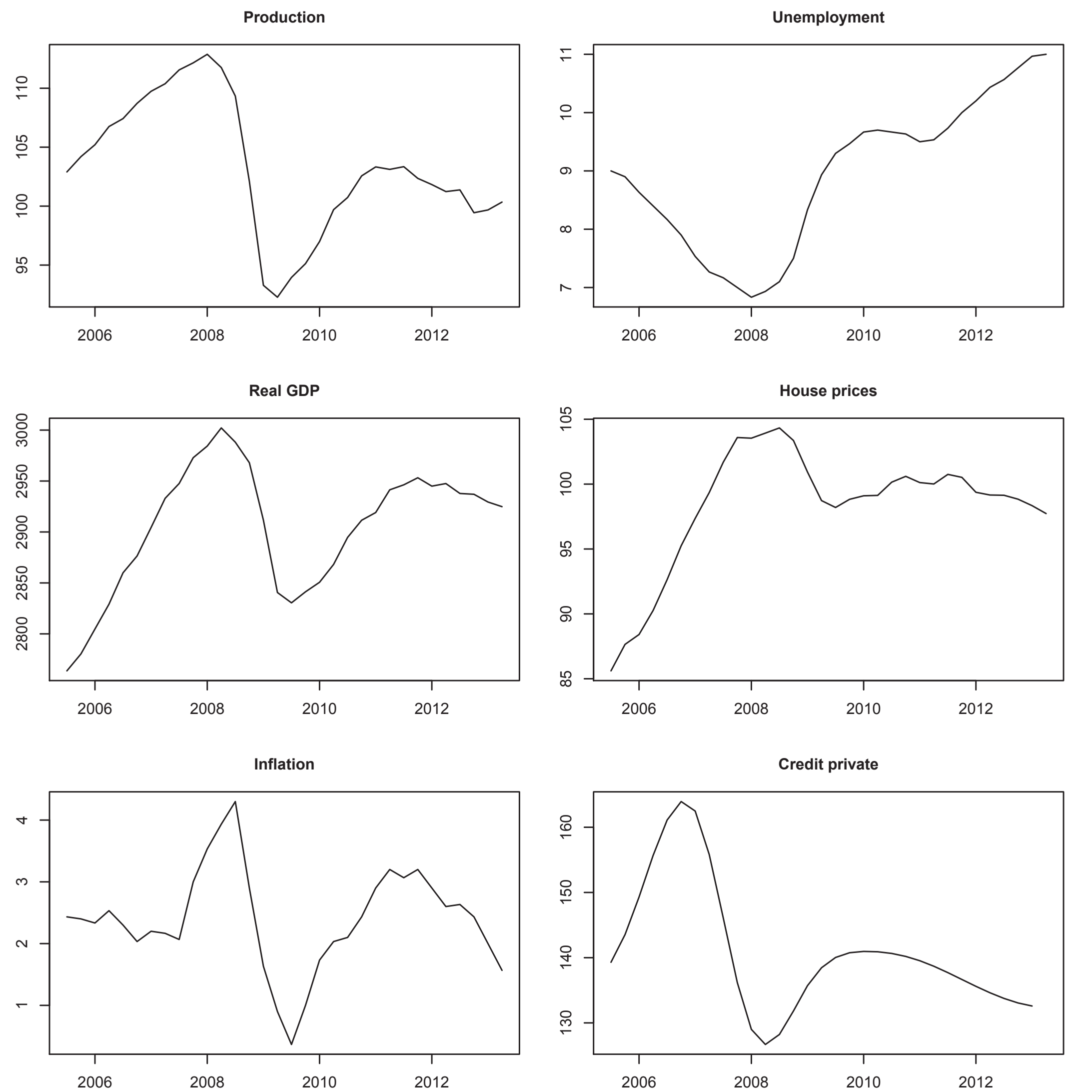

Figure 2.2 – Time evolution of macroeconomic variables
The figure presents quarterly time series of macroeconomic data from the European Union. The time series of observations cover the period from July 2005 to June 2013. For a detailed description of the macroeconomic variables we refer to Table 2.3. Data on domestic credit to private sector is obtained from the Worldbank's database, and all remaining data is from Datastream.

Most importantly, the early increase in banking system leverage and the notable decreases in aggregate Z-score and market-to-book values of equity at the onset of the International Financial Crisis and the European Sovereign Debt Crisis in 2008 and 2011 reveal that the former variables are expedient for the analysis and characterization of the banking system's level of financial turmoil. Likewise, the adverse macroeconomic spillover effects in the aftermath of both systemic crises are well captured by the variables production and real GDP. As indicated by the aggregated bank-specific and macroeconomic control variables, the crises are furthermore reflected in a sharp decline in system-wide profitability and loan quality. Furthermore, delayed in time, the economic downturns are subsequently reflected in increasing unemployment rates as well as in a decline of inflation and house prices. The variable credit private vividly reflects the evolving credit crunch.

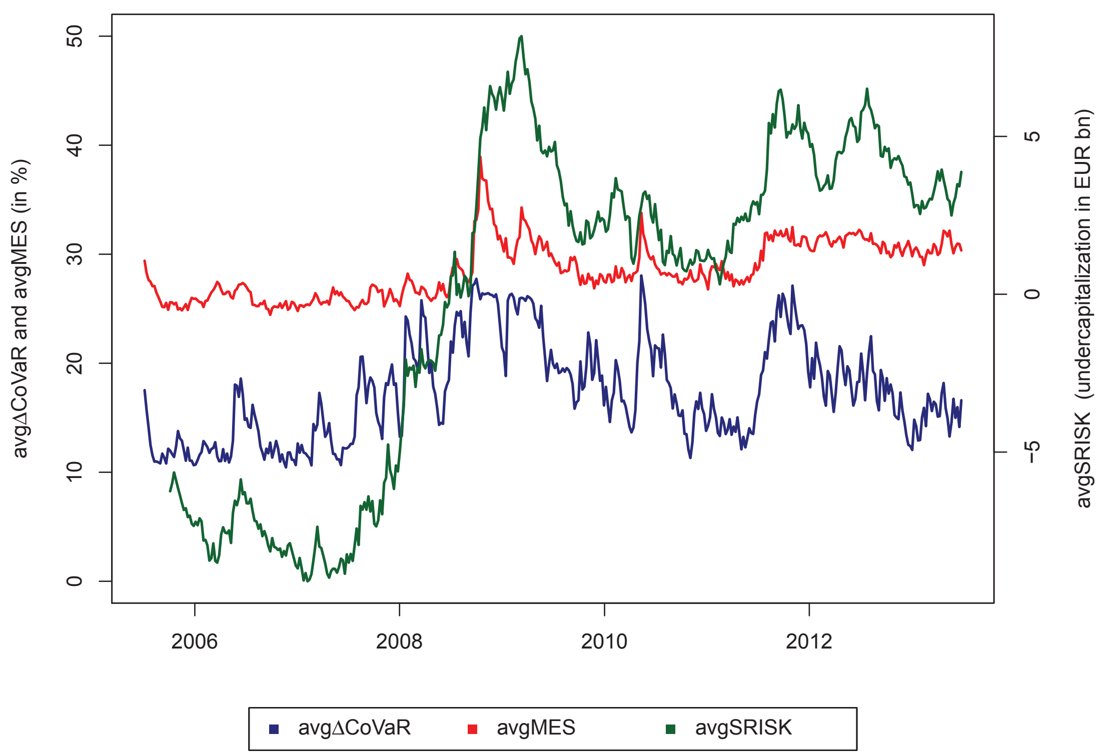

Figure 2.3 – Time evolution of systemic risk measures
The figure presents averages across the time series of weekly systemic risk measures of all 84 sample banks. The time series of observations cover the period from July 2005 to June 2013. The systemic risk measures are defined in detail in Section 2.3. All stock price and balance sheet data are obtained from Datastream.

Figure 2.3 exhibits the weekly time series of the SRMs that we calculate as outlined in Section 2.3.4. In particular, these are a banking system's *avg*MES, *avg*SRISK, and *avg*ΔCoVaR. At the first glance, the figure reveals that the three banking-system-level time series are generally able to gauge the overall level of systemic risk in the banking system since all of them exhibit peaks during the International Financial Crisis and the European Sovereign Debt Crisis. Nevertheless, $avg\Delta$CoVaR has much more swings in value over time than the other measures. As a result, *avg*MES and *avg*SRISK seem to be superior in the selective identification und prediction of true systemic events. In the following, we want to confirm that the previous conjectures remain valid by empirically evaluating our assessment criteria framework.

We apply a vector autoregressive (VAR) model to measure the directionalities and dependencies between the SRMs and the selected bank-specific and macroeconomic state variables. In particular, the VAR approach allows for the simultaneous analysis of the two-sided relationship between the SRMs' predictive power and their banking-system-specific determinants. Running the regressions requires that we harmonize data with respect to their sampling frequency. We perform the SRMs' regressions on the aggregated bank-specific and macroeconomic variables on a quarterly frequency. For time series with a higher frequency (SRMs, inflation, production, and unemployment), we calculate quarterly averages. Data on an annual frequency (nonperforming loans and credit private) are interpolated applying cubic splines. Table 2.4 exhibits the correlations between all quarterly time series. We use log-differences if time series are non-stationary to ensure that we do not violate the stationarity requirements.[8]

According to the Schwarz criterion, the data suggests a one lag structure. We thus employ a VAR system of the following type:

$$y_t = a + By_{t-1} + \epsilon_t \tag{2.5}$$

with $y_t \equiv (\mathrm{SRM}_t^{sys}, {x_t}^T)'$, where SRM_t^{sys} represents any of the three systemic risk measures *avg*MES, *avg*SRISK or $avg\Delta$CoVaR and x_t is either the vector of the aggregated bank-specific or macroeconomic variables. Parameter vector a denotes the intercepts, B is the coefficient matrix of the lagged regression variables y_{t-1}, and ϵ_t is a vector of standard Gaussian error terms.[9] We organize each of our result tables such that Panel A contains

[8] We perform several time series diagnostics. We test the quarterly time series for stationarity, heteroskedasticity, auto-correlation, and non-normality. According to Appendix-Table 2.7 we cannot reject the null hypothesis that the time series are stationary (Panel A) for all series except nonperforming loans and for most series we cannot reject the homoscedasticity and normality null hypotheses (Panel B and Panel D). All series exhibit strong auto-correlation (Panel C).

[9] Since all employed time series exhibit strong auto-correlation we again test the residuals of the estimated VAR systems for auto-correlation. However, we find no evidence that the residuals exhibit significant auto-correlation over time.

	SRMs			Bank-specific variables						Macroeconomic variables					
	*avg*MES	*avg*SRISK	*avg*ΔCoVaR	Leverage	*Z*-score	Market-to-book	Profitability	Nonperforming loans	Loan-to-deposit	Production	Real GDP	Inflation	Unemployment	House prices	Credit private
*avg*MES	1.000 ***	0.894 ***	0.725 ***	0.808 ***	0.096	-0.818 ***	-0.733 ***	0.672 ***	-0.615 ***	-0.597 ***	0.326 *	0.623 ***	0.535 **	0.384 *	-0.575 ***
*avg*SRISK		1.000 ***	0.697 ***	0.902 ***	0.073	-0.960 ***	-0.892 ***	0.767 ***	-0.782 ***	-0.742 ***	0.244	0.630 ***	0.625 ***	0.451 *	-0.708 ***
*avg*ΔCoVaR			1.000 ***	0.651 ***	-0.285	-0.578 ***	-0.509 **	0.573 ***	-0.267	-0.357 *	0.414 *	0.280	-0.016	0.622 ***	-0.613 ***
Leverage				1.000 ***	-0.097	-0.908 ***	-0.896 ***	0.799 ***	-0.706 ***	-0.756 ***	0.192	0.535 **	0.574 ***	0.380 *	-0.556 **
Z-score					1.000 ***	-0.238	0.063	-0.324 *	-0.445 *	0.213	0.332 *	0.586 ***	0.479 **	0.125	-0.051
Market-to-book						1.000 ***	0.895 ***	-0.718 ***	0.885 ***	0.699 ***	-0.304 *	-0.721 ***	-0.707 ***	-0.475 **	0.668 ***
Profitability							1.000 ***	-0.911 ***	0.798 ***	0.886 ***	-0.007	-0.513 **	-0.708 ***	-0.252	0.523 **
Nonperforming loans								1.000 ***	-0.595 ***	-0.855 ***	-0.048	0.330 *	0.482 **	0.261	-0.394 *
Loan-to-deposit									1.000 ***	0.678 ***	-0.122	-0.703 ***	-0.858 ***	-0.305 *	0.403 *
Production										1.000 ***	0.383 *	-0.171	-0.674 ***	0.069	0.246
Real GDP											1.000 ***	0.692 ***	-0.175	0.857 ***	-0.471 **
Inflation												1.000 ***	0.556 ***	0.594 ***	-0.554 **
Unemployment													1.000 ***	-0.160	-0.222
House prices														1.000 ***	-0.524 **
Credit private															1.000 ***

Table 2.4 – Correlation coefficients

The table exhibits correlations between systemic risk measures (SRMs), bank-specific variables, and macroeconomic variables at the banking system level. I.e., *avg*MES, *avg*SRISK, and *avg*ΔCoVaR represent time series of cross-sectional averages for the bank-level series of SRMs of all 84 sample banks. Likewise, the time series of the bank-specific variables refer to the aggregate of our sample banks, except for nonperforming loans and the loan-to-deposit ratio, which refer to the European Union (EU27). All time series are on a quarterly basis and cover the period from July 2005 to June 2013. The systemic risk measures are defined in detail in Section 2.3. For a detailed description of the bank-specific and macroeconomic variables we refer to Table 2.3. Correlation coefficients are assigned asterisks if they are statistically significant (*** = 0.1% confidence level; ** = 1% confidence level; * = 10% confidence level).

the results for avgMES, Panel B the results for avgSRISK, and Panel C the results for the $avg\Delta$CoVaR regressions. We express avgSRISK in EUR billion and avgMES and $avg\Delta$CoVaR are expressed in percentage terms. Each column represents an estimated regression equation with the lagged explanatory variables given in the rows. Thus, the header exhibits the dependent variables and the rows feature the corresponding lagged explanatory variables.

Table 2.5 presents the results of the VAR regressions of the analyzed SRMs on bank-specific state variables. We find that SRMs generally possess substantial predictive power for the future state of the banking system. Most notably, however, all three SRMs are highly significantly related to the levels of aggregate leverage and market-to-book, which are well-established indicators of financial distress. More precisely, a sharp increase in the level of avgMES, avgSRISK, and $avg\Delta$CoVaR coincides with a future increase in aggregate leverage which in turn increases the probability to experience a systemic crisis due to a deterioration of the banking system's capital structure and hence its loss-absorbing capacity. Likewise, increases in the SRMs coincide with a lower aggregate market-to-book value in the following period indicating that spikes in systemic risk, as measured by the latter, are linked to distressed and uncertain market environments in the future.

Increases in avgMES and avgSRISK are additionally reflected in a statistically significant decrease of the system-wide Z-score, which is tantamount with an expected future increase in aggregate default risk. Both measures' regression coefficients are significant at the 1% confidence level. Also $avg\Delta$CoVaR's level of systemic risk is negatively correlated with the aggregate level of the Z-score, the relationship is insignificant.

Differences in the SRMs' predictive power become more evident when shifting the focus to the bank-specific control variables proxying for system-wide profitability, credit risk, and liquidity risk. On the one hand, only the avgMES and the related avgSRISK predict a statistically significant decline of profitability in the case of an increase in the SRMs' systemic risk level. The directionality is furthermore in line with expectations. Systemic events that increase the banking system's fragility should eventually result in an underperforming banking sector. AvgMES is also able to significantly capture and forecast the ratio of nonperforming loans. On the other hand, although all three measures are negatively related to the system-wide loan-to-deposit ratio, only $avg\Delta$CoVaR adds explanatory power to the latter, indicating that banks, on average, reduce their LTD ratios in order to improve their funding liquidity during periods of financial turmoil.

	SRM	Leverage	Z-score	Market-to-book	Profitability	Nonperforming loans	Loan-to-deposit
Panel A – avgMES (in %)							
*avg*MES	0.288	2.093 ***	-0.417 ***	-0.040 **	-0.041 ***	0.031 **	-0.091
Leverage	-0.233	-0.124	0.020	0.031 **	0.003	-0.004	0.094
Z-score	-0.495	-0.369	0.454	0.056	0.021	-0.065	0.431
Market-to-book	-9.182 **	-11.152 *	0.634	1.445 ***	0.255 **	-0.325 *	1.804
Profitability	4.670	2.530	0.158	-0.437	0.362 *	-0.037	-0.147
Nonperforming loans	0.456	-0.445	0.463 *	-0.015	0.009	1.175 ***	-0.372
Loan-to-deposit	0.444 *	0.272	-0.134	-0.005	-0.005	0.082 ***	0.765 ***
adjusted R^2	0.647	0.896	0.870	0.951	0.966	0.999	0.978
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B – avgSRISK (in EUR *bn*)							
*avg*SRISK	0.674 ***	2.455 ***	-0.353 ***	-0.058 ***	-0.033 ***	0.010	-0.096
Leverage	-0.477 ***	0.440 **	0.007	0.016 *	-0.004	0.015 **	0.032
Z-score	-0.500	0.952	0.775 ***	0.003	0.019	0.047 **	0.151
Market-to-book	-14.267 ***	13.863 **	-0.927	0.778 **	0.052	0.102	0.832
Profitability	3.967	-0.452	-4.158	-0.261	0.076	-0.157	-1.342
Nonperforming loans	0.806	-6.430	-0.320	0.078	-0.115	0.959 ***	-2.307 **
Loan-to-deposit	0.551 **	0.329	-0.159	-0.005	-0.006	0.035 ***	0.813 ***
adjusted R^2	0.954	0.926	0.827	0.965	0.949	0.945	0.982
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel C – avgΔCoVaR (in %)							
avgΔCoVaR	0.376 *	0.934 ***	-0.109	-0.029 ***	-0.005	-0.008	-0.087 **
Leverage	-0.720 ***	0.305	0.035	0.017	0.001	0.011 *	0.022
Z-score	-1.045	1.214	0.766 ***	-0.010	0.028	0.027	0.048
Market-to-book	-21.195 ***	-1.829	1.802	1.029 ***	0.422 **	-0.210	0.396
Profitability	10.204	-11.880	-2.638	0.020	0.112	0.022	0.102
Nonperforming loans	4.042	-5.104	-0.541	0.047	-0.168	1.035 ***	-2.042 **
Loan-to-deposit	0.961 **	0.327	-0.190	0.004	-0.013	0.044 ***	0.847 ***
adjusted R^2	0.635	0.832	0.777	0.958	0.924	0.951	0.985
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 2.5 – VAR results bank-specific variables
All figures are estimated from quarterly time series of systemic risk measures at the banking system level (i.e., time series of cross-sectional averages for the bank-level series of SRMs of all 84 sample banks) and quarterly time series of bank-specific variables for the aggregate of our sample banks covering the period from July 2005 to June 2013. We estimate the VAR system $y_t = a + By_{t-1} + \epsilon_t$ with $y_t \equiv (SRM_t^{sys}, {x_t}^T)'$, where SRM_t^{sys} represents any of the three systemic risk measures *avg*MES, *avg*SRISK, or *avg*ΔCoVaR and x_t is the vector of aggregated bank-specific variables. Parameter vector a denotes the intercepts, B is the coefficient matrix of the lagged regression variables y_{t-1}, and ϵ_t is a vector of standard Gaussian error terms. The table is organized as follows. Panel A presents the results for the VAR systems with $SRM = avg$MES, Panel B the results for $SRM = avg$SRISK, and Panel C the results for $SRM = avg\Delta$CoVaR. The names of the lagged explanatory variables, to which the regression coefficients refer, are given in the respective rows and the dependent variables' names are given in the respective column headers. The systemic risk measures are defined in detail in Section 2.3. For a detailed description of the bank-specific variables we refer to Table 2.3. For the ease of exposition, we suppress the intercepts' values. The regression coefficients are assigned asterisks if they are statistically significant (*** = 1%-confidence level (cl); ** = 5%-cl; * = 10%-cl).

We check the robustness of our results performing several modifications. First, we drop Z-score to ensure that only leverage accounts for the feedback effect of systemic risk on institutions' aggregate default risk. Not surprisingly, our results remain valid. Especially the directionality and the significance of our two coefficients of interest leverage and market-to-book remain unchanged. Second, we test the stability of the main variables' coefficient estimates by excluding all control variables. The economic relevance of the SRMs for changes in leverage, Z-score, and market-to-book does not change substantially. All SRMs now determine the latter at the 1% confidence level. Altogether, we are able to confirm that all three SRMs possess significant predictive power for the state variables used to measure the banking system's level of financial distress. The dynamics of avgMES, avgSRISK, and $avg\Delta$CoVaR are thus in line with Criterion 1.

Table 2.6 presents the results of our analysis of interdependencies between the SRMs and macroeconomic state variables. According to Criterion 2, SRMs should have predictive power for macroeconomic state variables in order to be capable of identifying true systemic events or crises that cause negative spillover effects to the real economy, such as drops in output levels or aggregate economic wealth.

Our results demonstrate that avgMES and avgSRISK indeed provide significant predictive power for the state of the real economy. Most importantly, a sharp increase in the level of avgMES and avgSRISK is reflected in a subsequent decline in the European Union's aggregate level of industrial production. In contrast, the dynamics of $avg\Delta$CoVaR are not significantly related to future output levels. Surprisingly, though, none of the measures load significantly on real GDP. Yet, for avgSRISK and $avg\Delta$CoVaR, the relationship is actually positive and thus contradicts economic expectations. This fact may be attributed to various reasons. First of all, real GDP incorporates the economic value created within the financial sector itself. Moreover, the adjustments of GDP growth are driven to some extent by a country's service sector which is likely to be more sluggish than production because services usually involve a lot of contractual rigidities.

The superior predictive power of MES-based measures for the identification of the future state of the real economy becomes even more evident when focusing on the macroeconomic control variables. Only avgMES and avgSRISK load significantly positive on unemployment at the 1% and 5% confidence level, respectively. Thus, spikes in systemic risk, as measured by avgMES and avgSRISK, lead to lower production levels that coincide with lower levels of employment. Additionally, avgMES loads significantly negative on inflation, revealing that an increase in the level of the latter indicates a subsequent decrease in inflation rates. For instance, low inflation usually reflects low consumption growth, which in turn is negatively related to aggregate economic activity.

	SRM	Production	Real GDP	Inflation	Unemployment	House prices	Credit private
Panel A – avgMES (in %)							
*avg*MES	0.089	-0.730 ***	-0.255	-0.110 **	0.043 ***	-0.141	0.122
Production	-0.452 ***	1.078 ***	7.373 ***	0.129 ***	-0.050 ***	0.178 **	-0.813 ***
Real GDP	0.013	0.003	0.315 ***	-0.005	0.003 **	-0.003	-0.028
Inflation	2.433 ***	-1.733 **	-5.944	0.347 **	0.081 *	-0.609 *	5.100 ***
Unemployment	-0.127	1.356 ***	19.591 ***	0.379 ***	0.852 ***	0.334 **	-1.760 ***
House prices	0.061	0.009	6.320 ***	0.078 *	-0.019 *	0.960 ***	-0.379
Credit private	0.040	-0.003	0.136	-0.030 ***	-0.004 *	0.025	0.996 ***
adjusted R^2	0.800	0.951	0.985	0.880	0.997	0.982	0.956
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B – avgSRISK (in EUR *bn*)							
*avg*SRISK	0.436 *	-0.764 **	0.505	-0.026	0.045 **	-0.039	0.683 *
Production	-0.406	0.761 **	8.002 ***	0.163 **	-0.032 *	0.212	-0.214
Real GDP	0.000	-0.007	0.285 ***	-0.009 **	0.003 ***	-0.008	-0.046 *
Inflation	2.110 **	-0.660	-7.207	0.333	0.020	-0.602	3.697 ***
Unemployment	0.076	1.889 ***	19.290 ***	0.415 ***	0.822 ***	0.398 **	-2.243 ***
House prices	0.336 **	0.358 *	6.158 ***	0.117 **	-0.037 ***	1.032 ***	-0.707 ***
Credit private	-0.040	-0.035	0.092	-0.031 **	-0.001	0.031	0.952 ***
adjusted R^2	0.957	0.940	0.982	0.853	0.996	0.975	0.973
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel C – avgΔCoVaR (in %)							
*avg*ΔCoVaR	0.113	-0.196	0.066	-0.034	0.013 *	-0.033	0.103
Production	-0.578 **	1.307 ***	7.558 ***	0.161 ***	-0.063 ***	0.226 ***	-0.797 ***
Real GDP	0.007	-0.027	0.302 ***	-0.009 **	0.004 ***	-0.009	-0.024
Inflation	2.446 *	-1.819 **	-6.212	0.341 *	0.085 *	-0.634 *	4.990 ***
Unemployment	-1.791 **	1.168 **	19.765 ***	0.343 ***	0.864 ***	0.305 *	-1.604 **
House prices	0.279	0.275	6.390 ***	0.119 ***	-0.035 ***	1.011 ***	-0.436
Credit private	-0.030	-0.014	0.139	-0.032 ***	-0.004	0.023	1.001 ***
adjusted R^2	0.676	0.933	0.985	0.863	0.996	0.981	0.956
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 2.6 – VAR results macroeconomic variables

All figures are estimated from quarterly time series of systemic risk measures at the banking system level (i.e., time series of cross-sectional averages for the bank-level series of SRMs of all 84 sample banks) and quarterly time series of macroeconomic variables covering the period from July 2005 to June 2013. We estimate the VAR system $y_t = a + By_{t-1} + \epsilon_t$ with $y_t \equiv (SRM_t^{sys}, {x_t}^T)'$, where SRM_t^{sys} represents any of the three systemic risk measures *avg*MES, *avg*SRISK, or *avg*ΔCoVaR and x_t is the vector of macroeconomic variables. Parameter vector a denotes the intercepts, B is the coefficient matrix of the lagged regression variables y_{t-1}, and ϵ_t is a vector of standard Gaussian error terms. The table is organized as follows. Panel A presents the results for the VAR systems with $SRM = avg$MES, Panel B the results for $SRM = avg$SRISK, and Panel C the results for $SRM = avg\Delta$CoVaR. The names of the lagged explanatory variables, to which the regression coefficients refer, are given in the respective rows and the dependent variables' names are given in the respective column headers. The systemic risk measures are defined in detail in Section 2.3. For a detailed description of the macroeconomic variables we refer to Table 2.3. For the ease of exposition, we suppress the intercepts' values. The regression coefficients are assigned asterisks if they are statistically significant (*** = 1%-confidence level; ** = 5%-confidence level; * = 10%-confidence level).

No significant reactions are measurable for house prices. Though not significant, an increase in the measures predict future decreases in the value of real estate. This relation might be mainly attributed to the specific house price dynamics during the Subprime Crisis where housing prices acted as a main driver of systemic risk (Longstaff, 2010). Furthermore, none of the SRMs possesses substantial predictive power for the control variable credit private. Economic theory would suggest a negative response of the latter to the occurrence of systemic events, however, our empirical results cannot confirm such a relationship.

The results are furthermore robust to modifications in the VAR setup. We apply additional control variables such as the ratio of government debt to GDP and the German 12-month Bund rate to test for robustness. However, this does not influence the SRMs' predictive power for our baseline results. We further exclude real GDP from the regression equation in order to solely account for the measures' ability to predict future levels of production. Again, all previously mentioned results remain unchanged. $Avg\Delta$CoVaR is still insignificantly related to the dynamics of the aggregate level of industrial production.

Our evaluation methodology demonstrates that *avg*MES and *avg*SRISK possess significant explanatory power for the future state of the real economy. $Avg\Delta$CoVaR, on the other hand, is not in line with Criterion 2. Consequently, only the dynamics of *avg*MES and *avg*SRISK are informative for the identification of true systemic events. A sharp increase of the latter indicates a deterioration of the state of the banking system and a decrease in macroeconomic activity (as measured by aggregate production). A sharp increase in $avg\Delta$CoVaR, on the contrary, does not precisely distinguish between banking system turmoil with no macroeconomic effects and systemic banking crises that eventually trigger downturns in the real economy. Nevertheless, $avg\Delta$CoVaR is still informative about the general state of the banking system.

2.5.2 Drivers of systemic risk

In the following we investigate the bank characteristics that drive the banking system's overall level of systemic risk. Identifying the determinants of systemic risk not only allows supervisors to improve their monitoring of the banking system's vulnerabilities, but also to implement adequate regulatory measures geared at limiting the probability of systemic spillovers to the real economy. Although the predictive power for systemic events varies among the evaluated measures, we only refer to the bank-specific state variables from Section 2.4.2 as *fundamental drivers* of systemic risk if they significantly explain future variations in *avg*MES, *avg*SRISK, and $avg\Delta$CoVaR. This approach, in particular, allows for a robust and generally valid verification of the identified factors of influence.[10]

We expect a positive relation between leverage, nonperforming loans, and loan-to-deposit and future levels of systemic risk. Moreover, we expect future levels of systemic risk to be negatively related to changes in Z-score and market-to-book. The relationship between profitability and future levels of systemic risk, however, is not that clear cut. On the one hand, higher profitability could reduce the risk of future systemic events as a result of an enhanced propensity of setting up capital buffers. On the other hand, high profitability may simply reflect aggressive risk taking that eventually results in an increase of systemic risk.

For the discussion of our empirical findings we return to the results of our VAR regressions between bank-specific state variables and SRMs that we presented in Table 2.5. Indeed, the measures do not exploit all balance sheet information determining the dynamics of systemic risk. The variables market-to-book and loan-to-deposit possess significant predictive power for all three SRMs. A *one*-standard-deviation decline of the MTB ratio (increase of the LTD ratio) indicates a future increase in *avg*SRISK by €7.42*bn* (€2.17*bn*).[11] *Avg*MES and *avg*ΔCoVaR are influenced as follows. A *one*-standard-deviation decline of the MTB ratio (increase of the LTD ratio) increases *avg*MES and *avg*ΔCoVaR by absolute numbers by 4.77% (1.75%) and by 11.02% (3.79%), respectively.

The implications for financial supervision are twofold. First, the MTB ratio, capturing the market view about banks' aggregate risk of financial distress, itself may be used as a simple and efficient early warning indicator to monitor systemic risk. The MTB dynamics before the onset of the International Financial Crisis underline the latter. Figure 2.1 shows that the MTB ratio's decline started as early as in late 2006. Throughout 2007, the MTB dynamics indicate a significant deterioration in the European banking sector's asset values and hence the emerging risk of a systemic banking crisis.

The MTB ratio also sheds light on the fragility of the European banking system in the years following the peak of the European Sovereign Debt Crisis. In mid-2013, the ratio still fluctuated around mid-crisis levels, indicating high levels of systemic risk. Thus, another micro- or macroeconomic shock could have easily triggered another systemic event. To avoid the latter, the European Banking Authority (EBA) is establishing guidelines for

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[10] It is worth mentioning that according to the market efficiency hypothesis, we may only identify such drivers if SRMs fail to capture all contemporaneous available information determining future levels of systemic risk. Was all contemporaneous information to be captured by the measures, accounting-based bank characteristics would not be able to predict future variations of market-based SRMs.

[11] In order to evaluate the economic significance of the variables MTB and LTD on future systemic risk we multiply the variables' regression coefficients by their quarterly standard deviations ($\sigma_{\text{MTB}} = 0.520\%; \sigma_{\text{LTD}} = 3.946\%$). Thus, $-14.267 \times -0.520 \approx 7.42$ and $0.551 \times 3.946 \approx 2.17$, respectively.

more sustainable financial institutions on behalf of the European Parliament and Council (Directive 2013/36/EU, Article 107(3)). Given the fact that lower MTB values of equity can be mainly attributed to lower earnings expectations, higher earnings uncertainty, and elevated debt burdens (Chen and Zhang, 1998; Fama and French, 1995), our findings additionally indicate that banks' earnings volatility contributes to systemic risk. Thus, the EBA's guidelines should incentivize institutions to establish less volatile business models with higher earnings certainty such as to reduce their vulnerability in times of crises, thereby reducing institutions' aggregate systemic footprint.

Second, the significant impact of the aggregate loan-to-deposit ratio underlines the critical role of deposit funding and liquidity at the banking system level and highlights the importance of an expedient regulation of the latter. Notably, the LTD ratio of European banks ranks top in a global comparison. In early 2013, the average LTD ratio of European banks amounted to approximately 116%, whereas for US banks it amounted to approximately 82% (Buehler et al., 2013). A decline of aggregate LTD is likely to substantially lower systemic risk in the European banking system. As of June 2013, a *ceteris paribus* reduction of the LTD ratio to 100% would reduce the average bank's capital shortfall by roughly €8.82*bn*, reverting *avg*SRISK to pre-crisis levels.[12] The effects on *avg*MES and *avg*ΔCoVaR are of similar magnitude.

Supervisors are able to lower systemic risk by implementing prudent liquidity standards that contribute to a more resilient banking system. Therefore, our empirical findings support the new Basel III guidelines concerning limits on institutions' liquidity mismatch (Net Stable Funding Ratio) and the strengthening of the institutions' ability to survive periods of stress without market funding (Liquidity Coverage Ratio). A binding implementation of both regulatory ratios reduces the system-wide LTD ratio by definition and increases the banking system's propensity to survive periods of financial turmoil and distress.[13]

The bank-specific state variables Z-score, profitability, and nonperforming loans do not provide predictive power for future changes in systemic risk. Leverage possesses significant explanatory power for future levels of *avg*SRISK and *avg*ΔCoVaR. The direction of influence, however, is negative, which is counterintuitive at first glance because the measures themselves load significantly positive on leverage. The fact that higher levels of

[12] In order to estimate the *ceteris paribus* effect of a decline of LTD on aggregate systemic risk measured by *avg*SRISK, we multiply the regression coefficient of LTD by the assumed ratio change of 16% (116%−100%). That is: $0.551 \times -16 \approx -8.82$.

[13] Both the NSFR and the LCR were endorsed by European law in 2013 by the adoption of the Capital Requirements Regulation (Regulation 2013/575/EU.) that will be fully binding from 2019.

leverage coincide with lower future levels of *avg*SRISK and *avg*ΔCoVaR may be explained as follows. Both *avg*SRISK and *avg*ΔCoVaR are capable of capturing banking system turmoil *before* it is reflected by leverage. Materializing financial distress causes leverage to increase in the subsequent periods. However, contemporaneous internal and external actions undertaken to stabilize distressed institutions eventually result in a decline of the SRMs even though market valued leverage still increases.

Our results are furthermore robust to modifications in the VAR setup, that we elaborate on in Section 2.5.1. I.e., the performed variable modifications do not change the relevance of the identified drivers of systemic risk. In fact, the economic significance of the market-to-book and the loan-to-deposit ratio increases on average.

2.5.3 Some critical remarks on SRMs

To serve as a viable tool for banking supervision, SRMs should be in line with the definition of systemic risk and, as a consequence, possess significant predictive power for the state of the banking system and the real economy. Our assessment framework demonstrates the adequate predictive power of MES-based measures, whereas the dynamics of *avg*ΔCoVaR are not significantly related to the future trend of macroeconomic state variables.

The measures' expedience to identify episodes of future systemic events as early as possible is another desirable attribute. Figure 2.3 shows that MES-based risk measures reflected the first signs of a sharp increase of systemic risk in early 2008 (*avg*SRISK) and late 2008 (*avg*MES). The measures were thus able to identify significant increases of systemic risk prior to the collapse of Lehman Brothers. However, both SRMs are – to a great extent – determined by the dynamics of the aggregate market-to-book ratio that itself indicated a significant deterioration in the valuation of the European banking sector's assets as early as in 2007. An additional advantage of the MTB ratio as a proxy for the overall level of systemic risk in contrast to the SRMs analyzed in this paper is its independence of any statistical assumptions and simulation techniques.

Lastly, the measures differ with respect to their *degree of persistence*. This becomes most visible considering the measures' post-crisis dynamics. Even though government and central bank interventions had a calming effect on the financial markets (e.g., due to bank bailouts or government bond purchase programs), the European banking system's balance sheet and valuation fundamentals remained fragile. This risk persistence is very well captured by the dynamics of *avg*SRISK and MTB. The dynamics of *avg*MES and *avg*ΔCoVaR, in contrast, exhibit a mean reversion tendency with sharply declining levels of systemic risk coinciding with lower volatility in the financial markets. That is to say, the *avg*MES (*avg*ΔCoVaR) and the VSTOXX index, measuring the option implied volatility of the Euro Stoxx 50, have a correlation of 75.2% (89.4%).

The superior monitoring qualities of *avg*SRISK and aggregate MTB clearly indicate that systemic risk measurement and systemic risk measures should focus on and include stock market information and balance sheet data.

2.6 Conclusion

We propose a criteria-based framework to assess the systemic risk measures' (SRMs') viability as a monitoring tool for banking supervision comparing the MES, the SRISK, and the CoVaR measures at the banking system level. In particular, we investigate the measures' capability of capturing the level of systemic risk by focusing on their predictive power for the state of the banking system and the real economy. The measures are evaluated on the basis of a representative sample of European institutions covering the period from July 2005 to June 2013, which includes both the International Financial Crisis and the European Sovereign Debt Crisis. Moreover, we analyze the drivers of the banking system's overall level of systemic risk.

Our main findings reveal that all three SRMs generally possess substantial predictive power for the state of the banking system. Measures relating to the MES are furthermore able to significantly explain future variations in macroeconomic activity. The CoVaR's capability of capturing the future state of the real economy is rather poor, however. Consequentially, only the dynamics of MES and SRISK are informative for the identification of true systemic events. That is, a sharp increase of the latter coincides with a deterioration of the state of the banking system and a decrease in macroeconomic activity. A sharp increase in CoVaR, on the contrary, does not precisely distinguish between banking system turmoil with no macroeconomic effects and systemic banking crises that cause downturns in the real economy.

In addition, we are able to identify two *fundamental drivers* of systemic risk at the banking system level – the market-to-book (MTB) and the loan-to-deposit (LTD) ratio. The results have paramount implications. First, the aggregate MTB ratio itself may be used as a simple and efficient early warning indicator to monitor systemic risk. The latter indicated a significant deterioration of the European banking system as early as in 2007 pointing at the risk of a systemic banking crisis. Furthermore, the information content of the MTB dynamics also emphasizes the importance of incentivizing institutions to establish less volatile business models such as to strengthen their resilience to shocks in times of crises, thereby reducing the overall level of systemic risk. Second, the significance of the aggregate LTD ratio demonstrates that an effective regulation of funding liquidity risk is vital in order to contribute to a more resilient banking system and strongly confirms the necessity of the new Basel III guidelines geared to curb an institution's liquidity risk.

Finally, our findings highlight that including balance sheet data is beneficial for systemic risk measurement. This becomes particularly visible in a comparison between SRMs based on both balance sheet and stock market information and SRMs based exclusively on stock market information.

2.A Econometric approach

We model the bivariate return dynamics of institution i $\{r_i\}_t$ and the banking system $\{r_{sys}\}_t$ applying a bivariate conditionally heteroskedastic process as in Brownlees and Engle (2015):

$$r_{sys,t} = \sigma_{sys,t}\epsilon_{sys,t} \tag{2.6a}$$

$$r_{i,t} = \sigma_{i,t}\left(\rho_{i,sys,t}\epsilon_{sys,t} + \sqrt{1-\rho^2_{i,sys,t}}\epsilon_{i,t}\right), \tag{2.6b}$$

where $\sigma_{j,t},\ j \in \{sys, i\}$ denotes the time-varying (conditional) volatilities and $\rho_{j,t}$ the time-varying (conditional) correlations; $r_{j,t} = \ln(P_{j,t}/P_{j,t-1}) - \mu_j$ denotes the detrended logarithmic returns, where $P_{j,t}$ represents either bank i's stock price or the banking system stock price index at time t and μ_j simply stands for the mean return over the full length of our sample period.

The banking system stock price index reflects the stock price movements within our sample and is calculated as the average total asset weighted stock price of our sample of banks.[14] The residuals ϵ_i and ϵ_{sys} are distributed according to the bivariate distribution $\mathcal{F}_i$ capturing the tail dependence of the return series and are assumed to be uncorrelated but not independent. Over time, however, the residuals are assumed to be independent and identically distributed with *zero* mean and *unit* variance.

The time-varying volatilities of institution i ($\sigma_{i,t}$) and the banking system ($\sigma_{sys,t}$) are estimated individually for every institution i applying a univariate GARCH(1,1) process as proposed by Bollerslev (1986):

$$\sigma^2_{j,t} = \alpha_{0,j} + \alpha_{1,j}r^2_{j,t-1} + \beta_{1,j}\sigma^2_{j,t-1} \tag{2.7a}$$

$$\text{with} \qquad \xi_{j,t} = \frac{r_{j,t}}{\sigma_{j,t}}\ ; \quad j \in \{i, sys\}, \tag{2.7b}$$

where the $\xi_{j,t}$ denote the (correlated) standardized residuals derived from the univariate GARCH(1,1) processes which we use to model the time-varying correlation coefficient $\rho_{i,sys,t}$. As suggested by Brownlees and Engle (2015), we apply the Dynamic Conditional Correlation (DCC) GARCH model of Engle (2002) for the estimation of correlations.

Rather than directly modeling the correlation between institution i's return and the banking system return, the DCC GARCH approach models the time-varying correlation of the standardized residuals $\xi_{j,t}$, whereas their covariance matrix serves as a proxy for

[14] Our total-asset-weighted *banking system price index* has a correlation of 97.9% with the STOXX Europe 600 Banks and the TMI Banks Index.

the correlation matrix of returns $r_{i,t}$ and $r_{sys,t}$. The validity for this equivalence follows directly from the bivariate return process of Equation (2.6). For a detailed discussion of the DCC GARCH framework we refer to Appendix 2.B.

The h-day MES and CoVaR measures, nevertheless, cannot be expressed in closed-form solution as a function of volatility, correlation, and tail dependence and therefore have to be determined via simulation. Thus, for each institution i we simulate bivariate return series carrying out the following five steps:

(i) To model the volatility and correlation dynamics of $\{r_{sys}, r_i\}_t$, we first estimate the parameter vectors of the univariate GARCH(1,1) and the DCC GARCH processes $(\alpha_{0,j}, \alpha_{1,j}, \beta_{1,j})$ and (α, β), respectively.[15] All GARCH(1,1) and DCC GARCH parameters are estimated maximizing the corresponding log likelihood functions under the assumption that the residuals be Gaussian.[16]

(ii) Furthermore, the dynamics of $\{r_{sys}, r_i\}_t$ are assumed to be driven by the distribution $\mathcal{F}_i$ that we model using a t-copula and standard Gaussian marginal distributions. The bivariate t-copula is fitted to the series of residuals $\{\epsilon_{sys}, \epsilon_i\}_t$ from the entire sample period.[17]

(iii) In a third step, we simulate $S = 500,000$ paths of residuals with $h = 60$ days (a quarter of a year) length each. For every single path s, h independent pairs of residuals are drawn from the parameterized distribution $\hat{F}_i$:

$$\left\{ \begin{array}{c} \epsilon^s_{sys,t+\tau} \\ \epsilon^s_{i,t+\tau} \end{array} \right\}_{\tau=1}^{h} \sim \hat{F}_i \quad \text{for} \quad s = 1, \ldots, S. \tag{2.8}$$

(iv) In a fourth step, we employ the drawn residuals to calculate the daily bivariate returns for the simulated time interval $[t, t+h]$ by updating the volatilities $\{\sigma_{sys,t+\tau+1}, \sigma_{i,t+\tau+1}\}_{\tau=1}^{h-1}$ and correlations $\{\rho_{i,sys,t+\tau+1}\}_{\tau=1}^{h-1}$ on a daily basis (the de-

[15] We apply various time series diagnostic tests to the individual banks' series of daily log returns. I.e., we test for stationarity, heteroskedasticity, auto-correlation, and non-normality. According to Appendix-Table 2.8, we cannot reject the null hypotheses that the time series are stationary for all series. Most series, however, exhibit heteroskedasticity, strong auto-correlation, and non-normality.

[16] Note that this does not imply that the estimated return series are normally distributed over time. In fact, in literature it is well documented that the unconditional return distribution of a GARCH process is heavy-tailed and exhibits excess kurtosis.

[17] Recall that we use Gaussian error terms to estimate the GARCH and DCC GARCH parameters. To be consistent with our previous assumptions, we model the univariate residuals as standard Gaussian noise.

tailed procedure of how the daily correlations are updated is presented in Appendix 2.B). This yields the following return series:

$$\left\{ \begin{array}{c} r^s_{sys,t+\tau} \\ r^s_{i,t+\tau} \end{array} \right\}_{\tau=1}^{h} \quad \text{for} \quad s = 1, \ldots, S. \tag{2.9}$$

(v) In the last step, we determine the h-day cumulative returns of simulations $s = 1, \ldots, S$ at day t for institution i and the banking system (according to Equation (2.2)). Subsequently, the MES and ΔCoVaR measures are directly inferred from the simulated return series. We calculate weekly series of SRISK employing the weekly MES estimates and the corresponding daily market and quarterly balance sheet values as described in Section 2.3.2.

We perform the simulation procedure outlined in Steps 3–5 including the calculation of the systemic risk measures for each Wednesday within our sample period moving ahead one week in each step. We estimate the h-day MES and CoVaR measures from the simulated bivariate cumulative h-day returns as follows:

Marginal Expected Shortfall

The h-day MES is calculated using the average of institution i's cumulative h-day returns resulting from paths $s = 1, \ldots, S$ for which the cumulative return of the banking system is below threshold C:

$$\mathrm{MES}_t^{i,h}(C) = -\frac{\sum_{s=1}^{S} R^s_{i;[t,t+h]} \mathbb{1}\left\{ R^s_{sys;[t,t+h]} \leq C \right\}}{\sum_{s=1}^{S} \mathbb{1}\left\{ R^s_{sys;[t,t+h]} \leq C \right\}}. \tag{2.10}$$

$\mathbb{1}$ denotes an indicator variable that takes the value *one* if the market return is below threshold level C and *zero* otherwise.

Conditional Value at Risk

ΔCoVaR is calculated as the residual between bank i's "distress CoVaR" given by

$$\begin{aligned} \mathrm{CoVaR}_t^{sys|i \leq \mathrm{VaR},h}(q) &= \mathrm{VaR}_{t,q}\left(R^s_{sys;[t,t+h]}\right) \\ \text{with} \quad &\left\{ R^s_{sys;[t,t+h]} : \; R^s_{i;[t,t+h]} \leq \mathrm{VaR}_{t,q}\left(R^s_{i;[t,t+h]}\right)\right\} \end{aligned} \tag{2.11a}$$

and bank i's "median state CoVaR" given by

$$\begin{aligned}\mathrm{CoVaR}_t^{sys|i=\text{median},h}(q) &= \mathrm{VaR}_{t,q}\left(R^s_{sys;[t,t+h]}\right) \\ \text{with} \quad &\left\{R^s_{sys;[t,t+h]} : \ \nu^{s,h}_{i,t} - \sigma^{s,h}_{i,t} \leq R^s_{i;[t,t+h]} \leq \nu^{s,h}_{i,t} + \sigma^{s,h}_{i,t}\right\},\end{aligned} \tag{2.11b}$$

where $\nu^{s,h}_{i,t}$ is the simulated median h-day return of institution i and $\sigma^{s,h}_{i,t}$ the simulated standard deviation of institution i's h-day return.

2.B DCC GARCH

Recalling the bivariate return process from Equation (2.6) and the setup of the univariate GARCH(1,1) models from Equations (2.7a) and (2.7b), the following relationship holds:

$$\xi_{sys,t} = \epsilon_{sys,t} \tag{2.12a}$$

$$\xi_{i,t} = \rho_{i,sys,t}\epsilon_{sys,t} + \sqrt{1-\rho_{i,sys,t}^2}\epsilon_{i,t}. \tag{2.12b}$$

It is obvious that within the bivariate process the correlation variable $\rho_{sys,i,t}$ entirely captures the correlation between institution i and the banking system. Therefore, the residuals $\epsilon_{i,t}$ and $\epsilon_{sys,t}$ are uncorrelated by definition. However, this is not the case for the (correlated) residuals $\xi_{i,t}$ and $\xi_{sys,t}$ from the univariate GARCH(1,1) processes. This fact is used by Engle (2002) to estimate time-varying return correlations.

Using matrix notation the return vector of the market and institution i is given by:

$$R_t = \Sigma_t^{\frac{1}{2}}\epsilon_t, \tag{2.13}$$

where

$$\Sigma_t = \begin{bmatrix} \sigma_{sys,t}^2 & \rho_{i,sys,t}\sigma_{i,t}\sigma_{sys,t} \\ \rho_{i,sys,t}\sigma_{i,t}\sigma_{sys,t} & \sigma_{i,t}^2 \end{bmatrix} \tag{2.14}$$

is the covariance matrix of the return vector $R_t = (r_{sys,t}, r_{i,t})'$ and $\Sigma_t^{1/2}$ is the corresponding Cholesky transformation of Σ_t. The covariance matrix can be further decomposed to the following form:

$$\Sigma_t = D_t P_t D_t \tag{2.15a}$$

$$= \begin{bmatrix} \sigma_{sys,t} & 0 \\ 0 & \sigma_{i,t} \end{bmatrix} \begin{bmatrix} 1 & \rho_{i,sys,t} \\ \rho_{i,sys,t} & 1 \end{bmatrix} \begin{bmatrix} \sigma_{sys,t} & 0 \\ 0 & \sigma_{i,t} \end{bmatrix}, \tag{2.15b}$$

with P_t representing the correlation matrix of the return vector R_t. Since the residuals $\xi_{i,t}$ and $\xi_{sys,t}$ have *zero* mean and *unit* variance, the correlation matrix of the return vector and the covariance matrix of the residuals are equivalents and can be used to calculate the time-varying correlation variable $\rho_{i,sys,t}$. Following Engle (2009), the bivariate DDC

GARCH model at time t is fully specified by:

$$\rho_{i,sys,t} = \frac{q_{i,sys,t}}{\sqrt{q_{i,i,t} q_{sys,sys,t}}} \tag{2.16a}$$

$$q_{i,sys,t} = (1 - \alpha - \beta)\, \overline{q}_{i,sys} + \alpha \xi_{i,t-1} \xi_{sys,t-1} + \beta q_{i,sys,t-1} \tag{2.16b}$$

$$q_{sys,sys,t} = (1 - \alpha - \beta)\, \overline{q}_{sys,sys} + \alpha \xi_{sys,t-1} \xi_{sys,t-1} + \beta q_{sys,sys,t-1} \tag{2.16c}$$

$$q_{i,i,t} = (1 - \alpha - \beta)\, \overline{q}_{i,i} + \alpha \xi_{i,t-1} \xi_{i,t-1} + \beta q_{i,i,t-1} \tag{2.16d}$$

$$\overline{q}_{i,sys} = \frac{1}{n} \sum_{t=1}^{n} \xi_{i,t} \xi_{sys,t}. \tag{2.16e}$$

$\overline{q}$ is the average correlation within the sample period and the q values are the quasi-correlations extracted from residuals $\xi_{i,t}$ and $\xi_{sys,t}$. The decomposition of ρ_t into quasi-correlations ensures that the correlation matrix is positive definite. In analogy to the volatility GARCH models, the time-varying correlation of the DCC GARCH is heteroskedastic and depends on the lagged quasi-correlation values as well as on the lagged values of the GARCH(1,1) residuals $(\xi_{sys,t}, \xi_{i,t})$. Parameters α and β are estimated using the maximum likelihood method.

2.C Time series diagnostics

We conduct several diagnostic checks for the time series employed in our empirical analysis. Table 2.7 contains test results for the quarterly series of SRMs, bank-specific, and macroeconomic variables at the banking system level. Table 2.8 displays the test results for the individual banks' series of daily log returns.

	SRMs			Bank-specific variables						Macroeconomic variables					
	*avg*MES	*avg*SRISK	*avg*ΔCoVaR	Leverage	*Z*-score	Market-to-book	Profitability	Nonperforming loans	Loan-to-deposit	Production	Real GDP	Inflation	Unemployment	House prices	Credit private
Panel A – Unit roots & stationarity: Kwiatkowski-Phillips-Schmidt-Shin test															
p-value	0.737	0.445	0.282	0.551	0.490	0.195	0.766	0.010	0.990	0.671	0.756	0.900	0.953	0.990	0.990
statistic	-2.805	-2.047	-1.622	-2.323	-2.163	-1.395	-2.882	0.457	-4.546	-2.635	-2.857	-3.232	-3.632	-4.545	-4.475
Panel B – Heteroskedasticity: Breusch-Pagan test															
p-value	0.883	0.573	0.942	0.945	0.933	0.705	0.734	0.961	0.588	0.372	0.007	0.832	0.001	0.001	0.004
statistic	0.022	0.317	0.005	0.005	0.007	0.144	0.115	0.002	0.293	0.798	7.243	0.045	10.788	11.259	8.254
Panel C – Auto-correlation: Durbin-Watson test															
p-value	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
statistic	0.934	0.290	0.611	0.689	0.476	0.360	0.348	0.125	0.223	0.239	0.191	0.392	0.130	0.114	0.240
Panel D – Non-normality: Jarque-Bera test															
p-value	0.441	0.186	0.452	0.514	0.165	0.148	0.347	0.210	0.167	0.662	0.419	0.757	0.372	0.006	0.091
statistic	1.636	3.362	1.587	1.330	3.600	3.818	2.117	3.122	3.575	0.825	1.739	0.556	1.978	10.208	4.791

Table 2.7 – Time series diagnostics (levels): *p*-values and test statistics
The above table exhibits p-values of various statistical diagnostic tests on the quarterly time series used in our regressions in Section 2.5.1 and Section 2.5.2. All time series of observations range from 2005 to 2013. The table is organized as follows: Panel A exhibits the results of the Kwiatkowski-Phillips-Schmidt-Shin test with the null hypothesis that the time series are stationary, i.e., there is no unit root. Panel B presents the results of the Breusch-Pagan test with the null hypothesis that the time series are homoscedastic, i.e., there is no heteroskedasticity. Panel C gives the results of the Durbin-Watson test with the null hypothesis that the time series exhibit no auto-correlation. Panel D presents the results of the Jarque-Bera test with the null hypothesis that the time series follow the Gaussian distribution.

Statistic	#series	mean	min	$q = 0.25$	$q = 0.50$	$q = 0.75$	max	$\#p : p < 0.1$ (in %)	$\#p : p < 0.05$ (in %)	$\#p : p < 0.01$ (in %)
KPSS	84	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.00	0.00	0.00
Breusch-Pagan	84	0.1628	0.0000	0.0000	0.0004	0.1672	0.9883	71.43	63.10	55.95
Durbin-Watson	84	0.1656	0.0000	0.0003	0.0456	0.1923	0.9510	66.67	53.57	35.71
Jarque-Bera	84	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	100.00	100.00	100.00

Table 2.8 – Diagnostics of sample bank's daily log return series: p-values and test statistics
The above table exhibits p-values of various statistical diagnostic tests on the daily log return series for all 84 sample banks. All stock price data are obtained from Datastream and the analyzed time series range from 2005 to 2013. We perform the following tests: the Kwiatkowski-Phillips-Schmidt-Shin statistic tests the null hypothesis that the time series are stationary, i.e., there is no unit root; the Breusch-Pagan statistic tests the null hypothesis that the time series are homoscedastic, i.e., there is no heteroskedasticity. The Durbin-Watson statistic tests the null hypothesis that the time series exhibit no auto-correlation and the Jarque-Bera statistic tests the null hypothesis that the time series follow the Gaussian distribution. Column one specifies the respective test statistics. Column two gives the number of series tested and thus the number of test results. Column three gives the mean p-value of the test results, columns four to eight the quantiles, and columns nine to eleven provide the percentage of test results significant at the 10%, 5%, and 1% confidence levels.

3 Systemic importance, default risk, and profitability in the European banking system

3.1 Introduction

The recent International Financial Crisis has prompted the G20 to agree on the implementation of a set of new regulatory rules commonly known as Basel III with the purpose of improving micro- and macroprudential supervision and fostering the resilience of the banking system. In order to effectively achieve the former, the financial stability of systemically important banks (SIBs) is of great importance, as SIB failures are likely to trigger turmoil in the banking system with substantial spillover effects to the real economy. While the adverse consequences of SIBs' failures are more or less commonly known, it remains unclear whether SIBs are more vulnerable to banking system distress and economic downturns than non-SIBs. However, especially the identification of SIB-specific business cycle sensitivities is crucial for the development and execution of macroprudential stress-testing procedures as well as for the evaluation of policies relevant to SIBs, such as systemic importance surcharges or risk insensitive leverage ratio constraints.

Yet, current literature investigating public costs and benefits associated with SIBs primarily focuses on efficiency issues of the largest banks as well as on market distortions arising from implicit *too-big-to-fail* guarantees. Large banks' benefits can be mainly attributed to portfolio diversification effects and economies of scale and scope. For instance, Wheelock and Wilson (2012) document that large U.S. banks obtain significant and increasing returns to scale. De Haan and Poghosyan (2012) show that non-investment banks' quarterly earnings volatility decreases with bank size. In addition, Demsetz and Strahan (1997) find that portfolio diversification of large U.S. bank holding companies positively affects their default risk. The risk reduction benefit from diversification, though, is offset by above average leverage ratios and riskier lending activities.

Public costs can arise from market-implied too-big-to-fail guarantees. Analyzing banks' safety net subsidies from bank mergers and acquisitions, Molyneux et al. (2014) find that large banks are more likely to be rescued. Gandhi and Lustig (2015) provide evidence that large banks feature significantly lower risk-adjusted stock returns and similarly, Völz and Wedow (2011) find that CDS premia are distorted by bank size. Contrary to the previous findings, Demirgüç-Kunt and Huizinga (2013) find that banks' market-to-book ratios are negatively related to bank size indicating that beyond a certain threshold banks become *too-big-to-save*, which is priced by stock markets accordingly.

To the best of our knowledge, only Bertay et al. (2013) and Tabak et al. (2013) directly examine the financial stability of SIBs. Both studies find that systemic importance is not associated with higher levels of default risk, but larger banks are found to outperform smaller ones in terms of profitability. Bertay et al. (2013) additionally find that banks' *systemic size*, defined as a bank's size relative to the national economy, coincides with substantially weaker return patterns. However, the studies share the weakness of focusing on banks' balance sheet size as the principal indicator for systemic importance, albeit this identification method is coming short of a key feature of systemic importance which is an institution's exposure to systemwide failure (Acharya et al., 2012). Thus, Bertay et al. (2013) and Tabak et al. (2013) primarily analyze the risk and return efficiency of large banks, instead of capturing the underlying effects of systemic importance on banks' financial stability. Furthermore, existing literature does not investigate the particularities of SIBs' and non-SIBs' sensitivity to macroeconomic conditions.

The purpose of this paper is to explicitly analyze the relation between banks' systemic importance and their financial stability over the business cycle. In particular, we analyze in three steps whether SIBs exhibit default risk and return patterns that are distinctively different from non-SIBs. In a first step, we conduct a general examination of the determinants of bank profitability and default risk, which also includes a sensitivity analysis of the latter with respect to macroeconomic conditions. Second, we explore how systemic importance affects banks' financial stability and their sensitivity to economic expansions and contractions by grouping banks into quintiles according to their systemic relevance. In a last step, we investigate the time persistence of SIBs' particularities in their default risk and return patterns.

We conduct our analysis for the European banking system covering the period from July 2005 to June 2013 allowing for an investigation of SIBs' and non-SIBs' vulnerabilities during the International Financial Crisis and the subsequent European Sovereign Debt Crisis. As a measure of systemic importance we apply the SRISK concept (Acharya et al., 2012; Brownlees and Engle, 2015). SRISK is considered to be a measure for the externalities of bank distress and represents the measure of systemic importance that is most widely accepted in literature (Laeven et al., 2014).

Our main findings are as follows. First, SIBs' contemporaneous and future default risk and return characteristics feature above average pro-cyclicality with respect to macroeconomic conditions. A 1% increase of the GDP growth rate results in an improvement of SIBs' return on equity that is around 1.4% higher than that of non-SIBs. In the same way, SIBs' and non-SIBs' probabilities of default significantly differ in their sensitivity to economic expansions and contractions. We do not find evidence that non-SIBs exhibit cyclicality patterns that are distinctively different from average. Economic recessions therefore disproportionately impede the financial stability of SIBs.

Second, we find that systemic importance coincides with substantially weaker return patterns. In particular, SIBs' annual returns on equity are 4.7% lower than those of non-SIBs. SIBs' underperformance is furthermore persistent for three subsequent quarters. In contrast, the 20% least systemically important institutions feature annual returns that are 2.3% higher compared to systemically more important banks. However, we cannot observe that the systemic importance attribute of SIBs is reflected in higher levels of default risk, challenging the popular notion that SIBs' systemic nature significantly affects their risk-taking behavior as a result of perceived government bailout guarantees.

Contrary to this, SIBs exhibit levels of ameliorating default risk over time, possibly reflecting that this group of institutions engages in particularly strong recapitalization efforts in anticipation of higher capital requirements and reduced risk-taking as a response to the recent crises. The fact that SIBs eventually exhibit higher levels of default risk compared to non-SIBs can be primarily attributed to their equity ratios. Our results concerning the marginal effects of size on banks' default risk and return characteristics mainly confirm the findings of previous literature. We find that size is significantly negatively related to an institution's default risk. The effect of size on bank performance is positive though insignificant.

The results have paramount implications. The distinction between SIBs and non-SIBs is of particular importance for the development and execution of macroprudential stress-testing procedures as their different sensitivities with respect to economic shocks need to be accounted for in an adequate manner. Moreover, the results indicate that banks' balance sheet size should not be a primary concern for supervisors. Empirical evidence supports the existence of economies of scale and scope for large institutions. In addition, the divesture of large banks as a measure to increase banking stability may deteriorate risk management capacities and reduce market liquidity (IMF, 2014).

However, our results emphasize the usefulness of implementing binding leverage ratio constraints for SIBs for two reasons. First, the leverage ratio is much more countercyclical than the current regulation on risk-weighted assets (Brei and Gambacorta, 2015) and therefore an ideal candidate to effectively dampen the increased pro-cyclicality of SIBs' financial stability. Second, moderate balance sheet leverage ratio constraints of up to 5% substantially reduce SIBs' default probability by raising their substandard cushions of equity without affecting the median bank. The measure further limits banks' SRISK and hence public transfers from taxpayers in case of bank failures or restructurings.[1, 2]

Finally, the result that systemic importance is reflected in lower levels of profitability suggests that implicit government bailout guarantees for SIBs are costly to shareholders, too. In particular, our finding contradicts the view that such guarantees can be regarded as a free of charge long-term put option on shareholders' future income streams.

The remainder of this paper is organized as follows. Section 3.2 outlines the measurement method that we apply for the assessment of systemic importance, Section 3.3 elaborates on the sample selection and variables employed in our analysis, Section 3.4 presents and discusses our empirical results, and Section 3.5 concludes.

3.2 Measuring systemic importance

We measure institutions' systemic importance employing the *SRISK* proposed by Acharya et al. (2012). SRISK is a bank's time-varying expected undercapitalization conditional on a severe banking crisis and thus quantifies the amount of equity an institution has to raise in order to prevent bankruptcy. Institution i's SRISK at time t over time interval $[t, t+h]$ is defined as follows:

$$\mathrm{SRISK}_t^{i,h}(C,k) = \mathbb{E}\left[\text{capital shortfall}_{i;[t,t+h]} \,\middle|\, \text{crisis}\right]. \tag{3.1a}$$

A positive SRISK indicates an institution's propensity to be substantially adversely affected in the event of a distressed banking system and thus highlights the need of recapitalization. On the contrary, a negative SRISK suggests that a bank's cushion of capital is sufficiently large in order to withstand a banking system crisis. Applying the going concern loss absorbing capacity concept to better define a bank's undercapitalization, Equation (3.1a) can be rearranged into:

$$\mathrm{SRISK}_t^{i,h}(C,k) = \mathbb{E}\left[\{k \times (\text{debt} + \text{equity}) - \text{equity}\}_{i;[t,t+h]} \,\middle|\, \text{crisis}\right], \tag{3.1b}$$

where *debt* represents the book value of debt and *equity* the market value of equity. Consequently, institution i becomes insolvent during a severe banking crisis in case its equity

[1] It is important to note that enhanced risk-based capital requirements for SIBs (systemic importance surcharges) are also adequate in order to reduce their above average probability of default but are less appropriate to effectively tackle the increased pro-cyclical nature of the former.

[2] The reader should additionally note that, when the leverage ratio becomes a binding regulatory measure, it might lose its economic expediency and thus becomes an unreliable indicator in the spirit of Charles Goodhart (Goodhart's law), as banks reallocate their assets to optimize regulatory constraints and may find ways for regulatory arbitrage.

cushion decreases below fraction k of market valued total assets. Allowing parameter k to be the inverse of the Basel III maximum Leverage Ratio of 33.3; k can be interpreted as a Tier I Capital Adequacy Ratio of 3% on total marked valued assets instead of the Basel Capital Adequacy Ratio of 8% on risk-weighted assets. Eventually, SRISK can be calculated as a function of bank i's future stock market return conditional on a banking crisis:

$$\text{SRISK}_t^{i,h}(C,k) = k \times \text{debt}_{i,t} - (1-k)\left(1 - \text{MES}_t^{i,h}(C)\right) \times \text{equity}_{i,t}. \tag{3.1c}$$

MES denotes bank i's h-day *Marginal Expected Shortfall* and is defined as bank i's expected h-day stock return, given that the banking system's h-day return falls below a predefined threshold C, indicating a severe crisis in the banking system:

$$\text{MES}_t^{i,h}(C) = -\mathbb{E}\left[R_{i;[t,t+h]} \,\middle|\, R_{sys;[t,t+h]} \leq C\right], \tag{3.2}$$

with $R_{i;[t,t+h]}$ representing bank i's h-day stock return:

$$R_{i;[t,t+h]} = \exp\left(\sum_{\tau=1}^{h} r_{i,t+\tau}\right) - 1. \tag{3.3}$$

The h-day return $R_{sys;[t,t+h]}$ is defined analogously and represents the asset-weighted return of the respective banking system.

The measure's incorporated conditionality is of fundamental importance because we are particularly interested in institutions' responses to a distressed banking system. In a well-functioning banking system, the consequences of a bank failure do not need to be severe because competitors can acquire the bankrupt institution as a whole or in parts without impeding the functioning of the banking system. In times of crises, however, failing institutions may not be acquired due to competitors' (cash) constraints, resulting in a severe disruption of the financial system (Acharya et al., 2010). As a consequence, institutions exhibiting high levels of SRISK substantially contribute to the intensification of the crisis and thus pose a high risk to the banking system. We calculate weekly SRISK figures as presented in Section 2.3.4.

3.3 Data

This section briefly introduces our sample of banks, discusses bank characteristics and macroeconomic variables employed in the regression analysis, and provides descriptive summary statistics.

3.3.1 Sample selection

Our study investigates the dependence structure between systemic importance, default risk, and return characteristics of European banks. The selection of our sample is based on Döring et al. (2016) and covers the period from July 2005 to June 2013. The particular focus on the European banking system allows us to analyze the abovementioned dependencies in the context of two severe financial crises – the International Financial Crisis and the subsequent European Sovereign Debt Crisis.

The sample contains 84 banks from 15 European countries including Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. Due to bankruptcies, mergers and acquisitions, and new listings the number of sample banks changes over time with a maximum of 78 and a minimum of 51 banks per sample quarter. For a detailed exposition of our sample selection, we refer to Section 2.2.

3.3.2 Bank characteristics

Systemic importance

We measure systemic importance employing the SRISK concept as outlined in Section 3.2. Figure 3.1 exhibits the weekly SRISK time series for all sample banks covering the period from July 2005 to June 2013. Institutions' SRISK strongly increases at the onset of the International Financial Crisis in 2007, peaking after the default of Lehman Brothers on September 15, 2008. Despite a decrease after 2009, levels of SRISK remain significantly higher than prior to 2008 and exhibit another increase as a result of the European Sovereign Debt Crisis. Although prevailing high levels of SRISK stress the market's awareness of remaining threats in the European banking system, Figure 3.1 reveals substantial cross-sectional variation with SRISK values ranging from €-100,000m to €70,000m.

For the subsequent empirical analysis we compute quarterly SRISK series for each sample bank by averaging across the weekly SRISK values that refer to the respective quarter and express quarterly SRISK in €m. Consequently, institutions' SRISK quantifies the average amount of money the government or the taxpayer needs to raise in times of crises in order to prevent the latter from bankruptcy and can be considered to be a measure for the externalities of bank distress.

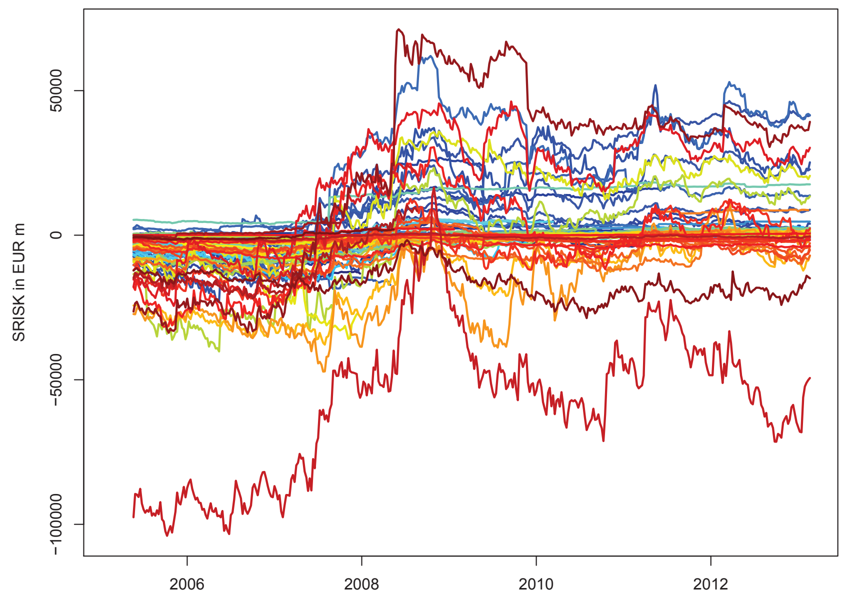


Figure 3.1 – Evolution of systemic importance
The figure presents time series of weekly SRISK for all sample banks covering the period from July 2005 to June 2013. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR m. All stock price and balance sheet data are obtained from Datastream.

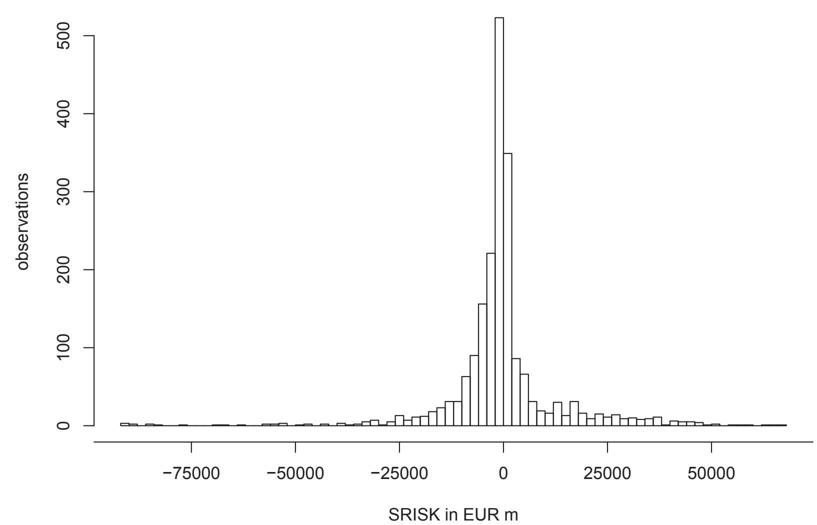


Figure 3.2 – Distribution of systemic importance
The figure presents the unconditional distribution of quarterly SRISK for the aggregate of all sample banks covering the period from July 2005 to June 2013. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR m. All stock price and balance sheet data are obtained from Datastream.

Figure 3.2 represents the histogram of quarterly SRISK for our sample of banks. The distribution of SRISK is heavy-tailed as a result of the size effect, with a substantial share of values in the left and right tails representing the largest banks within the sample. This fact emphasizes the notion that large banks do not have to be systemically risky by definition, i.e., SRISK separates large systemic from large non-systemic banks.

Risk and return

We capture the effect of systemic importance on banks' financial stability measuring the SRISK's influence on banks' default risk and return characteristics. We proxy default risk by using the Z-score. *Z-score* is defined as

$$Z\text{-}score_{i,t} = \frac{roa_{i,t} + car_{i,t}}{\sigma_i(roa)},$$

where roa represents the return on assets, car the capital asset ratio, and σ the return on assets' standard deviation over the sample period; t indicates the quarter and i the respective institution. The Z-score states the number of standard deviations an institution's return on assets needs to fall below its expected return in order for the bank to default (Roy, 1952; Boyd and Runkle, 1993). Hence, the measure is inversely related to bank default risk, with a high Z-score indicating a reduced probability of default. As a measure of an institution's return we employ *return on equity* which is defined as the annualized ratio of net income over book equity and expressed in percentage terms.

Control variables

Our analysis accounts for a number of bank-specific control variables that are likely to affect banks' default risk and return characteristics. In particular, we employ *assets*, defined as the natural logarithm of an institution's total assets (measured in €k), and *asset growth*, defined as the quarterly logarithmic change in total assets. Assets captures bank size. In literature it is often proposed that larger banks might be less risky and more profitable than their smaller peers as a result of sophisticated portfolio diversification techniques and returns of scale and scope (e.g. Diamond, 1984; Demsetz and Strahan, 1997; Feng and Serletis, 2010; Wheelock and Wilson, 2012). Accounting for a bank's asset growth rate is crucial because abnormal asset growth rates are likely to be reflected in banks' default risk and return characteristics.

Moreover, we employ the *equity ratio*, defined as the ratio of book equity over total assets. The latter proxies for a bank's balance sheet strength in periods of crises and thus, higher values indicate a lower risk of default. Lastly, we include the *net profit margin* which is defined as net income divided by gross sales and other operating revenue. The net profit margin captures the operating efficiency of a bank's return generating activities and should be positively related to bank performance. We express asset growth, equity ratio, and net profit margin in percentage terms. All daily stock price information and quarterly balance sheet data are collected from Datastream.

3.3.3 Macroeconomic variables

The bank-specific controls are complemented by a set of macroeconomic control variables including the variables GDP growth, inflation, and slope-yield-curve. *GDP growth* is the inflation-adjusted annualized growth rate of the European Union's gross domestic product. We include the GDP growth rate in order to analyze the economic cyclicality of banks' default risk and return patterns. We expect institutions to generally be positively affected by GDP growth. *Inflation* is the inflation rate computed from the Harmonised Index of Consumer Prices for the European Union. *Slope-yield-curve* reflects the "slope" of the European economy's yield curve. It is proxied by the differential between the 10- and 1-year German government bond yields. Moderate levels of inflation may positively affect bank performance. However, low yield curve slopes reduce banks' return on maturity transformation and could result in lower performance. All macroeconomic variables are collected from Datastream, sampled on a quarterly frequency, and expressed in percentage terms.

Figure 3.3 depicts time series of all employed macroeconomic control variables. As a result of the International Financial Crisis the GDP growth rate significantly dropped with the European economy sliding into a deep recession in late 2008. In 2010 the European Union experienced a short period of economic recovery, which was however nipped in the bud by the European Sovereign Debt Crisis starting in 2011. In analogy to GDP growth, inflation reached its highest levels shortly prior to the collapse of Lehman Brothers and was at its minimum in 2009 when distress in the banking system finally spilled over to the real sectors. Again, the economic recovery in 2010 led to an increase in inflation, which was reversed at the onset of the European Sovereign Debt Crisis in 2011.

The yield curve slope dynamics were primarily affected by a sharp decline of the short-term rate in early 2008. As a consequence, the spread between long- and short-term interest rates increased by roughly 200 basis points from 2008 to 2009 and thereafter remained on levels that were substantially higher than pre-crisis levels. Beyond the ECB's sharp reduction of its main refinancing rate, the yield curve dynamics can further be explained by an increased investors' demand for short-term riskless assets during the crises.

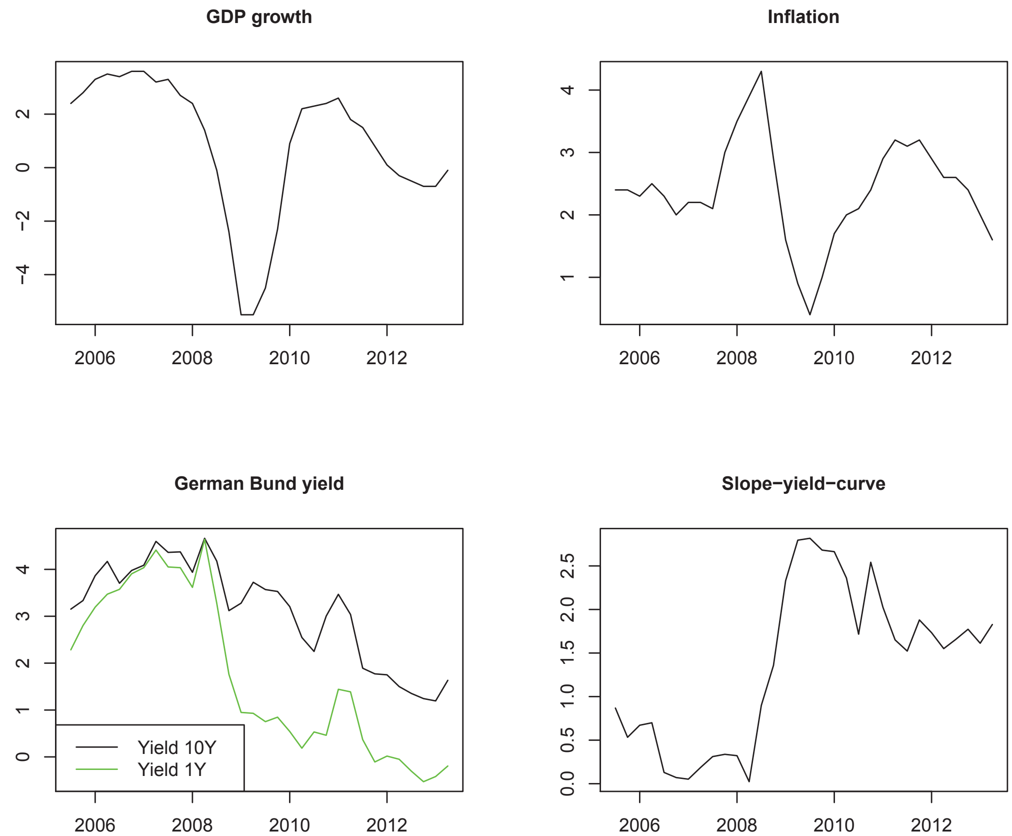


Figure 3.3 – **Evolution of macroeconomic variables**
The figure presents time series of quarterly macroeconomic data from the European Union covering the period from July 2005 to June 2013. *GDP growth* is the inflation-adjusted annualized growth rate of the EU's gross domestic product. *Inflation* is the inflation rate based on the Harmonised Index of Consumer Prices. *German Bund yield* is the German government bond yield and *slope-yield-curve* is the differential between the 10- and 1-year German government bond yields. All macroeconomic data are expressed in percentage terms and are obtained from Datastream.

3.3.4 Descriptive statistics

Table 3.1 provides summary statistics of all variables used in the main study. We only collect data for a particular sample bank and quarter if all its bank characteristics are available for that quarter, leaving us with 2,030 quarterly bank observations.

Institutions' levels of SRISK are slightly skewed to the left with a median value of €-771.07m. That is to say, even in crisis periods the majority of sample banks is adequately capitalized. The median sample bank is furthermore characterized by total assets of approximately €130bn[3], a return on equity of 10.09%, and a Z-score of 15.64.

[3] This corresponds to the natural logarithm of total assets, exp(18.69) ≈ €130,000,000k.

	Statistics			Quantiles				
	# obs	mean	std dev	min	$q = 0.25$	$q = 0.50$	$q = 0.75$	max
Bank characteristics								
SRISK	2,030	-398.04	13,584.22	-91,691.39	-3,930.28	-771.07	1,103.53	67,788.30
Z-score	2,030	20.57	20.15	-2.29	9.07	15.64	24.64	113.49
Return on equity	2,030	5.47	68.48	-2,086.72	4.77	10.09	15.82	138.85
Assets	2,030	18.85	1.45	14.40	17.63	18.69	20.12	21.68
Asset growth	2,030	2.28	13.27	-92.98	-0.90	0.93	4.06	423.07
Equity ratio	2,030	6.06	7.58	0.08	3.41	5.13	6.67	87.75
Net profit margin	2,030	13.06	137.69	-235.74	4.50	9.11	14.86	4,348.07
Macroeconomic variables								
GDP growth	32	0.86	2.60	-5.50	-0.35	1.65	2.73	3.60
Inflation	32	2.39	0.82	0.40	2.00	2.40	2.90	4.30
Slope-yield-curve	32	1.36	0.92	0.02	0.48	1.58	1.92	2.82

Table 3.1 – Summary statistics on bank characteristics and macroeconomic variables
The table presents summary statistics on quarterly sample bank characteristics and quarterly macroeconomic data from the European Union covering the period from July 2005 to June 2013. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR m. A bank's Z*-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where roa is the return on assets, car the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. *Assets* is the natural logarithm of an institution's total assets (in EUR k) and *asset growth* is the quarterly growth rate of total assets. *Equity ratio* is the ratio of book equity over total assets. The *net profit margin* is defined as net income divided by gross sales and other operating revenue. *GDP growth* is the inflation-adjusted annualized growth rate of the EU's gross domestic product. *Inflation* is the inflation rate based on the Harmonised Index of Consumer Prices and *slope-yield-curve* is the differential between the 10- and 1-year German government bond yields. Asset growth, equity ratio, net profit margin, and all macroeconomic variables are expressed in percentage terms. All data are obtained from Datastream.

Furthermore, institutions exhibit quarterly median asset growth rates of approximately one percent.

Sample banks substantially vary in terms of their balance sheet strength, which can be inferred from their equity ratio. Despite the median bank featuring an equity ratio of 5.13%, the 25%-quantile (75%-quantile) exhibits equity ratios of 3.41% (6.67%). The median net profit margin is at 9.11%. In order to control for outliers, we winsorize the upper and lower 1% quantiles of return on equity, asset growth, equity ratio, and net profit margin in our subsequent regression analysis.

	# obs	SRISK	Z-score	Return on equity	Assets	Asset growth	Equity ratio	Net profit margin
Austria	73	-3,503.05	15.87	13.73	18.87	1.46	5.58	9.78
Belgium	118	1,089.28	4.83	8.16	19.58	0.00	5.16	4.63
Denmark	64	-350.08	15.50	5.11	18.50	1.40	4.39	6.89
Finland	32	-671.42	26.22	10.02	17.34	2.76	6.14	7.00
France	157	7,129.25	16.98	7.64	20.79	0.00	3.25	6.76
Germany	133	3,000.95	12.05	7.74	20.01	0.04	2.69	5.45
Greece	180	-712.97	3.68	9.27	17.80	1.73	5.06	9.65
Ireland	54	-3,138.73	7.70	23.27	18.96	0.00	4.14	14.27
Italy	352	-759.64	19.73	6.04	17.84	1.31	7.12	7.69
Netherlands	44	1,739.27	11.17	19.44	20.92	0.00	2.87	8.23
Portugal	61	-1,630.54	22.09	12.94	17.88	1.76	4.65	10.20
Spain	249	-1,886.19	19.23	11.54	18.47	1.29	5.57	11.09
Sweden	128	-2,944.76	27.10	13.32	19.27	1.89	4.15	15.53
Switzerland	175	-1,820.19	10.59	9.90	17.29	0.52	7.08	15.16
United Kingdom	210	-1,258.23	19.17	14.04	19.99	0.32	3.95	9.65

Table 3.2 – Summary statistics on bank characteristics by country
The table exhibits median statistics of quarterly sample bank characteristics by country covering the period from July 2005 to June 2013. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR m. A bank's Z-*score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where roa is the return on assets, car the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. *Assets* is the natural logarithm of an institution's total assets (in EUR k) and *asset growth* is the quarterly growth rate of total assets. *Equity ratio* is the ratio of book equity over total assets. The *net profit margin* is defined as net income divided by gross sales and other operating revenue. Asset growth, equity ratio, and net profit margin are expressed in percentage terms. All data are obtained from Datastream.

To develop an understanding of regional particularities we present median statistics of bank characteristics by country in Table 3.2. Italian banks account for the largest share of quarterly bank observations, followed by Spain and the United Kingdom. Most notably, however, the measure of systemic importance varies from country to country at large. Banks from France, Germany, and the Netherlands appear to be the systemically most important. Greek institutions exhibit the highest probability of default. Danish and Italian banks, in contrast, are the least profitable.

Table 3.3 reports the correlation coefficients of all quarterly bank characteristics described above. The figures reveal a considerable negative relation between banks' systemic importance and their return on equity. To a lesser extent the same can be observed for systemic importance and Z-score. SRISK and return on equity are correlated with -0.29 and SRISK and Z-score are correlated with -0.16. Correlations between systemic importance, default risk, and return characteristics are all significant at the 0.1% level.

	Bank characteristics						
	SRISK	Z-score	Return on equity	Assets	Asset growth	Equity ratio	Net profit margin
SRISK	1.00						
Z-score	-0.16 ***	1.00					
Return on equity	-0.29 ***	0.15 ***	1.00				
Assets	0.16 ***	-0.17 ***	0.01	1.00			
Asset growth	-0.14 ***	0.04	0.18 ***	-0.06 **	1.00		
Equity ratio	-0.16 ***	0.18 ***	0.03	-0.50 ***	0.00	1.00	
Net profit margin	-0.33 ***	0.27 ***	0.77 ***	-0.16 ***	0.18 ***	0.29 ***	1.00

Table 3.3 – Correlation coefficients of bank characteristics
The table exhibits the correlation coefficients of all bank characteristics covering the period from July 2005 to June 2013. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR m. A bank's Z*-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where roa is the return on assets, car the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. *Assets* is the natural logarithm of an institution's total assets (in EUR k) and *asset growth* is the quarterly growth rate of total assets. *Equity ratio* is the ratio of book equity over total assets. The *net profit margin* is defined as net income divided by gross sales and other operating revenue. Asset growth, equity ratio, and net profit margin are expressed in percentage terms. All data are obtained from Datastream. The correlation coefficients are assigned asterisks if they are statistically significant (***, **, and * denotes significance at the 0.1%-, 1%-, and 10%-confidence levels).

3.4 Empirical evidence

In the following, we explore the dependence structure between institutions' systemic importance and their default risk and return characteristics. We do so by first analyzing the general determinants of risk and return in Section 3.4.1. Section 3.4.2 then focuses on subsamples categorized according to banks' systemic nature in order to explicitly capture the effects of systemic importance on their financial stability and sensitivity to economic expansions and contractions. Section 3.4.3 exhibits the time persistence of systemically important banks' particularities and Section 3.4.4 tests the robustness of our main results.

3.4.1 Determinants of institutions' default risk and return

A number of explanatory bank-specific and macroeconomic variables can generally be expected to determine institutions' default risk and return characteristics regardless of their systemic importance. More importantly, though, these variables may already capture the effect of systemic importance on the cross-sectional variation of institutions' default risk and return characteristics. We measure institutions' default risk and return characteristics employing institutions' Z-score and return on equity (roe). As a baseline regression we estimate the following models:

$$\begin{aligned} roe_{i,t} &= \alpha + \beta'\ BankControls_{i,t} + \gamma'\ MacroControls_t + \phi'\ BF_i + \theta'\ TF_t + \epsilon_{i,t} \\ Z\text{-}score_{i,t} &= \alpha + \beta'\ BankControls_{i,t} + \gamma'\ MacroControls_t + \phi'\ BF_i + \theta'\ TF_t + \epsilon_{i,t}, \end{aligned} \tag{3.4}$$

where *BankControls* represents a vector containing the bank-specific control variables assets, asset growth, equity ratio, and net profit margin and *MacroControls* denotes a vector of macroeconomic control variables consisting of GDP growth, inflation, and slope-yield-curve. In our regression analysis we further employ bank fixed (BF) as well as time fixed (TF) effects; α, β, γ, ϕ, and θ represent the regression coefficients and ϵ is Gaussian White Noise. All regressions are estimated applying standard error clustering at the bank level allowing for a fully general structure w.r.t. heteroskedasticity and serial cross-sectional correlation. We present the estimation results of Equation (3.4) in Table 3.4 which is organized as follows: Regressions (1), (2), and (3) feature the Z-score, whereas Regressions (4), (5), and (6) feature the return on equity as the dependent variable.

Our results demonstrate that banks' probability of default is primarily driven by bank-specific variables. In line with theory, the effect of size on Z-score is positive. Thus, large institutions are less likely to go bankrupt. Excessive growth of banks' balance sheets, on the contrary, is reflected in significantly higher levels of default risk confirming the notion that fast-growing banks take excess risk on their balance sheets and are thus more vulnerable. The equity ratio constitutes the major driver of bank default risk, however. Its influence is economically large and highly significant; a 1% increase of the equity ratio is reflected in a strong increase of the Z-score by 1.4. Finally, the net profit margin has a significantly negative impact on default risk by indirectly strengthening an institution's capital base. The explanatory power of macroeconomic variables is rather limited. The relation between the latter and a bank's Z-score is insignificant indicating that, in general, economic conditions do not substantially drive the average bank's probability of default.

Regarding the analysis of bank profitability we observe that increases of banks' net profit margin result in significantly higher return on equity levels. High equity ratios, however, are reflected in lower levels of profitability, though the influence is only slightly significant. Given the heated debates between bankers and regulators in light of the increased Basel III capital requirements, this result is not very surprising, as high returns on equity usually coincide with high leverage ratios that also imply a higher default risk.

The effect of size on return on equity is positive though insignificant.

In contrast to banks' default risk, we find evidence that macroeconomic conditions significantly drive an institution's profitability. Inflation generally possesses a positive impact on banks' return on equity. The explanatory power of the GDP growth rate, though, seems to be controversial at first glance. On the one hand, without controlling for the influence of bank-specific variables, the effect of GDP growth is economically significant. An increase in GDP by 1% results in an increase in the return on equity by 3.1%. On the other hand, GDP growth turns out to be statistically insignificant when including bank-specific control variables. In particular, the explanatory power of the net profit margin is likely to implicitly capture the effect of economic growth since both return on equity and net profit margin are directly affected by an institution's net income. Table 3.5 confirms this assumption. The net profit margin is significantly determined by the bank-specific variables assets, asset growth, and equity ratio. As a consequence, larger banks achieve higher return margins and higher capital ratios indicate a bank's ability to generate profits more efficiently. In addition, the economic cycle, as measured by GDP growth, substantially drives a bank's net profit margin. Hence, the pro-cyclicality of the average bank's return on equity in Regression (6) is indirectly determined and captured by the pro-cyclical nature of the net profit margin.

We finally examine whether our findings regarding the bank-specific control variables are driven by endogeneity issues. Therefore, we first adopt a dynamic regression specification that includes the lag of the dependent variables among the regressors to account for endogenous default risk and return persistence. The regression coefficients of the lagged risk and return variables indicate the speed of adjustment to equilibrium. A coefficient close to *one* implies that banks' levels of Z-score and return on equity persist over time. Values around *zero* mean that there is no persistency. Values in between indicate that default risk and return are somewhat persistent but will eventually return to their average levels. In a second regression setup, we lag all bank-specific regressors by one period in order to account for potential reverse causalities. Endogeneity can be a concern and might bias our results in case banks' risk and return characteristics cause banks to adjust their balance sheet size, growth rates or equity ratios. $L.$ denotes the one period lag of the corresponding variable. The results for the bank-specific control variables are presented in Table 3.6 and confirm our previous findings. Bank size coincides with higher levels of Z-score (lower probability of default), whereas higher asset growth rates reduce a bank's solvency. The net profit margin remains the major driver of the return on equity; however, the economic significance of the former decreases. Lastly, we find further evidence that higher equity ratios lower banks' profitability.

	Z-score			ROE		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Assets	2.914 ***		2.911 ***	0.904		0.889
	(1.034)		(1.021)	(2.572)		(2.821)
Asset growth	-0.052 ***		-0.050 ***	0.010		0.020
	(0.012)		(0.012)	(0.027)		(0.028)
Equity ratio	1.411 ***		1.410 ***	-0.691 *		-0.695 *
	(0.309)		(0.310)	(0.396)		(0.410)
Net profit margin	0.056 ***		0.061 ***	0.971 ***		1.004 ***
	(0.018)		(0.017)	(0.113)		(0.113)
GDP growth		-0.263	-0.066		3.133 ***	0.313
		(0.314)	(0.275)		(0.554)	(0.469)
Inflation		0.018	0.331		1.213 *	1.182 **
		(0.379)	(0.293)		(0.700)	(0.580)
Slope-yield-curve		0.809	-0.843		-3.445	-0.411
		(0.776)	(0.750)		(2.804)	(1.036)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank
adjusted R^2	0.399	0.039	0.423	0.629	0.198	0.639
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000
# obs	2,030	2,030	2,030	2,030	2,030	2,030

Table 3.4 – Determinants of default risk and return
All figures are estimated from quarterly sample bank characteristics and quarterly macroeconomic data from the European Union covering the period from July 2005 to June 2013. The table is organized as follows. Regressions (1), (2), and (3) feature Z-score as the dependent variable, whereas Regressions (4), (5), and (6) feature return on equity (roe) as the dependent variable. A bank's *Z-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where roa is the return on assets, car the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. *Assets* is the natural logarithm of an institution's total assets (in EUR k) and *asset growth* is the quarterly growth rate of total assets. *Equity ratio* is the ratio of book equity over total assets. The *net profit margin* is defined as net income divided by gross sales and other operating revenue. *GDP growth* is the inflation-adjusted annualized growth rate of the EU's gross domestic product. *Inflation* is the inflation rate based on the Harmonised Index of Consumer Prices and *slope-yield-curve* is the differential between the 10- and 1-year German government bond yields. Asset growth, equity ratio, net profit margin, and all macroeconomic variables are expressed in percentage terms. All data are obtained from Datastream. We estimate all regressions employing time and bank fixed effects and applying clustered standard errors at the bank level. For the ease of exposition, we suppress regression intercepts. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant (***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels).

	Net profit margin		
Variable	(1)	(2)	(3)
Assets	6.110 ***		6.511 ***
	(2.162)		(1.985)
Asset growth	0.089 **		0.118 **
	(0.043)		(0.046)
Equity ratio	2.128 ***		2.271 ***
	(0.543)		(0.558)
GDP growth		2.890 ***	4.052 ***
		(0.826)	(0.769)
Inflation		0.034	1.453
		(1.063)	(0.890)
Slope-yield-curve		-2.534	-3.219 *
		(2.199)	(1.866)
Bank fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank
adjusted R^2	0.089	0.173	0.244
p-value (F-statistic)	0.000	0.000	0.000
# obs	2,030	2,030	2,030

Table 3.5 – Drivers of the net profit margin
All figures are estimated from quarterly sample bank characteristics and quarterly macroeconomic data from the European Union covering the period from July 2005 to June 2013. The regressions feature the net profit margin as the dependent variable. The *net profit margin* is defined as net income divided by gross sales and other operating revenue and is expressed in percentage terms. *Assets* is the natural logarithm of an institution's total assets (in EUR k) and *asset growth* is the quarterly growth rate of total assets. *Equity ratio* is the ratio of book equity over total assets. *GDP growth* is the inflation-adjusted annualized growth rate of the EU's gross domestic product. *Inflation* is the inflation rate based on the Harmonised Index of Consumer Prices and *slope-yield-curve* is the differential between the 10- and 1-year German government bond yields. Net profit margin, asset growth, equity ratio, and all macroeconomic variables are expressed in percentage terms. All data are obtained from Datastream. We estimate all regressions employing time and bank fixed effects and applying clustered standard errors at the bank level. For the ease of exposition, we suppress regression intercepts. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant (***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels).

	Z-score		ROE	
Variable	(1)	(2)	(3)	(4)
Lag dependent	0.654 ***		0.426 ***	
	(0.044)		(0.099)	
Assets	1.349 ***		-0.677	
	(0.366)		(1.660)	
Asset growth	-0.088 ***		-0.004	
	(0.012)		(0.027)	
Equity ratio	0.609 ***		-0.634 **	
	(0.147)		(0.298)	
Net profit margin	0.039 ***		0.697 ***	
	(0.006)		(0.141)	
L.Assets		2.095 **		-0.416
		(0.924)		(1.535)
L.Asset growth		-0.041 ***		0.080 **
		(0.013)		(0.037)
L.Equity ratio		1.104 ***		-0.566 *
		(0.238)		(0.343)
L.Net profit margin		0.070 ***		0.808 ***
		(0.016)		(0.098)
Bank fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	No	Yes	No	Yes
Clustering level	Bank	Bank	Bank	Bank
adjusted R^2	0.739	0.326	0.724	0.466
p-value (F-statistic)	0.000	0.000	0.000	0.000
# obs	1,946	1,946	1,946	1,946

Table 3.6 – Endogeneity and banks' default risk and return
All figures are estimated from quarterly sample bank characteristics covering the period from July 2005 to June 2013. The table is organized as follows. Regressions (1) and (2) feature Z-score as the dependent variable, whereas Regressions (3) and (4) feature return on equity (roe) as the dependent variable. A bank's Z*-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where roa is the return on assets, car the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. *Lag dependent* is the one period lag of the dependent variable Z-score or return on equity. *Assets* is the natural logarithm of an institution's total assets (in EUR k) and *asset growth* is the quarterly growth rate of total assets. *Equity ratio* is the ratio of book equity over total assets. The *net profit margin* is defined as net income divided by gross sales and other operating revenue. Asset growth, equity ratio, and net profit margin are expressed in percentage terms. L. indicates the one period lag of the corresponding variable. All data are obtained from Datastream. We estimate all regressions employing time fixed and/or bank fixed effects and applying clustered standard errors at the bank level. For the ease of exposition, we suppress the regressions' intercepts. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant (***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels).

3.4.2 Impact of systemic importance on default risk and return

We now turn towards the influence of systemic importance on banks' default risk and return characteristics. However, evaluating the effects of systemic importance by means of theoretical considerations is a complex task because opposing marginal effects between the drivers of systemic importance need to be taken into account. As demonstrated by SRISK, in particular, these are an institution's size, MES, and leverage.

Especially the effect of size is ambiguous. On the one hand, large institutions can be expected to be less risky and more profitable as a result of superior portfolio diversification, enhanced risk management techniques, and returns of scale and scope (cf. Section 3.3.2). On the other hand, institutions exceeding a too-big-to-fail size threshold may take excessive risk on their balance sheets due to the perception of implicit government bailout guarantees. The effects of MES and leverage are more uniform. Reflecting investors' expectations about which institutions suffer most in times of financial crises, banks with higher levels of MES should be more affected by distressed financial markets, resulting in less favorable risk and return characteristics. High levels of leverage boost institutions' return on equity which in turn is bought at the price of an increased risk of default.

The previous discussion highlights the difficulty to derive the total of these effects from theory, stressing the necessity to analyze dependencies between systemic importance, default risk, and return characteristics empirically. This is especially true because the individual drivers of systemic importance do not need to be of any concern, but it is the (non-linear) combination of the latter breeding institutions' systemic importance.

Figure 3.4 presents scatterplots revealing the relationship between institutions' systemic importance and their default risk and return characteristics. The left panel displays the relation between SRISK and Z-score and the right panel exhibits the relation between SRISK and return on equity.

Institutions' SRISK and Z-score exhibit a weakly negative linear relationship. In contrast, the negative relationship between institutions' SRISK and return on equity is more pronounced in that high levels of SRISK are reflected in an inferior performance. For a more detailed analysis, we split our sample of banks into five subsamples. We rank sample banks according to their systemic importance in decreasing order in each quarter and allocate them to quintiles. Quintile 1 contains institutions with the highest systemic importance whereas Quintile 5 contains institutions with the lowest. Hence, we refer to Quintile 1 banks as systemically important banks (SIBs).

To develop a better understanding about the dependencies between banks' systemic importance and their default risk and return characteristics, we calculate mean descriptive

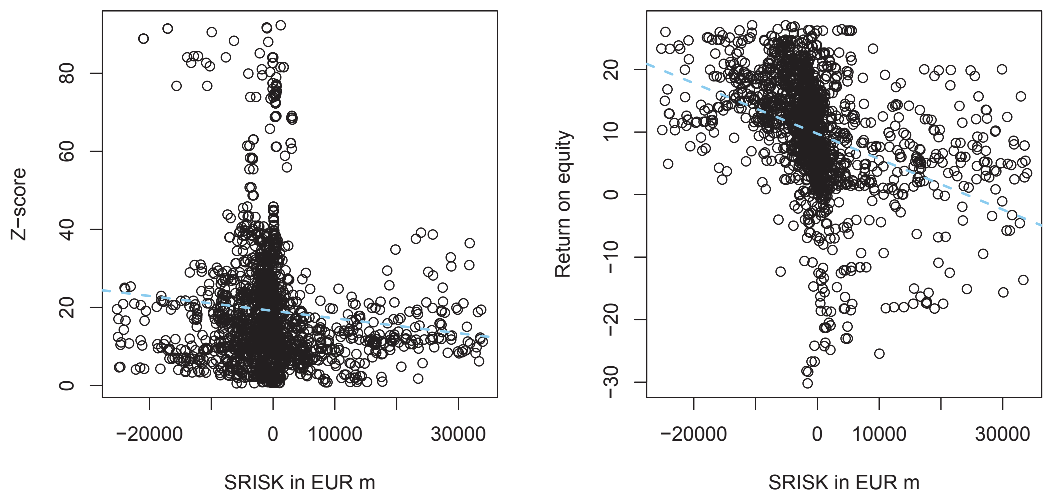


Figure 3.4 – Systemic importance, default risk, and return
The figure presents the relationship between the sample banks' quarterly systemic importance, default risk, and return characteristics covering the period from July 2005 to June 2013. The blue dashed lines indicate the linear relation of the aforementioned. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR *m*. A bank's *Z-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where roa is the return on assets, car the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. For the ease of exposition, we suppress the variables' upper and lower 2.5% quantiles. All data are obtained from Datastream.

statistics for both Z-score and return on equity for each quintile. We additionally explore the relevance of institutions' systemic importance over time by calculating quarterly leads of Z-score and return on equity for up to four quarters.

Table 3.7 presents the results. $Lead = k$, $k \in \{0, 1, 2, 3, 4\}$ indicates the k-quarter lead of the corresponding quintiles' mean default risk and return characteristics. For instance, $Lead = 0$ presents contemporaneous default risk and return characteristics; $Lead = 2$ gives the mean characteristics of Z-score and return on equity in the second quarter after the institutions were assigned to the respective quintiles. The main findings are as follows. We observe that systemic importance coincides with consistently higher levels of default risk and lower profitability. Both, institutions' Z-score and return on equity substantially increase with decreasing systemic importance. Contemporaneous return on equity only amounts to 2.91% in Quintile 1, but steadily increases across quintiles up to 13.90% in Quintile 5. For contemporaneous Z-score, differences are not as evident in a comparison between Quintiles 2, 3, and 4, but are more pronounced in a comparison between Quintiles 1 and 5, with Z-score amounting to 15.79 and 26.66, respectively. The

			Quintiles								
		Sample	1st		2nd		3rd		4th		5th
Lead = 0	Z-score	20.533	15.789	(0.004)	19.071	(0.179)	20.780	(0.964)	20.719	(0.000)	26.662
	ROE	8.354	2.911	(0.004)	6.192	(0.302)	7.424	(0.000)	11.721	(0.001)	13.900
Lead = 1	Z-score	20.454	15.907	(0.002)	19.531	(0.485)	20.436	(0.924)	20.308	(0.000)	26.356
	ROE	8.157	2.706	(0.002)	6.359	(0.760)	6.739	(0.000)	11.615	(0.005)	13.633
Lead = 2	Z-score	20.346	16.057	(0.003)	19.603	(0.588)	20.317	(0.740)	19.871	(0.000)	26.055
	ROE	7.905	2.221	(0.000)	6.700	(0.862)	6.483	(0.000)	11.347	(0.039)	12.932
Lead = 3	Z-score	20.228	16.178	(0.002)	20.002	(0.948)	20.090	(0.612)	19.410	(0.000)	25.579
	ROE	7.612	1.852	(0.000)	7.237	(0.398)	6.177	(0.000)	10.841	(0.159)	12.046
Lead = 4	Z-score	20.097	16.232	(0.001)	20.590	(0.489)	19.639	(0.595)	18.934	(0.000)	25.224
	ROE	7.226	2.041	(0.000)	6.896	(0.610)	6.252	(0.004)	9.800	(0.154)	11.194

Table 3.7 – Summary statistics of institutions' default risk and return characteristics categorized by systemic importance
The table presents mean values of the sample banks' (lead) quarterly default risk and return characteristics for various subsamples covering the period from July 2005 to June 2013. The table is organized as follows. Column three (Sample) presents the mean values obtained for the uncategorized sample. Columns 4, 6, 8, 10, and 12 present mean values of subsamples representing the institutions falling in the respective header quintile within each quarter. Numbers in parentheses represent p-values of a two-sample t-test between the adjacent quintile mean values. We apply SRISK as a categorization criterion. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR m. A bank's *Z-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where roa is the return on assets, car the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. All data are obtained from Datastream. $Lead = k$, $k \in \{0, 1, 2, 3, 4\}$ indicates the k-quarter lead of the corresponding subsamples' mean default risk and return characteristics.

observed patterns are predominantly persistent for all four quarter leads (see p-values of two-sample t-tests in parentheses).

In the following, we want to confirm if the previously observed patterns remain valid after controlling for the explanatory variables employed in Section 3.4.1. Additionally, we want to explore whether or not a bank's systemic nature affects its sensitivity to macroeconomic conditions. We therefore modify our regression analysis in order to explicitly account for the influence of institutional systemic importance:

$$\begin{aligned} roe_{i,t} &= \alpha + \beta'\ BankControls_{i,t} + \gamma'\ MacroControls_t \\ &\quad + \kappa\ SysRisk_{i,t} + \delta\ SysRisk_{i,t} * GDP\,growth_t + \phi'\ BF_i + \theta'\ TF_t + \epsilon_{i,t} \\ Z\text{-}score_{i,t} &= \alpha + \beta'\ BankControls_{i,t} + \gamma'\ MacroControls_t \\ &\quad + \kappa\ SysRisk_{i,t} + \delta\ SysRisk_{i,t} * GDP\,growth_t + \phi'\ BF_i + \theta'\ TF_t + \epsilon_{i,t} \end{aligned} \tag{3.5}$$

The distinctive new features of the above regressions are the two additional terms SysRisk and SysRisk * GDP growth, where *SysRisk* is a dummy variable that within a given quarter equals *one* in case a bank's SRISK corresponds to a respective quintile and *zero* otherwise. SysRisk reveals the marginal effect of systemic importance on banks' Z-score and return on equity in the cross-section of quintiles. The interaction term *SysRisk * GDP growth* captures the subsamples' cyclicality. In other words, the interaction term measures the quintile-specific default risk and return sensitivity to economic expansions and contractions. Vectors *BankControls* and *MacroControls* are defined as in Equation (3.4) and contain the control variables assets, asset growth, equity ratio, net profit margin, GDP growth, inflation, and slope-yield-curve. We again perform the regressions employing bank fixed and time fixed effects and estimate all regressions allowing for clustered standard errors at the bank level. Table 3.8 presents the regression results and is organized as follows. The table header states the quintile to which the dummy variable SysRisk refers and the regressions' dependent variables are indicated by the subheader.

As highlighted by the SysRisk dummy variable, we observe a significantly negative relationship between institutions' systemic importance and their return on equity in the cross-section of quintiles. Banks in the group of the 20% systemically most important institutions exhibit annual returns that are 4.7% lower than those of non-SIBs. In contrast, the 20% least systemically important institutions feature annual returns that are 2.3% higher compared to systemically more important banks. For Quintiles 2, 3, and 4 the marginal effect of systemic importance on return on equity does not significantly differ from zero. The observed pattern suggests that implicit government bailout guarantees for SIBs are costly to shareholders, too. Put differently, our finding contradicts the view that such guarantees can be regarded as a free of charge long-term put option on shareholders' future income streams. The net profit margin, though, remains the major driver of institutions' return characteristics for all quintile subsamples.

Higher levels of systemic importance, on the other hand, cannot be associated with higher levels of contemporaneous default risk. Thus, we do not find evidence that institutions' systemic nature significantly affects their risk-taking behavior. This challenges the assumption that SIBs take on excessive risks due to their *too-important-to-fail* status. The variations of institutions' Z-score are primarily determined by the control variables assets, asset growth, net profit margin, and most importantly by the equity ratio. Across quintiles, a 1% increase of the equity ratio is reflected in an increase of the Z-score by approximately 1.4. According to Table 3.1, the median equity ratio amounts to 5.13%. In contrast, our calculations reveal that Quintile 1 and Quintile 5 banks' mean equity ratios amount to 4.02% and 6.73%, respectively. Regulators therefore would be able to significantly decrease SIBs' default probability by introducing balance sheet leverage ratios of up to 5% without affecting the median bank.

	Quintile 1		Quintile 2		Quintile 3		Quintile 4		Quintile 5	
	Z-score	ROE	*Z*-score	ROE	*Z*-score	ROE	*Z*-score	ROE	*Z*-score	ROE
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Assets	2.951 ***	1.396	2.908 ***	0.888	2.913 ***	0.865	2.923 ***	1.019	2.892 ***	0.786
	(1.016)	(2.895)	(1.014)	(2.809)	(1.021)	(2.810)	(1.025)	(2.811)	(1.012)	(2.842)
Asset growth	-0.047 ***	-0.003	-0.050 ***	0.020	-0.050 ***	0.021	-0.048 ***	0.021	-0.051 ***	0.015
	(0.012)	(0.032)	(0.012)	(0.027)	(0.012)	(0.028)	(0.012)	(0.028)	(0.012)	(0.028)
Equity ratio	1.415 ***	-0.609	1.407 ***	-0.690 *	1.408 ***	-0.699 *	1.409 ***	-0.686 *	1.406 ***	-0.717 *
	(0.311)	(0.405)	(0.309)	(0.408)	(0.309)	(0.411)	(0.308)	(0.407)	(0.313)	(0.416)
Net profit margin	0.065 ***	0.977 ***	0.061 ***	1.006 ***	0.062 ***	1.004 ***	0.063 ***	1.001 ***	0.060 ***	0.996 ***
	(0.017)	(0.114)	(0.017)	(0.114)	(0.017)	(0.113)	(0.016)	(0.113)	(0.017)	(0.113)
GDP growth	-0.094	0.191	-0.099	0.372	-0.045	0.298	-0.048	0.460	-0.058	0.347
	(0.273)	(0.429)	(0.269)	(0.501)	(0.270)	(0.483)	(0.274)	(0.466)	(0.296)	(0.499)
Inflation	0.351	1.183 **	0.317	1.214 **	0.323	1.197 **	0.335	1.226 **	0.321	1.129 *
	(0.295)	(0.570)	(0.292)	(0.598)	(0.296)	(0.578)	(0.291)	(0.592)	(0.279)	(0.631)
Slope-yield-curve	-0.800	-0.911	-0.858	-0.364	-0.859	-0.361	-0.820	-0.389	-0.844	-0.418
	(0.764)	(1.030)	(0.746)	(1.048)	(0.751)	(1.040)	(0.764)	(1.058)	(0.778)	(1.089)
SysRisk ∗ GDP growth	0.142 **	1.192 *	0.142	-0.257	-0.124	0.084	-0.105	-0.541 **	-0.076	-0.364
	(0.071)	(0.624)	(0.087)	(0.319)	(0.096)	(0.342)	(0.067)	(0.210)	(0.131)	(0.307)
SysRisk	0.746	-4.678 **	-0.257	0.655	-0.015	-0.301	-0.309	0.595	0.426	2.293 *
	(0.481)	(2.219)	(0.278)	(0.978)	(0.269)	(0.743)	(0.348)	(0.559)	(0.379)	(1.203)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
adjusted R^2	0.428	0.648	0.424	0.639	0.424	0.638	0.425	0.640	0.424	0.640
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
# of obs.	2,030	2,030	2,030	2,030	2,030	2,030	2,030	2,030	2,030	2,030

Table 3.8 – Systemic importance, bank default risk, and return
All figures are estimated from quarterly sample bank characteristics and quarterly macroeconomic data from the European Union covering the period from July 2005 to June 2013. The table is organized as follows. Regressions that are assigned odd numbers feature Z-score as the dependent variable, whereas regressions with assigned even numbers feature return on equity (roe) as the dependent variable. A bank's *Z-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where *roa* is the return on assets, *car* the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. *Assets* is the natural logarithm of an institution's total assets (in EUR k) and *asset growth* is the quarterly growth rate of total assets. *Equity ratio* is the ratio of book equity over total assets. The *net profit margin* is defined as net income divided by gross sales and other operating revenue. *GDP growth* is the inflation-adjusted annualized growth rate of the EU's gross domestic product. *Inflation* is the inflation rate based on the Harmonised Index of Consumer Prices and *slope-yield-curve* is the differential between the 10- and 1-year German government bond yields. Asset growth, equity ratio, net profit margin, and all macroeconomic variables are expressed in percentage terms. *SysRisk ∗ GDP growth* denotes an interaction term between SysRisk and GDP growth. *SysRisk* is a dummy variable that within a given quarter equals *one* in case a bank's *SRISK* falls within the sample banks' respective quintile as given in the table header and *zero* otherwise. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR m. All data are obtained from Datastream. For all above regressions we employ time and bank fixed effects and apply clustered standard errors at the bank level. For the ease of exposition we suppress the regressions' intercepts. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant (***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels).

Figure 3.5 presents the marginal effects of systemic importance on banks' default risk and return on equity by SRISK quintile. The marginal contributions represent estimates $\hat{\kappa}$ of Equation (3.5). Employing two standard deviation confidence bands, the graph reveals a logarithmic-shaped relationship between systemic importance and return on equity. As mentioned previously, we do not observe a significant impact of the marginal effects of systemic importance on banks' default risk characteristics.

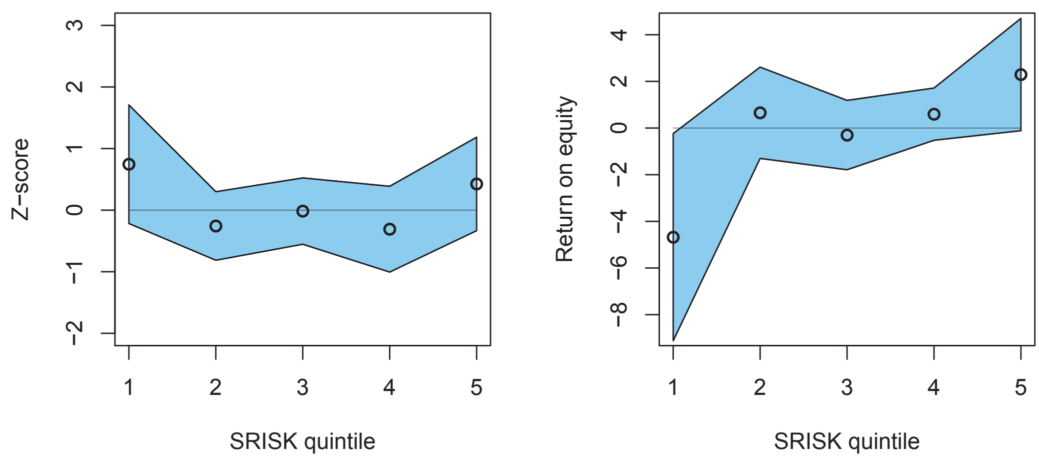


Figure 3.5 – Marginal contribution of systemic importance by quintile
The graph presents marginal contributions of banks' systemic importance to their Z-score and return on equity as a function of their systemic relevance. The marginal contributions represent regression coefficients of dummy variable *SysRisk* and are estimated according to Equation (3.5) from our sample of banks covering the period from July 2005 to June 2013. Banks are grouped in quintiles according to their systemic importance. We apply SRISK as a categorization criterion. The blue shaded area indicates the two standard deviation confidence bands. Standard deviations are estimated allowing for clustered standard errors. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR m. A bank's *Z-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where roa is the return on assets, car the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. All stock price and balance sheet data are obtained from Datastream.

In addition, the results demonstrate that SIBs' and non-SIBs' Z-scores substantially differ in their economic cyclicality, which can be deduced from the quintile-specific interaction term. I.e., the significance of variable SysRisk $*$ GDP growth in Regression (1) reveals that an increase of the GDP growth rate results in an above average improvement of SIBs' default risk characteristics when compared to those of non-SIBs. Economic booms thus disproportionately lower Quintile 1 institutions' probability of default and vice versa. Yet, non-SIBs' probability of default is insignificantly related to the macroeconomic interaction term suggesting that the latter do not exhibit default risk cyclicality patterns that are distinctively different from those of the average bank.

Table 3.8 also indicates an elevated pro-cyclicality of SIBs' profitability patterns. While, in general, GDP growth has no additional explanatory power for banks' return on equity when accounting for the pro-cyclical net profit margin (cf. Tables 3.4 and 3.5), the macroeconomic variable provides further insights into the cross-section of quintiles. In particular, we observe that the profitability of Quintile 1 banks is more sensitive to economic fluctuations than the return characteristics of non-SIBs, though the interaction term coefficient is statistically only significant at the 5.6% level. We cannot find a similar effect for Quintiles 2 to 5. If anything, non-SIBs' return characteristics seem to feature below average pro-cyclicality with respect to economic conditions.[4]

3.4.3 Systemically important banks' risk and return dynamics

We now analyze if systemically important banks' particularities concerning their default risk and return characteristics are persistent over time. This type of analysis necessitates the incorporation of a time lag structure into the previous regression:

$$\begin{aligned}
roe_{i,t} &= \alpha + \beta' \ BankControls_{i,t} + \gamma' \ MacroControls_t + \kappa \ SysRisk_{i,t-k} \\
&\quad + \delta \ SysRisk_{i,t-k} * GDP\,growth_t + \phi' \ BF_i + \theta' \ TF_t + \epsilon_{i,t} \\
Z\text{-}score_{i,t} &= \alpha + \beta' \ BankControls_{i,t} + \gamma' \ MacroControls_t + \kappa \ SysRisk_{i,t-k} \\
&\quad + \delta \ SysRisk_{i,t-k} * GDP\,growth_t + \phi' \ BF_i + \theta' \ TF_t + \epsilon_{i,t}.
\end{aligned} \tag{3.6}$$

Accordingly, Equation (3.6) includes lags of variable SysRisk in order to capture banks' future default risk and return dynamics. SysRisk is either lagged by $k = 0, 1, 2, 3$, or 4 quarters. This regression specification additionally allows to account for endogeneity issues between banks' systemic importance and their default risk and return characteristics. Endogeneity might be a concern and bias our results, if banks' risk and return characteristics are causing banks to adjust their systemic importance. However, given the latent character of systemic importance, we think that this problem is limited. We present the results obtained for Quintile 1 institutions in Table 3.9. The table header indicates the quarter lag to which the dummy variable SysRisk refers.

[4] It is important to note that by definition, given the validity of our results concerning the above average cyclicality of SIBs' default risk and return characteristics, the group of non-SIBs cannot feature patterns similar to those of SIBs on average.

	Lag = 0		*Lag = 1*		*Lag = 2*		*Lag = 3*		*Lag = 4*	
	Z-score	ROE	*Z*-score	ROE	*Z*-score	ROE	*Z*-score	ROE	*Z*-score	ROE
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Assets	2.951 ***	1.396	3.249 ***	0.939	3.483 ***	0.434	3.690 ***	0.001	3.876 ***	-0.626
	(1.016)	(2.895)	(1.177)	(2.960)	(1.238)	(2.996)	(1.363)	(3.001)	(1.459)	(2.970)
Asset growth	-0.047 ***	-0.003	-0.045 ***	-0.002	-0.048 ***	0.011	-0.055 ***	0.011	-0.055 ***	0.028
	(0.012)	(0.032)	(0.012)	(0.030)	(0.012)	(0.031)	(0.014)	(0.031)	(0.014)	(0.035)
Equity ratio	1.415 ***	-0.609	1.469 ***	-0.651	1.482 ***	-0.660	1.496 ***	-0.671	1.513 ***	-0.751 *
	(0.311)	(0.405)	(0.328)	(0.418)	(0.329)	(0.429)	(0.336)	(0.444)	(0.346)	(0.449)
Net profit margin	0.065 ***	0.977 ***	0.063 ***	0.993 ***	0.063 ***	0.992 ***	0.063 ***	0.992 ***	0.061 ***	1.001 ***
	(0.017)	(0.114)	(0.016)	(0.114)	(0.016)	(0.112)	(0.016)	(0.112)	(0.016)	(0.114)
GDP growth	-0.094	0.191	-0.038	0.294	-0.062	0.419	-0.065	0.442	-0.103	0.005
	(0.273)	(0.429)	(0.258)	(0.419)	(0.232)	(0.354)	(0.232)	(0.334)	(0.269)	(0.457)
Inflation	0.351	1.183 **	0.429	1.102 *	0.414	1.258 **	0.317	1.606 ***	0.305	1.264 **
	(0.295)	(0.570)	(0.275)	(0.595)	(0.285)	(0.551)	(0.288)	(0.579)	(0.283)	(0.605)
Slope-yield-curve	-0.800	-0.911	-0.813	-1.492	-0.934	-0.840	-1.062	-0.864	-0.803	-0.523
	(0.764)	(1.030)	(0.699)	(1.032)	(0.745)	(1.024)	(0.773)	(1.027)	(0.677)	(0.999)
SysRisk $*$ GDP growth	0.142 **	1.192 *	0.151 *	1.358 **	0.176 **	1.484 **	0.202 **	1.584 **	0.220 **	1.369 *
	(0.071)	(0.624)	(0.079)	(0.625)	(0.086)	(0.658)	(0.095)	(0.706)	(0.099)	(0.718)
SysRisk	0.746	-4.678 **	1.035 **	-4.440 **	1.310 ***	-5.095 ***	1.585 ***	-4.851 **	1.739 ***	-3.765 *
	(0.481)	(2.219)	(0.447)	(1.857)	(0.460)	(1.866)	(0.456)	(2.075)	(0.479)	(1.953)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
adjusted R^2	0.428	0.648	0.443	0.653	0.451	0.655	0.454	0.652	0.456	0.644
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
# of obs.	2,030	2,030	1,946	1,946	1,862	1,862	1,778	1,778	1,694	1,694

Table 3.9 – Systemically important banks' risk and return dynamics

All figures are estimated from quarterly sample bank characteristics and quarterly macroeconomic data from the European Union covering the period from July 2005 to June 2013. The table is organized as follows. Regressions that are assigned odd numbers feature Z-score as the dependent variable, whereas regressions with assigned even numbers feature return on equity (roe) as the dependent variable. A bank's *Z-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where *roa* is the return on assets, *car* the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. *Assets* is the natural logarithm of an institution's total assets (in EUR k) and *asset growth* is the quarterly growth rate of total assets. *Equity ratio* is the ratio of book equity over total assets. The *net profit margin* is defined as net income divided by gross sales and other operating revenue. *GDP growth* is the inflation-adjusted annualized growth rate of the EU's gross domestic product. *Inflation* is the inflation rate based on the Harmonised Index of Consumer Prices and *slope-yield-curve* is the differential between the 10- and 1-year German government bond yields. Asset growth, equity ratio, net profit margin, and all macroeconomic variables are expressed in percentage terms. *SysRisk $*$ GDP growth* denotes an interaction term between SysRisk and GDP growth. *SysRisk* is a dummy variable that within a given quarter equals *one* in case a bank's *SRISK* ranks among the 20% highest values (Quintile 1) within all sample banks and *zero* otherwise. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR m. All data are obtained from Datastream. For all above regressions we employ time and bank fixed effects and apply clustered standard errors at the bank level. Lag $k \in \{0, 1, 2, 3, 4\}$ indicates that the corresponding regression employs the *k-th* quarter lag of dummy variable SysRisk. For the ease of exposition we suppress the regressions' intercepts. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant (***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels).

First of all, Table 3.9 demonstrates that Quintile 1 institutions persistently underperform in comparison to the non-systemic sample bank for the following three consecutive quarters, which is indicated by a highly significant SysRisk dummy. Moreover, the above average pro-cyclicality of SIBs' profitability patterns becomes evident over time because their future return characteristics are persistently and significantly affected by GDP growth. A 1% increase of the GDP growth rate results in an improvement of SIBs' return on equity that is around 1.4% higher than that of non-SIBs.[5] During economic downturns or crises, however, SIBs' return generating activities are affected worst. Likewise, SIBs' future default risk characteristics are disproportionately affected by the state of the real economy.

From a theoretical point of view, without specifying a bank's business model, the economic cyclicality can, at least in part, be attributed to the size and leverage effect. By definition leverage increases the cyclical behavior of banks. In contrast, the size effect should reduce cyclicality due to larger banks' portfolio diversification benefits, economies of scope, and enhanced risk management capabilities that smooth their net incomes over time. SIBs rank among both the largest and the most leveraged. Obviously, the leverage effect dominates the size effect for Quintile 1 banks. SIBs' interconnectedness and economic integration may, however, additionally reinforce the pro-cyclicality of their default risk and return dynamics.

The resulting implications for regulation and supervision are twofold. First of all, for the development and execution of macroprudential stress-testing procedures the former distinctions are particularly important because SIBs' and non-SIBs' sensitivities with respect to macroeconomic shocks need to be accounted for in an adequate manner. Second, the increased pro-cyclicality of SIBs' default risk and return characteristics again highlights the usefulness of a regulation on leverage ratio constraints for the latter due to the fact that the leverage ratio is much more counter-cyclical than the current regulation on risk-weighted assets (Brei and Gambacorta, 2015). It is worth mentioning, however, that when the leverage ratio becomes a binding regulatory measure, it might lose its economic expediency and thus becomes an unreliable indicator in the spirit of Charles Goodhart (Goodhart's law), as banks reallocate their assets to optimize regulatory constraints and may find ways for regulatory arbitrage.

The results further reveal that in consecutive quarters, SIBs exhibit patterns of ameliorating levels of default risk. That is, banks that are classified as systemically important

[5] We calculate the SIB-specific time invariant return sensitivity by averaging across the estimated interaction term coefficients for lag length $k = 0, 1, 2, 3$, and 4.

steadily increase their Z-score within the subsequent four quarters, which may be explained as follows. On the one hand, SIBs disproportionately eliminated excess risk on their balance sheets as a response to the recent crises. On the other hand, Quintile 1 banks increased their capital ratios in anticipation of higher capital requirements. E.g., EU banks that are identified as systemically important have to fulfill enhanced capital requirements by 2016. For more details we refer to Directive 2013/36/EU (CRD IV).

The persistence of the marginal effects of systemic importance on SIBs' default risk and return dynamics also becomes very visible in Figure 3.6 which represents the estimates of coefficient $\hat{\kappa}$ from Equation (3.6). The blue shaded area indicates the two standard deviation confidence bands.

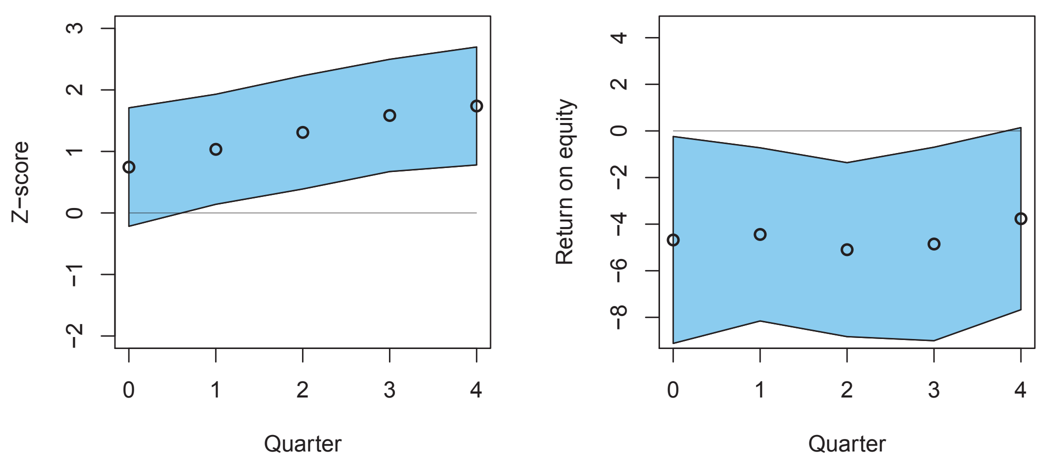


Figure 3.6 – Systemically important banks' default risk and return dynamics
The graph presents the marginal contributions of systemic importance on banks' Z-score and return on equity over time. The marginal contributions represent regression coefficients of (lagged) dummy variable *SysRisk* and are estimated according to Equation (3.6) from our sample of banks covering the period from July 2005 to June 2013. SysRisk refers to *Quintile 1* banks. We apply SRISK as a categorization criterion. Lag length $k \in \{0, 1, 2, 3, 4\}$ indicates that the corresponding dummy variable is lagged by k quarters. The blue shaded area indicates the two standard deviation confidence bands. Standard deviations are estimated allowing for clustered standard errors. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR m. A bank's Z*-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where roa is the return on assets, car the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. All stock price and balance sheet data are obtained from Datastream.

3.4.4 Robustness checks

In order to evaluate the stability of our results, we perform various robustness checks. In a first step, we change the subsample categorization from quintiles to quartiles and rerun the estimation of Equations (3.5) and (3.6). That is to say, SIBs are now defined as the 25% systemically most important banks within a given quarter. Most importantly, we are able to confirm our main results. Appendix-Tables 3.10 and 3.11 present the estimates. We additionally redefine the dummy variable SysRisk in order to capture the ten systemically most important banks within a given quarter. Again, the results under the *Top10* specification are similar to those reported in Section 3.4.3, though SIBs' default risk dynamics are now less significantly affected by macroeconomic growth (Appendix-Table 3.12).

Regarding the drivers of SRISK, we conduct a more rigorous robustness check including MES as an independent variable in Equation (3.6). We compute quarterly time series of MES by averaging across the weekly MES values referring to the respective quarter and express quarterly MES in percentage terms. In theory, banks featuring a lower MES are less affected by distressed financial markets, which in turn should be reflected in more favorable default risk and return dynamics. Appendix-Table 3.13 contains the estimates and supports our key findings. Institutions featuring higher levels of MES exhibit lower returns on equity. The effect of MES on banks' default risk characteristics is positive, though only slightly significant. The results confirm that SIBs' default risk and return dynamics cannot simply be explained by the sum of the SRISK drivers' marginal effects.

Furthermore, our results may be biased due to the simultaneous analysis of the marginal and cyclical effects of systemic importance on banks' default risk and return characteristics. In order to eliminate these concerns, we re-estimate Equations (3.5) and (3.6) including either the dummy variable SysRisk or the interaction term SysRisk * GDP growth. Panel A of Appendix-Table 3.14 contains the coefficients of interest for Quintile 1 institutions' Z-score and Panel B for Quintile 1 institutions' return on equity.

The observed particularities in SIBs' default risk and return patterns remain valid. All dummy variables and interaction terms within the Z-score regressions are at least significant at the 5% level. Consequentially, the results allow to reject the hypothesis that SIBs take excessive risks as a result of perceived government bailout guarantees. In addition, the economic significance of the cyclical effect of systemic importance on banks' probability of default strongly increases. The economic significance of the effect of systemic importance on banks' return characteristics decrease, however. Under the current regression specification, SIBs exhibit contemporaneous returns on equity that are 3.2% lower than those of non-SIBs while a 1% increase of the GDP growth rate results in an improvement of Quintile 1 banks' return characteristics that is around 0.6% higher than that of the average non-systemic bank. The default risk and return patterns of non-SIBs stay unchanged.

In order to account for the possibility that our main results are partly driven by endogenous default risk and return persistence, we again adopt a dynamic regression model specification by including the lag of the dependent variable among the regressors of Equation (3.6). Panel A of Appendix-Table 3.15 contains the key estimates. Variable *lag dependent* denotes the one period lag of the variable Z-score or return on equity. The results show that banks' default risk and return characteristics indeed feature time persistency. However, given the regression coefficients of the lagged dependent variables – approximately 0.65 for lagged Z-score and 0.40 for lagged return on equity – both measures will quickly return to their average levels. More important, though, we find that SIBs exhibit weaker contemporaneous return patterns than non-SIBs and that SIBs' systemic nature does not adversely affect their probability of default. Moreover, SIBs future default risk dynamics are significantly more pro-cyclical with respect to economic growth than those of non-SIBs. SIBs' future return patterns still feature some above average pro-cyclicality at the 10% confidence level.

We additionally use the generalized method of moments (GMM) estimation technique adopted by Arellano and Bond (1991) to re-estimate the dynamic regression model specification of Panel A. The GMM approach allows us to treat all explanatory variables as endogenous and uses their lagged values as their instruments. We thus deal with potential reverse causality effects between banks' default risk and return characteristics and the employed bank-specific regressors by treating all bank-specific control variables as endogenous. The macroeconomic control variables' time series are expected to be exogenous. We use the entire lag structure of the endogenous variables as their instruments and apply a finite sample correction as in Windmeijer (2005). Panel B of Appendix-Table 3.15 shows the coefficients of interest. Our results regarding the cyclical effects of systemic importance on Quintile 1 banks' default risk and return characteristics remain fairly unaltered. The magnitude of SIBs' underperformance, when compared to non-SIBs, slightly increases; however, the significance of the marginal effect decreases. As in Panel A, we are unable to find significant support for the perspective that a bank's systemic relevance adversely affects its probability of default. In total, the former robustness checks underline that endogeneity concerns are not significantly affecting our main results.

As an alternative to SRISK, we further use a measure of systemic importance in the spirit of the *Systemic Expected Shortfall* (SES) proposed by Acharya et al. (2010), where the time-varying version of the (unobservable) SES can be approximated by the MES.

Using the latter as the categorization criterion for systemic importance, we are able to confirm our results for SIBs' cyclical and marginal performance particularities at the 5% and 10% confidence level, respectively. Furthermore, systemic importance still cannot be associated with higher levels of banks' contemporaneous default risk. Institutions' MES, however, does not clearly differentiate between the economic cyclicality of SIBs' and non-SIBs' default risk characteristics. Appendix-Table 3.16 presents the results.

3.5 Conclusion

This paper analyzes how banks' systemic importance affects their financial stability on the basis of a broad representative sample of European banks covering the period from July 2005 to June 2013 which includes both the International Financial Crisis and the European Sovereign Debt Crisis. We evaluate banks' financial stability by focusing on their default risk and return characteristics and measure systemic importance by employing the SRISK concept. The latter quantifies the amount of government transfers needed in case of a bank failure and can be considered a measure for the externalities of bank distress.

Our findings are as follows. On the one hand, higher levels of systemic importance are not reflected in higher levels of contemporaneous default risk, challenging the popular notion that SIBs take excessive risks as a result of their too-important-to-fail status. Yet, existing differences in SIBs' and non-SIBs' default risk characteristics can be primarily attributed to variations in their equity ratios. Interestingly, our analysis further reveals that SIBs exhibit patterns of ameliorating default risk over time. The latter is likely to reflect recapitalization efforts in anticipation of higher capital requirements and reduced risk-taking as a response to the recent crises.

On the other hand, we find that institutions' systemic importance coincides with substantially weaker return patterns. In particular, SIBs exhibit annual returns on equity that are 4.7% lower than those of non-SIBs. This contradicts the shareholders' view that implicit government tail-risk guarantees for SIBs can be regarded as a free of charge long-term put option on their future income streams.

Furthermore, SIBs' contemporaneous and future default risk and return characteristics feature above average pro-cyclicality with respect to economic conditions. We do not find evidence that non-SIBs exhibit cyclicality patterns that are distinctively different from those of the average institution. Economic recessions thus disproportionately impede SIBs' financial stability. The distinctions between SIBs' and non-SIBs' are particularly important for the development and execution of macroprudential stress-testing procedures, because their different sensitivities with respect to economic shocks need to be accounted for in an adequate manner. The increased cyclicality of SIBs' financial stability additionally demonstrates that a close monitoring of economic integration and interconnectedness is of vital importance for the stability of the banking system.

In contrast to the popular notion that large institutions are most hazardous, we find that size is significantly negatively related to an institution's default risk, suggesting that the divesture of large institutions as a measure to increase banking stability would be inappropriate. In general, such measures can reduce economies of scale and scope, deteriorate risk management capacities, and adversely affect market liquidity (IMF, 2014).

Our results emphasize, however, the usefulness of imposing binding leverage ratio constraints on SIBs in order to effectively reduce their above average pro-cyclical behavior. The measure further limits banks' SRISK and thereby public transfers from taxpayers in case of bank failures or restructurings. It is worth mentioning, however, that when the leverage ratio becomes a binding regulatory measure, it might lose its economic expediency and thus becomes an unreliable indicator in the spirit of Charles Goodhart (Goodhart's law), as banks reallocate their assets to optimize regulatory constraints and may find ways for regulatory arbitrage.

3.A Supplementary tables

	Quartile 1		Quartile 2		Quartile 3		Quartile 4	
	Z-score	ROE	*Z*-score	ROE	*Z*-score	ROE	*Z*-score	ROE
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Assets	2.971 ***	1.393	2.899 ***	0.941	2.931 ***	1.032	2.901 ***	0.803
	(1.017)	(2.877)	(1.021)	(2.811)	(1.031)	(2.799)	(1.016)	(2.809)
Asset growth	-0.049 ***	-0.006	-0.050 ***	0.018	-0.049 ***	0.019	-0.051 ***	0.014
	(0.012)	(0.030)	(0.012)	(0.027)	(0.012)	(0.028)	(0.012)	(0.028)
Equity ratio	1.419 ***	-0.619	1.408 ***	-0.683 *	1.406 ***	-0.685 *	1.409 ***	-0.712 *
	(0.312)	(0.406)	(0.310)	(0.407)	(0.307)	(0.409)	(0.313)	(0.413)
Net profit margin	0.062 ***	0.978 ***	0.061 ***	1.005 ***	0.062 ***	1.001 ***	0.060 ***	0.993 ***
	(0.017)	(0.114)	(0.017)	(0.114)	(0.017)	(0.113)	(0.016)	(0.114)
GDP growth	-0.095	0.114	-0.082	0.379	-0.032	0.464	-0.054	0.356
	(0.273)	(0.432)	(0.267)	(0.513)	(0.266)	(0.474)	(0.293)	(0.487)
Inflation	0.339	1.170 *	0.328	1.195 **	0.336	1.164 **	0.329	1.161 **
	(0.295)	(0.636)	(0.292)	(0.593)	(0.297)	(0.582)	(0.291)	(0.580)
Slope-yield-curve	-0.848	-0.931	-0.837	-0.438	-0.830	-0.478	-0.854	-0.533
	(0.754)	(1.056)	(0.743)	(1.049)	(0.751)	(1.031)	(0.750)	(1.033)
SysRisk $*$ GDP growth	0.141 **	1.216 **	0.058	-0.249	-0.132 **	-0.447 *	-0.071	-0.404
	(0.068)	(0.542)	(0.105)	(0.323)	(0.062)	(0.257)	(0.116)	(0.300)
SysRisk	0.203	-4.011 **	-0.068	0.233	-0.178	0.653	0.217	2.151 **
	(0.389)	(1.601)	(0.316)	(0.846)	(0.295)	(0.763)	(0.370)	(1.057)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
p-value (*F*-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
# of obs.	2,030	2,030	2,030	2,030	2,030	2,030	2,030	2,030

Table 3.10 – Robustness tests: Systemic importance, bank default risk, and return

All figures are estimated from quarterly sample bank characteristics and quarterly macroeconomic data from the European Union covering the period from July 2005 to June 2013. The table is organized as follows. Regressions that are assigned odd numbers feature *Z*-score as the dependent variable, whereas regressions with assigned even numbers feature return on equity (roe) as the dependent variable. A bank's *Z-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where *roa* is the return on assets, *car* the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. *Assets* is the natural logarithm of an institution's total assets (in EUR k) and *asset growth* is the quarterly growth rate of total assets. *Equity ratio* is the ratio of book equity over total assets. The *net profit margin* is defined as net income divided by gross sales and other operating revenue. *GDP growth* is the inflation-adjusted annualized growth rate of the EU's gross domestic product. *Inflation* is the inflation rate based on the Harmonised Index of Consumer Prices and *slope-yield-curve* is the differential between the 10- and 1-year German government bond yields. Asset growth, equity ratio, net profit margin, and all macroeconomic variables are expressed in percentage terms. *SysRisk $*$ GDP growth* denotes an interaction term between SysRisk and GDP Growth. *SysRisk* is a dummy variable that within a given quarter equals *one* in case a bank's *SRISK* falls within the sample banks' respective quartile as given in the table header and *zero* otherwise. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR m. All data are obtained from Datastream. For all above regressions we employ time and bank fixed effects and apply clustered standard errors at the bank level. For the ease of exposition we suppress the regressions' intercepts. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant (***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels).

	Lag = 0		*Lag = 1*		*Lag = 2*		*Lag = 3*		*Lag = 4*	
	Z-score	ROE	*Z*-score	ROE	*Z*-score	ROE	*Z*-score	ROE	*Z*-score	ROE
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Assets	2.971 ***	1.393	3.257 ***	0.865	3.480 ***	0.339	3.701 ***	-0.088	3.848 **	-0.489
	(1.017)	(2.877)	(1.181)	(2.947)	(1.246)	(2.973)	(1.375)	(2.992)	(1.482)	(2.966)
Asset growth	-0.049 ***	-0.006	-0.046 ***	-0.002	-0.048 ***	0.018	-0.055 ***	0.021	-0.054 ***	0.035
	(0.012)	(0.030)	(0.012)	(0.032)	(0.012)	(0.033)	(0.013)	(0.033)	(0.014)	(0.034)
Equity ratio	1.419 ***	-0.619	1.473 ***	-0.670	1.485 ***	-0.697	1.502 ***	-0.721	1.514 ***	-0.768 *
	(0.312)	(0.406)	(0.328)	(0.421)	(0.330)	(0.433)	(0.338)	(0.448)	(0.346)	(0.452)
Net profit margin	0.062 ***	0.978 ***	0.061 ***	0.995 ***	0.061 ***	1.002 ***	0.061 ***	1.006 ***	0.058 ***	1.009 ***
	(0.017)	(0.114)	(0.016)	(0.115)	(0.016)	(0.114)	(0.016)	(0.113)	(0.016)	(0.114)
GDP growth	-0.095	0.114	-0.055	0.301	-0.044	0.247	-0.068	0.376	-0.148	0.116
	(0.273)	(0.432)	(0.257)	(0.425)	(0.231)	(0.406)	(0.232)	(0.348)	(0.264)	(0.428)
Inflation	0.339	1.170 *	0.379	1.303 **	0.408	1.204 **	0.379	1.335 **	0.269	1.299 **
	(0.295)	(0.636)	(0.277)	(0.597)	(0.287)	(0.564)	(0.282)	(0.539)	(0.267)	(0.547)
Slope-yield-curve	-0.848	-0.931	-0.876	-1.210	-0.880	-1.117	-1.054	-0.882	-0.902	-0.179
	(0.754)	(1.056)	(0.694)	(1.018)	(0.741)	(1.135)	(0.765)	(1.046)	(0.667)	(0.832)
SysRisk $*$ GDP growth	0.141 **	1.216 **	0.155 **	1.201 **	0.164 **	1.233 **	0.183 **	1.255 **	0.211 **	1.037 *
	(0.068)	(0.542)	(0.074)	(0.550)	(0.076)	(0.563)	(0.080)	(0.601)	(0.085)	(0.612)
SysRisk	0.203	-4.011 **	0.692 *	-3.231 **	0.864 **	-2.847 *	1.154 ***	-2.373	1.203 ***	-1.370
	(0.389)	(1.601)	(0.385)	(1.474)	(0.386)	(1.573)	(0.422)	(1.815)	(0.409)	(1.830)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
p-value (*F*-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
# of obs.	2,030	2,030	1,946	1,946	1,862	1,862	1,778	1,778	1,694	1,694

Table 3.11 – Robustness tests: Systemically important banks' risk and return dynamics (Quartile 1 regressions)
All figures are estimated from quarterly sample bank characteristics and quarterly macroeconomic data from the European Union covering the period from July 2005 to June 2013. The table is organized as follows. Regressions that are assigned odd numbers feature *Z*-score as the dependent variable, whereas regressions with assigned even numbers feature return on equity (roe) as the dependent variable. A bank's *Z-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where roa is the return on assets, car the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. *Assets* is the natural logarithm of an institution's total assets (in EUR k) and *asset growth* is the quarterly growth rate of total assets. *Equity ratio* is the ratio of book equity over total assets. The *net profit margin* is defined as net income divided by gross sales and other operating revenue. *GDP growth* is the inflation-adjusted annualized growth rate of the EU's gross domestic product. *Inflation* is the inflation rate based on the Harmonised Index of Consumer Prices and *slope-yield-curve* is the differential between the 10- and 1-year German government bond yields. Asset growth, equity ratio, net profit margin, and all macroeconomic variables are expressed in percentage terms. *SysRisk* $*$ *GDP growth* denotes an interaction term between SysRisk and GDP growth. *SysRisk* is a dummy variable that within a given quarter equals *one* in case a bank's *SRISK* ranks among the 25% highest values (Quartile 1) within all sample banks and *zero* otherwise. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR m. All data are obtained from Datastream. For all above regressions we employ time and bank fixed effects and apply clustered standard errors at the bank level. Lag $k \in \{0, 1, 2, 3, 4\}$ indicates that the corresponding regression employs the *k-th* quarter lag of dummy variable SysRisk. For the ease of exposition we suppress the regressions' intercepts. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant (***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels).

	Lag = 0		*Lag = 1*		*Lag = 2*		*Lag = 3*		*Lag = 4*	
	Z-score	ROE	Z-score	ROE	Z-score	ROE	Z-score	ROE	Z-score	ROE
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Assets	2.954 ***	1.160	3.242 ***	0.536	3.427 ***	0.077	3.593 **	-0.191	3.718 **	-0.755
	(1.026)	(2.845)	(1.186)	(2.882)	(1.245)	(2.928)	(1.387)	(3.029)	(1.511)	(3.143)
Asset growth	-0.049 ***	0.004	-0.046 ***	-0.001	-0.050 ***	0.020	-0.054 ***	0.027	-0.058 ***	0.034
	(0.012)	(0.032)	(0.012)	(0.031)	(0.012)	(0.030)	(0.014)	(0.030)	(0.013)	(0.031)
Equity ratio	1.418 ***	-0.654	1.473 ***	-0.708 *	1.480 ***	-0.715 *	1.496 ***	-0.720	1.507 ***	-0.793 *
	(0.313)	(0.405)	(0.330)	(0.415)	(0.330)	(0.427)	(0.340)	(0.442)	(0.351)	(0.457)
Net profit margin	0.062 ***	0.993 ***	0.060 ***	1.002 ***	0.061 ***	1.005 ***	0.060 ***	1.011 ***	0.059 ***	1.013 ***
	(0.017)	(0.112)	(0.016)	(0.112)	(0.016)	(0.112)	(0.016)	(0.113)	(0.016)	(0.116)
GDP growth	-0.068	0.107	0.001	0.173	-0.053	0.460	-0.023	0.482	-0.117	0.211
	(0.274)	(0.461)	(0.261)	(0.461)	(0.231)	(0.369)	(0.233)	(0.357)	(0.263)	(0.417)
Inflation	0.356	1.163 *	0.475 *	0.835	0.438	1.206 **	0.390	1.424 ***	0.323	1.204 **
	(0.298)	(0.652)	(0.278)	(0.631)	(0.282)	(0.567)	(0.280)	(0.544)	(0.259)	(0.538)
Slope-yield-curve	-0.865	-0.665	-0.829	-1.617	-1.060	-0.480	-1.007	-0.899	-0.911	-0.226
	(0.755)	(1.082)	(0.694)	(1.162)	(0.736)	(1.038)	(0.762)	(1.046)	(0.654)	(0.836)
SysRisk $*$ GDP growth	0.133	0.959 **	0.150	1.107 **	0.169	1.199 **	0.202 *	0.920 **	0.229 **	0.496
	(0.083)	(0.425)	(0.097)	(0.448)	(0.106)	(0.513)	(0.108)	(0.426)	(0.110)	(0.372)
SysRisk	0.588	-4.023 *	1.017 *	-4.784 **	1.334 **	-4.369 ***	1.433 ***	-3.116 **	1.419 ***	-3.553 **
	(0.512)	(2.357)	(0.533)	(1.851)	(0.519)	(1.522)	(0.488)	(1.500)	(0.460)	(1.796)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
# of obs.	2,030	2,030	1,946	1,946	1,862	1,862	1,778	1,778	1,694	1,694

Table 3.12 – Robustness tests: Systemically important banks' risk and return dynamics (Top10 regressions)
All figures are estimated from quarterly sample bank characteristics and quarterly macroeconomic data from the European Union covering the period from July 2005 to June 2013. The table is organized as follows. Regressions that are assigned odd numbers feature Z-score as the dependent variable, whereas regressions with assigned even numbers feature return on equity (roe) as the dependent variable. A bank's *Z-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where *roa* is the return on assets, *car* the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. *Assets* is the natural logarithm of an institution's total assets (in EUR k) and *asset growth* is the quarterly growth rate of total assets. *Equity ratio* is the ratio of book equity over total assets. The *net profit margin* is defined as net income divided by gross sales and other operating revenue. *GDP growth* is the inflation-adjusted annualized growth rate of the EU's gross domestic product. *Inflation* is the inflation rate based on the Harmonised Index of Consumer Prices and *slope-yield-curve* is the differential between the 10- and 1-year German government bond yields. Asset growth, equity ratio, net profit margin, and all macroeconomic variables are expressed in percentage terms. *SysRisk $*$ GDP growth* denotes an interaction term between SysRisk and GDP growth. *SysRisk* is a dummy variable that within a given quarter equals *one* in case a bank's *SRISK* ranks among the ten highest values (Top10) within all sample banks and *zero* otherwise. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR m. All data are obtained from Datastream. For all above regressions we employ time and bank fixed effects and apply clustered standard errors at the bank level. Lag $k \in \{0, 1, 2, 3, 4\}$ indicates that the corresponding regression employs the *k-th* quarter lag of dummy variable SysRisk. For the ease of exposition we suppress the regressions' intercepts. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant (***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels).

	Lag = 0		*Lag = 1*		*Lag = 2*		*Lag = 3*		*Lag = 4*	
	Z-score	ROE	*Z*-score	ROE	*Z*-score	ROE	*Z*-score	ROE	*Z*-score	ROE
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Assets	2.947 ***	1.376	3.250 ***	0.945	3.486 ***	0.444	3.700 ***	0.038	3.894 ***	-0.551
	(1.034)	(2.661)	(1.204)	(2.724)	(1.265)	(2.780)	(1.388)	(2.791)	(1.481)	(2.764)
Asset growth	-0.048 ***	-0.009	-0.047 ***	-0.008	-0.050 ***	0.003	-0.058 ***	-0.001	-0.059 ***	0.014
	(0.012)	(0.030)	(0.012)	(0.029)	(0.012)	(0.030)	(0.014)	(0.030)	(0.014)	(0.032)
Equity ratio	1.414 ***	-0.612	1.469 ***	-0.654	1.480 ***	-0.669	1.493 ***	-0.682	1.511 ***	-0.761 *
	(0.310)	(0.392)	(0.326)	(0.405)	(0.327)	(0.415)	(0.334)	(0.429)	(0.343)	(0.433)
Net profit margin	0.059 ***	0.953 ***	0.057 ***	0.968 ***	0.056 ***	0.968 ***	0.057 ***	0.966 ***	0.054 ***	0.972 ***
	(0.018)	(0.113)	(0.018)	(0.114)	(0.017)	(0.112)	(0.017)	(0.112)	(0.017)	(0.114)
MES	-0.043 *	-0.189 **	-0.047 *	-0.182 **	-0.049 *	-0.182 **	-0.049 *	-0.192 **	-0.050 *	-0.210 **
	(0.026)	(0.095)	(0.025)	(0.091)	(0.025)	(0.090)	(0.026)	(0.090)	(0.027)	(0.094)
GDP growth	-0.106	0.137	-0.056	0.223	-0.080	0.353	-0.076	0.398	-0.115	-0.045
	(0.272)	(0.392)	(0.253)	(0.381)	(0.228)	(0.320)	(0.227)	(0.298)	(0.262)	(0.412)
Inflation	0.304	0.975 *	0.378	0.905	0.359	1.053 **	0.257	1.370 **	0.243	1.006 *
	(0.280)	(0.549)	(0.261)	(0.579)	(0.267)	(0.529)	(0.271)	(0.533)	(0.271)	(0.573)
Slope-yield-curve	-0.758	-0.726	-0.753	-1.260	-0.899	-0.712	-1.050	-0.815	-0.778	-0.416
	(0.727)	(0.877)	(0.659)	(0.887)	(0.703)	(0.846)	(0.734)	(0.856)	(0.638)	(0.854)
SysRisk $*$ GDP growth	0.127 *	1.128 *	0.136 *	1.298 **	0.161 *	1.428 **	0.187 *	1.524 **	0.206 **	1.312 *
	(0.072)	(0.603)	(0.080)	(0.599)	(0.087)	(0.628)	(0.095)	(0.675)	(0.099)	(0.688)
SysRisk	0.878 *	-4.096 *	1.169 **	-3.919 **	1.424 ***	-4.669 ***	1.692 ***	-4.434 **	1.834 ***	-3.368 *
	(0.504)	(2.281)	(0.465)	(1.816)	(0.474)	(1.793)	(0.468)	(1.969)	(0.490)	(1.860)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
p-value (*F*-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
# of obs.	2,030	2,030	1,946	1,946	1,862	1,862	1,778	1,778	1,694	1,694

Table 3.13 – Robustness tests: Systemically important banks' risk and return dynamics (including MES as independent variable) All figures are estimated from quarterly sample bank characteristics and quarterly macroeconomic data from the European Union covering the period from July 2005 to June 2013. The table is organized as follows. Regressions that are assigned odd numbers feature Z-score as the dependent variable, whereas regressions with assigned even numbers feature return on equity (roe) as the dependent variable. A bank's *Z-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where *roa* is the return on assets, *car* the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. *Assets* is the natural logarithm of an institution's total assets (in EUR k) and *asset growth* is the quarterly growth rate of total assets. *Equity ratio* is the ratio of book equity over total assets. The *net profit margin* is defined as net income divided by gross sales and other operating revenue. *MES* measures a bank's expected stock market return conditional on the banking system's tail return. *GDP growth* is the inflation-adjusted annualized growth rate of the EU's gross domestic product. *Inflation* is the inflation rate based on the Harmonised Index of Consumer Prices and *slope-yield-curve* is the differential between the 10- and 1-year German government bond yields. Asset growth, equity ratio, net profit margin, MES, and all macroeconomic variables are expressed in percentage terms. *SysRisk $*$ GDP growth* denotes an interaction term between SysRisk and GDP growth. *SysRisk* is a dummy variable that within a given quarter equals *one* in case a bank's *SRISK* ranks among the 20% highest values (Quintile 1) within all sample banks and *zero* otherwise. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR m. All data are obtained from Datastream. For all above regressions we employ time and bank fixed effects and apply clustered standard errors at the bank level. Lag $k \in \{0, 1, 2, 3, 4\}$ indicates that the corresponding regression employs the *k-th* quarter lag of dummy variable SysRisk. For the ease of exposition we suppress the regressions' intercepts. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant (***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels).

Panel A – Z-score

	Lag = 0		*Lag = 1*		*Lag = 2*		*Lag = 3*		*Lag = 4*	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SysRisk ∗ GDP growth	0.204 **		0.231 **		0.267 ***		0.298 ***		0.311 **	
	(0.081)		(0.091)		(0.103)		(0.114)		(0.122)	
SysRisk		0.963 **		1.251 ***		1.536 ***		1.811 ***		1.945 ***
		(0.485)		(0.466)		(0.495)		(0.501)		(0.533)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
# of obs.	2,030	2,030	1,946	1,946	1,862	1,862	1,778	1,778	1,694	1,694

Panel B – return on equity

	Lag = 0		*Lag = 1*		*Lag = 2*		*Lag = 3*		*Lag = 4*	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SysRisk ∗ GDP growth	0.613 **		0.642 **		0.691 **		0.770 **		0.693 **	
	(0.295)		(0.297)		(0.303)		(0.306)		(0.330)	
SysRisk		-3.190 ***		-2.941 ***		-2.870 ***		-2.499 ***		-2.068 **
		(1.075)		(0.959)		(0.923)		(0.950)		(0.803)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
# of obs.	2,030	2,030	1,946	1,946	1,862	1,862	1,778	1,778	1,694	1,694

Table 3.14 – Robustness tests: Systemically important banks' risk and return dynamics (separate regression analysis)
All figures are estimated from quarterly sample bank characteristics and quarterly macroeconomic data from the European Union covering the period from July 2005 to June 2013. The table is organized as follows. Panel A features Z-score as the dependent variable, whereas Panel B features return on equity as the dependent variable. A bank's *Z-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where *roa* is the return on assets, *car* the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. *SysRisk* ∗ *GDP growth* denotes an interaction term between SysRisk and GDP growth. *SysRisk* is a dummy variable that within a given quarter equals *one* in case a bank's *SRISK* ranks among the 20% highest values (Quintile 1) within all sample banks and *zero* otherwise. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR *m*. *GDP growth* is the inflation-adjusted annualized growth rate of the EU's gross domestic product expressed in percentage terms. All data are obtained from Datastream. For all above regressions we employ time and bank fixed effects and apply clustered standard errors at the bank level. Lag $k \in \{0, 1, 2, 3, 4\}$ indicates that the corresponding regression employs the k-*th* quarter lag of dummy variable SysRisk. For the ease of exposition we suppress the regressions' intercepts and the coefficients of all control variables employed in Equation (3.6). Standard errors are given in parentheses. Regression coefficients are assigned asterisks if they are statistically significant (***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels).

Panel A – endogenous risk and return persistence

	Lag = 0		*Lag = 1*		*Lag = 2*		*Lag = 3*		*Lag = 4*	
	Z-score	ROE	*Z*-score	ROE	*Z*-score	ROE	*Z*-score	ROE	*Z*-score	ROE
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lag dependent	0.651 ***	0.414 ***	0.671 ***	0.406 ***	0.672 ***	0.390 ***	0.665 ***	0.375 ***	0.659 ***	0.365 ***
	(0.045)	(0.097)	(0.039)	(0.100)	(0.039)	(0.102)	(0.039)	(0.104)	(0.040)	(0.107)
SysRisk * GDP growth	0.037	0.515	0.048 *	0.625	0.062 **	0.740 *	0.075 **	0.768 *	0.085 **	0.572
	(0.028)	(0.345)	(0.029)	(0.380)	(0.032)	(0.428)	(0.034)	(0.462)	(0.037)	(0.413)
SysRisk	0.433 **	-2.750 **	0.519 ***	-1.913	0.639 ***	-2.737 *	0.773 ***	-2.328	0.794 ***	-0.754
	(0.204)	(1.253)	(0.163)	(1.223)	(0.194)	(1.561)	(0.203)	(1.692)	(0.238)	(1.510)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	No	No	No	No	No	No	No	No	No
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
p-value (*F*-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
# of obs.	1,946	1,946	1,862	1,862	1,778	1,778	1,694	1,694	1,610	1,610

Panel B – reverse causalities

	Lag = 0		*Lag = 1*		*Lag = 2*		*Lag = 3*		*Lag = 4*	
	Z-score	ROE	*Z*-score	ROE	*Z*-score	ROE	*Z*-score	ROE	*Z*-score	ROE
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lag dependent	0.659 ***	0.397 ***	0.655 ***	0.393 ***	0.656 ***	0.384 ***	0.654 ***	0.376 ***	0.650 ***	0.377 ***
	(0.038)	(0.100)	(0.038)	(0.101)	(0.037)	(0.104)	(0.038)	(0.104)	(0.039)	(0.106)
SysRisk ∗ GDP growth	0.032	0.528	0.051	0.619 *	0.074 **	0.755 *	0.082 **	0.773 *	0.081 *	0.542
	(0.030)	(0.340)	(0.034)	(0.368)	(0.037)	(0.406)	(0.042)	(0.443)	(0.043)	(0.388)
SysRisk	0.523 ***	-3.424 **	0.770 ***	-2.528 *	0.837 ***	-2.879	1.001 ***	-2.492	0.935 ***	-0.942
	(0.197)	(1.496)	(0.198)	(1.300)	(0.240)	(1.765)	(0.252)	(1.819)	(0.282)	(1.612)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Test for AR(1) (*p*-value)	0.000	0.031	0.000	0.030	0.000	0.024	0.000	0.031	0.000	0.032
Test for AR(2) (*p*-value)	0.095	0.351	0.093	0.421	0.091	0.390	0.123	0.490	0.120	0.388
Hansen test (*p*-value)	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
# of obs.	1,862	1,862	1,862	1,862	1,778	1,778	1,694	1,694	1,610	1,610

Table 3.15 – Robustness tests: Systemically important banks' risk and return dynamics (endogeneity issues)

Table 3.15 – continued:
All figures are estimated from quarterly sample bank characteristics and quarterly macroeconomic data from the European Union covering the period from July 2005 to June 2013. The table is organized as follows. Panel A exhibits the results of Equation (3.6) including the one period lag of the regressions' dependent variable among the bank-specific regressors and Panel B exhibits the results of the same regression employing the generalized method of moments (GMM) estimation technique with finite sample correction. Regressions that are assigned odd numbers feature Z-score as the dependent variable, whereas regressions with assigned even numbers feature return on equity (roe) as the dependent variable. A bank's *Z-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where *roa* is the return on assets, *car* the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. *Lag dependent* is the one period lag of the dependent variable Z-score or return on equity. *SysRisk* $*$ *GDP growth* denotes an interaction term between SysRisk and GDP growth. *SysRisk* is a dummy variable that within a given quarter equals *one* in case a bank's *SRISK* ranks among the 20% highest values (Quintile 1) within all sample banks and *zero* otherwise. *SRISK* is a bank's expected undercapitalization conditional on a future financial crisis expressed in EUR *m*. *GDP growth* is the inflation-adjusted annualized growth rate of the EU's gross domestic product expressed in percentage terms. All data are obtained from Datastream. For all above regressions we employ time fixed and/or bank fixed effects and apply clustered standard errors at the bank level. Lag $k \in \{0, 1, 2, 3, 4\}$ indicates that the corresponding regression employs the *k-th* quarter lag of dummy variable SysRisk. For the ease of exposition we suppress the regressions' intercepts and the coefficients of all control variables. Standard errors are given in parentheses. The Hansen test refers to the difference-in-Hansen tests statistic of exogeneity of the instruments in GMM dynamic model estimation ($H0$: instruments are exogenous). AR(1) and AR(2) refer to the Arellano-Bond test that the average auto-covariance in residuals of order one and two, respectively, is zero. The regression coefficients are assigned asterisks if they are statistically significant (***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels).

	Lag = 0		*Lag = 1*		*Lag = 2*		*Lag = 3*		*Lag = 4*	
	Z-score	ROE	*Z*-score	ROE	*Z*-score	ROE	*Z*-score	ROE	*Z*-score	ROE
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Assets	2.930 ***	0.398	3.197 ***	-0.189	3.360 ***	-0.327	3.526 **	-0.555	3.660 **	-0.813
	(1.026)	(2.522)	(1.188)	(2.606)	(1.256)	(2.841)	(1.403)	(2.962)	(1.527)	(3.067)
Asset growth	-0.050 ***	0.019	-0.048 ***	0.015	-0.050 ***	0.033	-0.053 ***	0.031	-0.057 ***	0.038
	(0.012)	(0.027)	(0.012)	(0.028)	(0.012)	(0.029)	(0.014)	(0.031)	(0.014)	(0.031)
Equity ratio	1.409 ***	-0.678 *	1.461 ***	-0.743 *	1.470 ***	-0.757 *	1.484 ***	-0.764 *	1.491 ***	-0.794 *
	(0.309)	(0.394)	(0.325)	(0.409)	(0.326)	(0.428)	(0.334)	(0.446)	(0.343)	(0.460)
Net profit margin	0.063 ***	0.971 ***	0.061 ***	0.987 ***	0.059 ***	1.010 ***	0.058 ***	1.019 ***	0.057 ***	1.020 ***
	(0.017)	(0.113)	(0.016)	(0.115)	(0.016)	(0.115)	(0.016)	(0.115)	(0.016)	(0.116)
GDP growth	-0.047	-0.090	0.022	-0.035	-0.006	0.437	0.017	0.471	-0.072	0.193
	(0.278)	(0.463)	(0.265)	(0.463)	(0.234)	(0.402)	(0.236)	(0.378)	(0.272)	(0.458)
Inflation	0.329	1.181 *	0.422	0.592	0.390	1.226 *	0.373	1.403 **	0.307	1.230 **
	(0.297)	(0.637)	(0.280)	(0.680)	(0.283)	(0.687)	(0.277)	(0.581)	(0.263)	(0.540)
Slope-yield-curve	-0.836	-0.403	-0.822	-1.654	-0.957	-0.246	-0.965	-0.748	-0.880	-0.186
	(0.755)	(1.087)	(0.686)	(1.187)	(0.732)	(1.216)	(0.768)	(1.093)	(0.658)	(0.840)
SysRisk $*$ GDP growth	-0.100	1.778 **	-0.120	1.665 **	-0.107	1.222 *	-0.108	0.719	-0.093	0.692
	(0.071)	(0.721)	(0.079)	(0.739)	(0.075)	(0.631)	(0.093)	(0.460)	(0.116)	(0.521)
SysRisk	0.161	-4.552 *	0.323	-4.745 *	0.333	-2.759	0.461	-2.041 *	0.654	-1.072
	(0.412)	(2.412)	(0.457)	(2.517)	(0.420)	(1.726)	(0.492)	(1.126)	(0.484)	(1.116)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
p-value (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
# of obs.	2,030	2,030	1,946	1,946	1,862	1,862	1,778	1,778	1,694	1,694

Table 3.16 – Robustness tests: Systemically important banks' risk and return dynamics (MES as categorization criterion)
All figures are estimated from quarterly sample bank characteristics and quarterly macroeconomic data from the European Union covering the period from July 2005 to June 2013. The table is organized as follows. Regressions that are assigned odd numbers feature Z-score as the dependent variable, whereas regressions with assigned even numbers feature return on equity (roe) as the dependent variable. A bank's *Z-score* is a measure of bank solvency and is defined as $(roa_t + car_t)/\sigma_{roa}$, where *roa* is the return on assets, *car* the capital asset ratio, and σ denotes the standard deviation; t refers to the respective quarter. *Return on equity* is defined as the annualized ratio of net income over book equity expressed in percentage terms. *Assets* is the natural logarithm of an institution's total assets (in EUR k) and *asset growth* is the quarterly growth rate of total assets. *Equity ratio* is the ratio of book equity over total assets. The *net profit margin* is defined as net income divided by gross sales and other operating revenue. *GDP growth* is the inflation-adjusted annualized growth rate of the EU's gross domestic product. *Inflation* is the inflation rate based on the Harmonised Index of Consumer Prices and *slope-yield-curve* is the differential between the 10- and 1-year German government bond yields. Asset growth, equity ratio, net profit margin, and all macroeconomic variables are expressed in percentage terms. *SysRisk* $*$ *GDP growth* denotes an interaction term between SysRisk and GDP growth. *SysRisk* is a dummy variable that within a given quarter equals *one* in case a bank's *MES* ranks among the ten highest values (Top10) within all sample banks and *zero* otherwise. *MES* is a bank's expected h-day stock return given that the banking system's h-day return falls below a predefined threshold C, indicating a severe crisis in the banking system expressed in percentage terms. All data are obtained from Datastream. For all above regressions we employ time and bank fixed effects and apply clustered standard errors at the bank level. Lag $k \in \{0, 1, 2, 3, 4\}$ indicates that the corresponding regression employs the k-*th* quarter lag of dummy variable SysRisk. For the ease of exposition we suppress the regressions' intercepts. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant (***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels).

4 Risk-adjusted bank performance and income diversification

4.1 Introduction

Euro area banks are still suffering from the consequences of the International Financial Crisis of 2007 to 2009 and the European Sovereign Debt Crisis. Especially the significantly higher regulatory capital requirements introduced in response to the systemic event that followed the Lehman bankruptcy with the aim to increase the resilience of the European banking system squeeze bank profitability.[1] Moreover, the current approach of the European Central Bank to revive the euro area economy with rock bottom interest rates becomes a growing drag on banks' profitability as returns from maturity transformation erode and negative interest rates cannot easily be passed on to depositors. Enhanced competition from Fintechs, i.e., financial technology companies, and the trend towards a higher digitization of banking services and products is not particularly helpful for traditional credit institutions either.

As profitability in general and margins from interest income activities in particular, decrease, supervisors and regulators increasingly urge banks to rethink their current business models (see, e.g., Deutsche Bundesbank, 2014, Financial Stability Review). In contrast to the public opinion, the former do care about future bank profitability because sustainably profitable institutions are less likely to default in times of crises and thus increase banking system stability. The newly introduced Supervisory Review and Evaluation Process (SREP) follows this line of argument and directly assesses the sustainability of European banks' business models for regulatory purposes.

One possibility to increase banks' business model profitability is, given the current economic environment, and besides cost cutting efforts, the increased diversification into non-interest income activities. Such a diversification could be especially advantageous for commercial banks, co-operative banks, and savings banks that rely heavily on interest income (Demirgüç-Kunt and Huizinga, 2010).

From a theoretical point of view, based on the insights of Markowitz (1952) and his approach to portfolio theory, the diversification into non-interest income activities should smooth a bank's revenue and income streams and thus increase its risk-return profile as long as interest income and non-interest income activities do not exhibit a perfect

[1] The Basel III capital requirements were endorsed by European law in 2013 by the adoption of the Capital Requirements Regulation (Regulation 2013/575/EU).

positive correlation. Furthermore, diversifying into activities such as fees, commissions, and trading could soften the squeeze of banks' net interest margins. In contrast to the former, however, an increase in the non-interest income share could also lead to higher earnings volatility over the business cycle (Stiroh and Rumble, 2006), increased organizational complexity, decreased benefits from specialization, and cross-subsidization effects between interest income and non-interest income generating activities (Lepetit et al., 2008), reducing the benefits of diversification.

To enrich the debate about income diversification, this paper provides empirical evidence on whether an increase in banks' non-interest income share increases their risk-adjusted performance patterns. We consider this issue for a large sample of euro area banks covering the period from 2007 to 2014, which is especially useful as current literature focuses mainly on the U.S. banking system but lacks studies covering the European banking system (Busch and Kick, 2015). However, given the differences between the U.S. and the European banking systems, insights from the former are unlikely to be appropriate for the latter (DeYoung and Rice, 2004).

Our paper contributes to the literature in three important ways. To the best of our knowledge, we are the first to measure the effect of income diversification on banks' profitability patterns employing the variable return on risk-weighted assets (RoRWA). We make use of this particular profitability ratio for the following reasons. First, the RoRWA directly proxies for the underlying risk of banks' credit, market, and operational exposures and thus makes the performance of banks' business models more comparable than measures like the return on assets or the return on equity, which do not account for different levels of risk taking. Second, maximizing measures in the spirit of a bank's return on risk-adjusted capital should, at least in theory, maximize the value of market equity and hence overall bank performance. We proxy for income diversification and its subcomponents by calculating the shares of non-interest income, fee income, trading income, and other non-interest income in total operating income.

Moreover, we conduct a careful analysis of the underlying factors that determine the relationship between income diversification and profitability. For this reason, we explicitly control for the effects of different type of banks and bank sizes. Finally, instead of estimating the income diversification effects employing OLS regressions and later on conducting robustness tests using IV regressions in order to control for endogeneity issues, we rigorously make use of the two-step system GMM (generalized method of moments) approach developed by Arellano and Bover (1995) and Blundell and Bond (1998). The system GMM estimation technique has two major advantages. First, the approach directly allows us to treat all explanatory variables as endogenous, which is essential given the fact that we can easily expect reverse causalities between bank performance, income diversification, and bank-specific control variables. Second, the system GMM estimator simultaneously controls for unobserved heterogeneity across sample banks by first differencing all regression variables.

Our empirical analysis reveals that a diversification into non-interest related activities significantly increases euro area banks' return on risk-weighted assets, supporting the existence of economies of scope. That is to say, an increase in both the fee income share and the trading income share increases the average bank's risk-adjusted performance pattern. Yet, the economic significances of both diversification measures differ substantially. On average, banks can boost their performance twice as much by relatively expanding their trading activities instead of trying to expand their relative income from fees and commissions. We additionally find evidence that diversifying into other non-interest income activities is disadvantageous for a bank's profitability. The latter is in line with the point of view that income diversification is only beneficial if it is based on core banking activities.

We conduct a number of robustness tests, which indicate that the economic significances that we find in our baseline regression analysis are fairly robust. However, we also find that the relation between non-interest income diversification and aggregate bank profitability is substantially driven by bank type and bank size. Especially investment banks and banks with a stock exchange listing excel at utilizing economies of scope resulting from fee generating activities, whereas the evidence that other type of banks can actually increase their return on risk-weighted assets by relatively increasing their business related to fees and commissions is less clear-cut. This less significant relation for other type of banks, namely commercial banks, co-operative banks, and savings banks, thus gives rise to the conjecture that for the latter the dark side of diversification outweighs, i.e., the additional revenues from increases in the fee income share do not significantly exceed the additional expenses and potential costs from cross-subsidization.

The effect of the trading income share on banks' return patterns is not distorted by the type of a bank, but depends on bank size. Small banks are able to significantly increase their return on risk-weighted assets by diversifying their revenue streams into trading activities. Nevertheless, the diversification of small banks' revenue streams into trading income generating activities cannot be easily realized in practice. The implementation of new trading desks, especially for banks that have not been engaged in trading in the past, comes at very high costs and needs supervisory permission. Small banks could, however, without the need to establish own trading desks, participate from the advantages of an increased trading income share by setting up co-operation models with specialized financial institutions.

In contrast, for medium-sized and large banks, the trading income share is insignificantly related to risk-adjusted bank profitability. As a consequence, increasing these banks' trading activities, on average, should not substantially enhance their performance patterns, suggesting that medium-sized and large banks already exhibit optimal trading income ratios.

The remainder of the paper is structured as follows. Section 4.2 provides an overview of the literature related to bank profitability and income diversification, Section 4.3 elaborates on the sample selection, the variables employed in our analysis, the estimation methodology, and gives summary statistics, Sections 4.4 and 4.5 present and discuss our empirical results and robustness tests, and Section 4.6 concludes.

4.2 Related literature

The literature on the determinants of bank profitability can be broadly separated into studies analyzing the effects of internal determinants, external determinants or both. The internal determinants include bank-specific variables and the external determinants represent macroeconomic and industry-specific variables such as GDP growth, bank regulation or industry concentration. In the following, we present a selection of important contributions to the literature.

Early work done by Short (1979) showed that a greater industry concentration is beneficial for bank profitability and Bourke (1989) found that higher capital ratios and higher interest rates lead to higher profits. More recent studies such as Demirgüç-Kunt and Huizinga (1999), Micco et al. (2007), and Pathan and Faff (2013) find that bank taxation, deposit insurance regulation, legal and political indicators, bank ownership, and board structure significantly affect bank profitability.

Focusing on bank-specific variables, García-Herrero et al. (2009), among others, provide further evidence that a bank's capital ratio is significantly positively related to its return on assets, Berger and Bouwman (2013) show that banks with higher capital ratios tend to perform better in times of crises, and Goddard et al. (2013) and Dietrich and Wanzenried (2011) provide empirical evidence that operational efficiency, total loan growth, and lower funding costs positively affect bank profitability. Recent studies analyzing the link between the business cycle and macroeconomic conditions and bank profitability in more detail are Albertazzi and Gambacorta (2009) and Bolt et al. (2012). Both studies find a significant and positive relation between the growth rates of a country's gross domestic product and the performance of financial institutions. The former relation is especially intense in times of crises.

Empirical research on the effects of income diversification on banks' return patterns can be divided into studies highlighting aggregate benefits as well as drawbacks, the latter mainly for the U.S. banking system. Stiroh (2004) assesses the effects of income diversification on bank risk, measured by a bank's Z-score, and risk-adjusted bank profitability, calculated using the Sharpe-ratio, for the U.S. banking industry for the 1984 to 2001 period. He finds that an above average reliance on non-interest income, particularly on trading income, is reflected in higher risks and lower risk-adjusted profits. Likewise, DeYoung and Rice (2004) observe that, on average, a higher non-interest income share is associated with an inferior risk-return trade-off and that well-managed U.S. commercial banks increase their non-interest income activities less quickly.

Stiroh and Rumble (2006) further analyze the benefits of income diversification for financial holding companies in the U.S. for the period of 1997 to 2002. They find evidence that diversification benefits exist between financial holding companies, however, those benefits are offset by the costs of an increased exposure to the more volatile activities that hide behind aggregate non-interest income. Studying the effect of diversification on the financial performance of U.S. credit unions in detail, Goddard et al. (2008) show that income diversification exhibits a negative relationship with banks' risk-adjusted and unadjusted return patterns for all but the largest financial institutions. These results are in line with previous work done by Rogers and Sinkey Jr. (1999), who find evidence that U.S. banks with well above average non-interest income shares tend to be larger but exhibit less risk. Mercieca et al. (2007) investigate the increase of small European credit institutions' non-interest income shares over the 1997 to 2003 period but are unable to find direct diversification benefits.

Contrary to the former studies, Smith et al. (2003), Demirgüç-Kunt and Huizinga (2010), Sanya and Wolfe (2011), and Busch and Kick (2015) find that income diversification significantly increases the average bank's profitability. That is to say, Smith et al. (2003) show that the increased importance of non-interest income for European banks stabilized profits in the European banking industry in the 1994 to 1998 period and Demirgüç-Kunt and Huizinga (2010) find that, using an international sample of listed banks, banks can increase their return on assets by expanding into fee generating activities. Furthermore, they show that income diversification provides some risk reduction benefits at low levels.

Examining a sample of emerging market banks, Sanya and Wolfe (2011) empirically show that diversification into non-interest income generating activities decreases banks' insolvency risk and increases their profitability. Busch and Kick (2015) analyze the relationship between fee income and banks' risk-adjusted performance patterns for German banks between 1995 and 2011. A bank's risk-adjusted performance is calculated by dividing the profitability measure by its standard deviation. They find evidence that universal banks' return on equity and return on total assets, both on a risk-adjusted basis, are significantly positively related to the banks' level of income diversification. However, they also find that banks with higher non-interest income shares charge lower interest margins, indicating cross-subsidization or cross-selling effects.

4.3 Data and empirical method

This section explains the sample bank selection, discusses the different bank characteristics and macroeconomic variables employed in the regression analysis, provides descriptive summary statistics, and highlights the econometric regression methodology.

4.3.1 Sample selection

Our empirical analysis focuses on banks headquartered in euro area countries and covers the period from 2007 to 2014. By restricting the sample to the 2007 to 2014 period, we ensure that most institutions report their risk-weighted assets using at least the Basel II regulatory requirements.[2] The availability of such a regulatory framework is especially crucial for us for the calculation of comparable and sufficiently risk-sensitive performance measures (see Section 4.3.2 for more details).

All bank-level data in this study are taken from Bankscope. That is, we select all banks from the Bankscope database that fit our geographical restrictions and report total risk-weighted assets in their annual statements. The resulting sample contains 2,374 different sample banks with a total of 10,092 annual bank observations. The sample banks are from 13 euro area countries including Austria, Belgium, Cyprus, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, the Netherlands, Portugal, and Spain.

4.3.2 Measures of bank performance and income diversification

We measure a bank's performance employing the profitability ratio return on risk-weighted assets (RoRWA). We make use of this particular profitability ratio for two reasons. First, the metric proxies for the riskiness of banks' credit, market, and operational exposures

[2] Banks headquartered in the euro area generally implemented the Basel II Directives 2006/48/EC and 2006/49/EC in 2007.

and thus makes the performance of banks' different business models more comparable than measures like the return on assets or the return on equity, which do not account for different levels of risk taking. Second, maximizing measures in the spirit of a bank's return on risk-adjusted capital should, at least in theory, maximize the value of market equity and hence overall bank performance. We define *RoRWA* as a bank's operating profit divided by its total risk-weighted assets expressed in percentage terms:

$$RoRWA_{i,t} = \frac{operating\ profit_{i,t}}{risk\text{-}weighted\ assets_{i,t}} \times 100, \qquad (4.1)$$

where t indicates the year and i the respective institution. The operating profit is the pre-tax profit adjusted for non-recurring and non-operating income and expenses and thus measures a bank's profits resulting from its general business activities.

In order to calculate the degree of banks' income diversification, we breakdown an institution's operating income into its subcomponents. Operating income is generally defined as the sum of interest income and non-interest income; whereas non-interest income contains the income statement items fee income, trading income, and other non-interest income. Other non-interest income summarizes the residual positions net gains and losses on assets at fair value through the income statement, net insurance income, and other operating income.

Using these data, we construct a bank's *non-interest income share* (NII share) as the share of non-interest income in total operating income as follows:

$$NII\ share_{i,t} = \frac{non\text{-}interest\ income_{i,t}}{non\text{-}interest\ income_{i,t} + interest\ income_{i,t}} \times 100, \qquad (4.2)$$

with:

$$Non\text{-}interest\ income_{i,t} = |fee\ income_{i,t}| + |trading\ income_{i,t}| + |other\ non\text{-}interest\ income_{i,t}|.$$

|...| denotes the absolute value of the income statement item. Taking absolute values ensures that the NII share is bounded between 0% and 100% and adequately represents the relative size of banks' non-interest income related business activities even if parts of the respective income streams are negative, i.e., result in annual losses. A higher NII share indicates that an institution's total revenues are less dependent on the traditional interest income generated by its loan portfolios. In other words, institutions with a higher NII share are more orientated towards revenues coming from fee generating and trading activities.

Analogously, we define measures to capture a bank's *fee income share* (fee share), *trading income share* (trading share), and *other non-interest income share* (other NII share) as a percentage of total operating income:

$$\textit{Fee share}_{i,t} = \frac{|\textit{fee income}_{i,t}|}{\textit{non-interest income}_{i,t} + \textit{interest income}_{i,t}} \times 100 \tag{4.3a}$$

$$\textit{Trading share}_{i,t} = \frac{|\textit{trading income}_{i,t}|}{\textit{non-interest income}_{i,t} + \textit{interest income}_{i,t}} \times 100 \tag{4.3b}$$

$$\textit{Other NII share}_{i,t} = \frac{|\textit{other NII income}_{i,t}|}{\textit{non-interest income}_{i,t} + \textit{interest income}_{i,t}} \times 100. \tag{4.3c}$$

In line with Equation 4.2, the different diversification measures are, by definition, bounded between 0% and 100% and individually proxy for the overall relative importance of a bank's fee income, trading income, and other non-interest income. For example, a fee income share (trading income share) of 25 (10) would indicate that 25% (10%) of the operating income is related to fee generating (trading) activities. The other NII share measures the relative amount of operating income that is not related to interest income, fee income, and trading income. We therefore refer to the former as a measure of the share of banks' non-core banking activities.[3]

4.3.3 Control and dummy variables

Our subsequent empirical analysis of the relationship between bank performance and income diversification necessitates the inclusion of a set of bank-specific and macroeconomic control and dummy variables since we expect these variables to directly affect a bank's risk-adjusted performance.

The control variable *assets* is defined as the natural logarithm of an institution's total assets measured in €*m* and captures bank size. The *capital ratio* is the ratio of book equity to total assets and proxies for a bank's loss absorbing capacity and capital strength. *Asset growth* measures the annual growth rate of total assets and *loan growth* measures the annual growth rate of total gross loans. Both controls are included to account for the possibility that above or below average asset and loan growth rates have a substantial effect on bank performance.

Next, we use the variable *loan loss reserves*, which is defined as the ratio of loan

[3] One could note that because the other NII share includes the accounting adjustments of financial assets at fair value through the income statement, the other NII share and the trading income share are interrelated. However, this is not the case. Net gains and losses on assets related to trading activities (e.g., equity and debt securities and derivatives) are correctly considered as trading income.

loss reserves to total loans, to control for the banks' underlying loan portfolio quality. The variables *overhead costs*, *personnel costs*, and *nonpersonnel costs* are constructed to capture the main drivers of potential cost efficiencies. To be more specific, overhead costs is the ratio of overhead expenses to total assets and personnel costs and nonpersonnel costs are defined as personnel expenses to total assets and nonpersonnel expenses to total assets, respectively.

The bank-specific control variable *net interest margin* is the quotient of a bank's net interest income and its average interest earning assets. This measure is especially important to evaluate how successful a bank can invest its deposits and own funds. Additionally, we use the two variables *liquid assets* and *nondeposit funding* to control for the consequences of taking liquidity risks. Liquid assets is the share of liquid assets in total assets and nondeposit funding is the share of nondeposit short-term funding in total deposits and short-term funding. We additionally make use of the *cost income ratio*, which is defined as the ratio of operating expenses relative to total operating income, to measure aggregate bank efficiency. We express all former ratios and growth rates in percentage terms.

Besides the inclusion of a set of bank-specific control variables, we construct a number of dummy variables in order to account for the effect of bank type on bank performance. In particular, we differentiate between co-operative banks, savings banks, investment banks, and listed banks. Banks that are not classified as co-operative bank, savings bank, or investment bank are labeled as commercial bank. To classify banks into these groups, we make use of the bank type identifier available in Bankscope. That is to say, the variable *co-operative bank* is a dummy variable that is one for co-operative banks and zero otherwise; the variable *savings bank* is a dummy variable that is one for savings banks and zero otherwise; and the variable *investment bank* is a dummy variable that is one for investment banks and zero otherwise. Likewise, the measure *listed* is a dummy variable that is one for listed banks and zero otherwise.

Finally, four macroeconomic control variables are used. All of them are obtained from the World Bank database. We use the variable *GDP growth* to capture the economic cyclicality of banks' performance patterns. We generally expect institutions to better perform in countries with higher GDP growth rates. GDP growth is measured using the annual growth rate of real GDP. Real GDP is defined as nominal GDP deflated by the GDP deflator. The macro control *GDP per capita* is constructed by dividing a country's gross domestic product by its population and is a good indicator for a country's economic development and financial market sophistication. We measure GDP per capita in €k.

Inflation measures the steady increase in the general price level over time and acts as a proxy for a stable economy. Generally, a moderate inflation target is regarded as positive

(Mundell, 1963; Tobin, 1965). Furthermore, above or below average inflation rates could affect bank performance and influence banks to expand or reduce their non-interest income activities (Demirgüç-Kunt and Huizinga, 2010). Lastly, the control variable *interest rate* is calculated as the yield on 10-year government bonds and proxies for the sample countries' general solvency. The variables GDP growth, inflation, and interest rate are expressed in percentage terms.

Table 4.1 on the next page provides a summary of all bank characteristics and macroeconomic variables used in our main study including their description and data source. All variables of Table 4.1 are sampled on an annual frequency.

Label	Description	Source
Bank performance and income diversification		
RoRWA	Return on risk-weighted assets: Operating profit as a percentage of total risk-weighted assets (if not otherwise specified)	Bankscope
NII share	Non-interest income share: Share of non-interest income (sum of fee income, trading income, and other non-interest income) in total operating income expressed in percentage terms	Bankscope
Fee share	Share of fee income in total operating income expressed in percentage terms	Bankscope
Trading share	Share of trading income in total operating income expressed in percentage terms	Bankscope
Other NII share	Other non-interest income share: Share of other non-interest income in total operating income expressed in percentage terms	Bankscope
Bank-specific control variables		
Assets	Natural logarithm of total assets in millions of euros	Bankscope
Capital ratio	Book equity as a percentage of total assets	Bankscope
Asset growth	Annual growth rate of total assets expressed in percentage terms	Bankscope
Loan growth	Annual growth rate of total gross loans expressed in percentage terms	Bankscope
Loan loss reserves	Loan loss reserves as a percentage of total gross loans	Bankscope
Overhead costs	Overhead expenses divided by total assets expressed in percentage terms	Bankscope
Personnel costs	Personnel expenses divided by total assets expressed in percentage terms	Bankscope
Nonpersonnel costs	Nonpersonnel expenses divided by total assets expressed in percentage terms	Bankscope
Net interest margin	Net interest income as a percentage of average earning assets	Bankscope
Liquid assets	Share of liquid assets in total assets expressed in percentage terms	Bankscope
Nondeposit funding	Share of nondeposit short-term funding in total deposits and short-term funding expressed in percentage terms	Bankscope
Cost income ratio	Ratio of operating expenses relative to total operating income expressed in percentage terms	Bankscope
Bank-specific dummy variables		
Co-operative bank	Dummy variable that is one for co-operative banks and zero otherwise	Bankscope
Savings bank	Dummy variable that is one for savings banks and zero otherwise	Bankscope
Investment bank	Dummy variable that is one for investment banks and zero otherwise	Bankscope
Listed	Dummy variable that is one for listed banks and zero otherwise	Bankscope
Macroeconomic control variables		
GDP growth	Real growth rate of gross domestic product expressed in percentage terms	World Bank
GDP per capita	Gross domestic product per capita in thousands of euros	World Bank
Inflation	Inflation measured by the annual growth rate of the GDP deflator expressed in percentage terms	World Bank
Interest rate	Interest rate calculated as the yield on 10-year government bonds expressed in percentage terms	World Bank

Table 4.1 – Definition of variables
The table shows the label, description, and data source of the main variables used in the regression analysis. All data are sampled on an annual frequency and cover the period from 2007 to 2014.

4.3.4 Descriptive statistics and correlation matrix

Table 4.2 provides summary statistics of all bank characteristics and macroeconomic variables used in the main study. Note that for all calculations and analyses, we winsorize the bank-specific control variables at the 1% level in order to control for outliers. Table 4.3 additionally reports the correlation coefficients of all bank-specific and macroeconomic control variables.

The figures of Table 4.2 reveal that the average sample bank has an annual RoRWA of approximately 1.05% and a NII share of 30.70%. That is, interest income accounts for 69.30% of aggregate operating income. However, banks substantially vary in terms of their NII shares, which can be inferred from the corresponding standard deviation of 17.08%. Splitting the NII share into its subcomponents shows that the bulk of non-interest income results from fee generating activities. Banks' trading activities account for 5.48% of total operating income and are only slightly higher than the income share of 3.84% realized by the residual income variable other NII share.

The median sample bank is furthermore characterized by total assets of approximately €837m[4] and a capital ratio of 8.75%. Institutions' annual asset growth rates have a median value of 3.66%. The loan portfolio exhibits a slightly higher median growth rate of approximately 3.97%. The average bank's cost income ratio is 67.11%. Moreover, co-operative banks and savings banks, respectively, account for 58% and 17% of all sample bank observations. Only a minority of 5% of observations correspond to investment banks. The residual value of 20% of bank observations are from commercial banks.

The macroeconomic statistics show that the GDP growth rates of the sample countries averaged at around 0.16% during the 2007 to 2014 period. Furthermore, GDP per capita ranges between €39k and €97k and the median inflation rate of the 13 euro area countries was approximately 1.49%.

Figure 4.1 plots the frequency distribution of the NII share, fee income share, trading income share, and other NII share for our sample of euro area banks. The vertical bars represent 5% intervals. Both the distribution of the NII share and of the fee income share peak around values of 20%. More than 5% of banks, however, rely only on interest income. Relatively few banks rely almost exclusively on non-interest income. The majority of banks do not generate income from trading activities. As a result, the distribution of the trading income share is highly skewed to the right with most probability mass being around the first two frequency intervals. The distribution of banks' other NII share is very similar. Almost no bank has a NII share of more than 25% of total operating income.

[4] This corresponds to the natural logarithm of total assets, $\exp(6.73) \approx$ €837m.

	Statistics					
	# obs	mean	median	std dev	min	max
Bank performance and income diversification						
RoRWA	10,092	1.05	1.10	1.86	-7.53	7.61
NII share	10,076	30.70	27.78	17.08	0.00	100.00
Fee share	10,076	21.39	20.25	12.54	0.00	100.00
Trading share	10,076	5.48	0.00	10.65	0.00	94.44
Other NII share	10,076	3.84	0.00	8.57	0.00	100.00
Bank-specific control variables						
Assets	10,092	7.34	6.73	2.38	3.47	13.37
Capital ratio	10,092	9.55	8.75	4.85	1.57	36.90
Asset growth	9,973	5.46	3.66	11.94	-20.07	68.22
Loan growth	9,925	6.09	3.97	14.28	-28.46	84.38
Loan loss reserves	10,092	2.82	1.97	2.94	0.00	13.92
Overhead costs	10,082	2.19	2.12	1.01	0.15	8.50
Personnel costs	10,051	1.25	1.23	0.58	0.01	4.35
Nonpersonnel costs	10,082	0.95	0.86	0.55	0.00	4.10
Net interest margin	10,079	2.39	2.43	0.85	0.21	4.69
Liquid assets	10,092	14.11	9.86	13.26	1.61	77.78
Nondeposit funding	10,065	22.24	16.42	21.83	0.00	100.00
Cost income ratio	10,028	67.11	66.67	15.65	26.32	128.00
Bank-specific dummy variables						
Co-operative bank	10,092	0.58	1.00	0.49	0.00	1.00
Savings bank	10,092	0.17	0.00	0.37	0.00	1.00
Investment bank	10,092	0.05	0.00	0.21	0.00	1.00
Listed	10,092	0.08	0.00	0.27	0.00	1.00
Macroeconomic control variables						
GDP growth	104	0.16	0.40	3.14	-9.13	8.40
GDP per capita	104	41.79	39.22	15.67	24.06	96.71
Inflation	104	1.33	1.49	1.48	-4.26	4.53
Interest rate	104	4.04	3.82	2.95	0.00	22.50

Table 4.2 – Descriptive statistics
The table presents summary statistics for the main sample bank characteristics and macroeconomic indicators. All data are sampled on an annual frequency and cover the period from 2007 to 2014. For a detailed description of the variables we refer to Table 4.1.

	Bank-specific and macroeconomic control variables															
	Assets	Capital ratio	Asset growth	Loan growth	Loan loss reserves	Overhead costs	Personnel costs	Nonpersonnel costs	Net interest margin	Liquid assets	Nondeposit funding	Cost income ratio	GDP growth	GDP per capita	Inflation	Interest rate
Assets	1.00															
Capital ratio	-0.36 ***	1.00														
Asset growth	-0.05 ***	0.04 ***	1.00													
Loan growth	-0.01	0.05 ***	0.62 ***	1.00												
Loan loss reserves	0.04 ***	-0.01	-0.07 ***	-0.14 ***	1.00											
Overhead costs	-0.33 ***	0.42 ***	0.03 **	0.10 ***	0.02	1.00										
Personnel costs	-0.37 ***	0.41 ***	0.02 *	0.08 ***	0.03 **	0.83 ***	1.00									
Nonpersonnel costs	-0.24 ***	0.33 ***	0.06 ***	0.13 ***	0.01	0.83 ***	0.63 ***	1.00								
Net interest margin	-0.43 ***	0.28 ***	0.12 ***	0.11 ***	0.11 ***	0.39 ***	0.40 ***	0.32 ***	1.00							
Liquid assets	0.15 ***	0.03 ***	0.07 ***	0.10 ***	-0.06 ***	0.04 ***	-0.02 *	0.10 ***	-0.29 ***	1.00						
Nondeposit funding	0.28 ***	-0.13 ***	0.01	-0.05 ***	0.13 ***	-0.28 ***	-0.30 ***	-0.22 ***	-0.44 ***	0.19 ***	1.00					
Cost income ratio	-0.11 ***	-0.02 *	-0.05 ***	0.01	-0.07 ***	0.42 ***	0.36 ***	0.41 ***	-0.08 ***	0.06 ***	-0.21 ***	1.00				
GDP growth	0.04 ***	-0.06 ***	-0.06 ***	0.04 ***	-0.24 ***	-0.01	-0.01	-0.02 *	-0.06 ***	0.03 ***	-0.02	0.04 ***	1.00			
GDP per capita	0.04 ***	-0.13 ***	-0.14 ***	-0.02 *	-0.38 ***	-0.07 ***	-0.06 ***	-0.07 ***	-0.14 ***	0.11 ***	0.02 *	0.01	0.39 ***	1.00		
Inflation	-0.13 ***	0.05 ***	0.10 ***	0.12 ***	-0.28 ***	0.10 ***	0.09 ***	0.09 ***	0.23 ***	0.04 ***	-0.16 ***	-0.01	0.05 ***	0.32 ***	1.00	
Interest rate	0.08 ***	0.08 ***	0.11 ***	0.04 ***	0.35 ***	0.00	-0.04 ***	0.04 ***	0.06 ***	0.04 ***	0.15 ***	-0.02	-0.42 ***	-0.55 ***	-0.22 ***	1.00

Table 4.3 – Sample correlations

The table exhibits correlations between all bank-specific and macroeconomic control variables. All data are sampled on an annual frequency and cover the period from 2007 to 2014. For a detailed description of the bank-specific and macroeconomic control variables we refer to Table 4.1. Correlation coefficients are assigned asterisks if they are statistically significant (*** = 0.1% confidence level; ** = 1% confidence level; * = 10% confidence level).

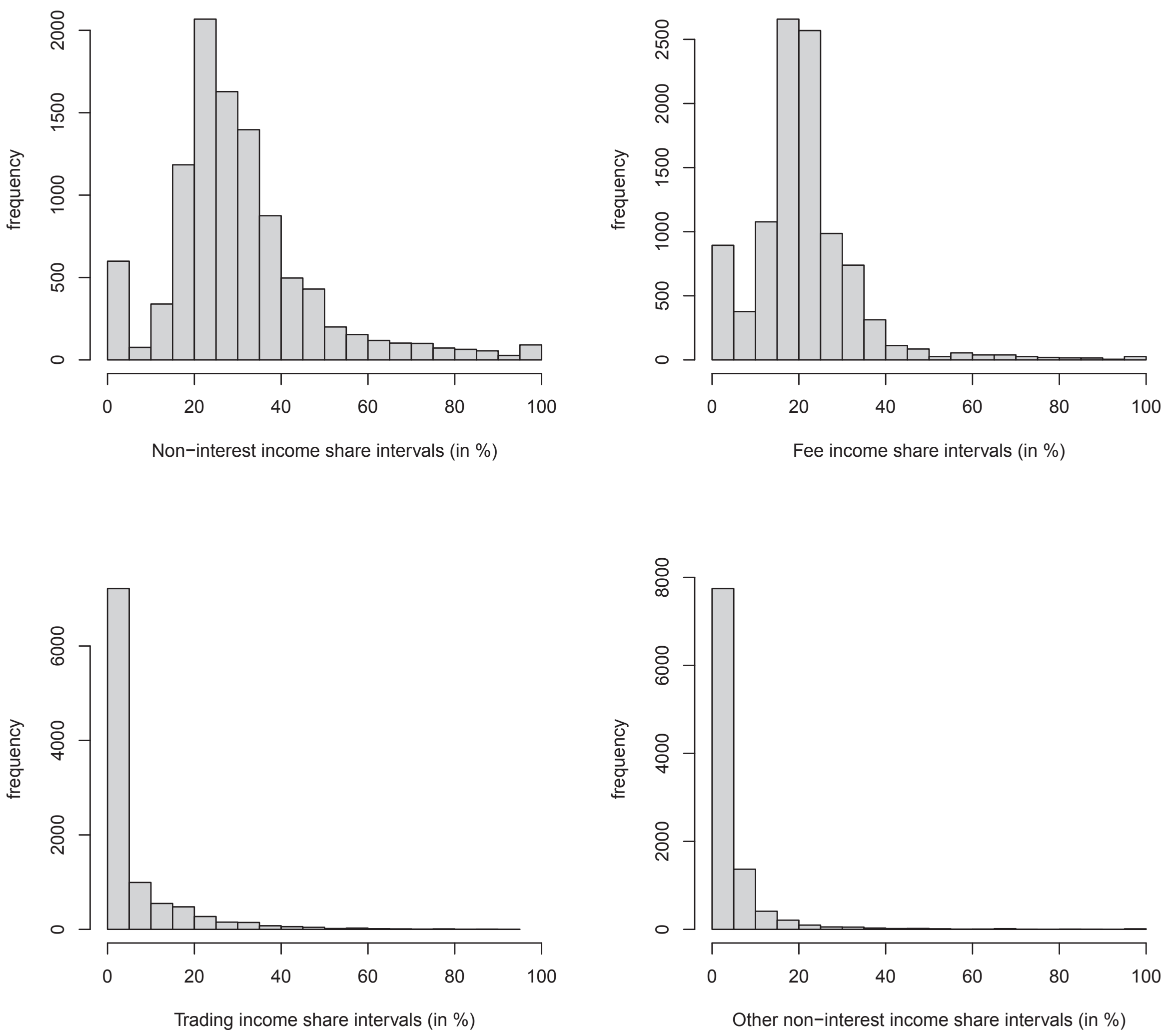


Figure 4.1 – Distribution of the non-interest income share and its subcomponents
The figure presents the distribution of the non-interest income share and its subcomponents fee income share, trading income share, and other non-interest income share for the aggregate of all sample banks covering the period from 2007 to 2014. The *non-interest income share* represents the share of non-interest income in total operating income. Non-interest income is the sum of fee income, trading income, and other non-interest income. The *fee income share*, *trading income share*, and *other non-interest income share* are the shares of fee income, trading income, and other non-interest income in total operating income. The vertical bars represent 5% intervals. All ratios are sampled on an annual frequency and expressed in percentage terms. The data are obtained from Bankscope.

Table 4.4 on the next page shows descriptive statistics for the bank performance and income diversification variables for different sample bank subsets. The subsets differentiate between bank type, bank size, and stock exchange listing. Bank type comprises the groups commercial banks, co-operative banks, savings banks, and investment banks. As mentioned previously, the classification of banks into these four groups is based on the bank type identifier available in Bankscope. The category bank size differentiates between small banks, medium-sized banks, and large banks. The classification of bank size is based on total assets. Small banks (large banks) are defined as the 25% smallest (25% largest) banks in the entire sample of banks with respect to total assets at time t. Medium-sized banks are banks with total assets in the second and third quartile. Finally, we differentiate between banks that have a stock exchange listing (listed banks) and those that do not have a listing (unlisted banks).

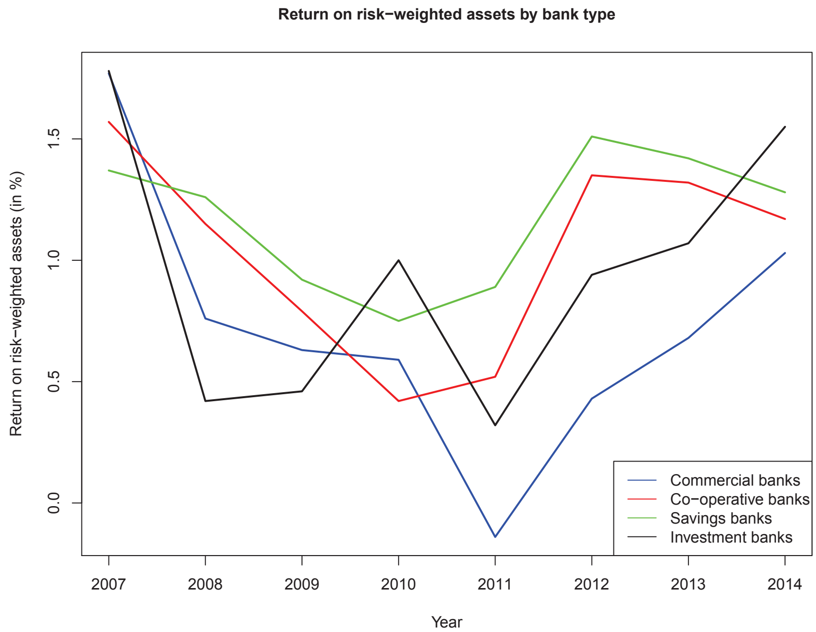
The data show that co-operative banks (1.12%) and savings banks (1.31%) are, on a risk-adjusted basis, much more profitable than commercial banks (0.67%). Investment banks (0.93%) realize returns on risk-weighted assets that are comparable to those of the average bank. The NII share is highest for investment banks (54.08%) and lowest for co-operative banks and savings banks (25.63% and 28.36%, respectively). The differences are most obvious for the trading income share. Whereas commercial banks and investment banks have a trading income share of approximately 9.03% and 16.55%, respectively, savings banks' average trading income shares only amount to 2.00%, followed by co-operative banks with a share of 4.34%.

The same patterns hold for small and large banks. On the one hand, small banks, which are to a great extend co-operative banks and savings banks, have an average RoRWA of 1.22% and generate around 22.65% of their operating income from non-interest related activities. On the other hand, large banks exhibit returns on risk-weighted assets of 0.70% and have a NII share of 38.86%. Banks with a stock exchange listing have an average NII share of 44.30% and are, surprisingly, the least profitable. Banks of this group only realize average risk-adjusted returns of approximately 0.36%.

The circumstance that larger banks underperform their smaller peers over the 2007 to 2014 period has probably many reasons. One particular important issue, however, is likely to be the fact that the former disproportionately suffered during the International Financial Crisis and the European Sovereign Debt Crisis due to their elevated international exposures and interconnectedness.

		Bank performance and income diversification									
		RoRWA		NII share		Fee share		Trading share		Other NII share	
Category	# obs	mean	std dev	mean	std dev	mean	std dev	mean	std dev	mean	std dev
Bank type											
Commercial banks	2,041	0.67	2.74	41.80	20.11	26.43	17.09	9.03	13.33	6.34	12.35
Co-operative banks	5,898	1.12	1.40	25.63	13.07	18.76	8.94	4.34	8.83	2.53	6.93
Savings banks	1,676	1.31	1.47	28.36	9.51	22.28	7.68	2.00	6.04	4.08	5.10
Investment banks	477	0.93	2.93	54.08	24.54	29.12	24.95	16.55	17.69	8.41	12.19
Bank size											
Small banks	2,523	1.22	1.73	22.65	18.87	17.94	15.53	3.15	9.29	1.56	6.15
Medium-sized banks	5,045	1.14	1.66	30.63	14.25	22.22	10.28	5.24	10.22	3.17	6.34
Large banks	2,524	0.70	2.29	38.86	16.58	23.16	12.66	8.26	12.05	7.44	12.52
Stock exchange listing											
Listed banks	767	0.36	2.62	44.30	16.75	26.77	13.64	10.61	12.18	6.92	11.37
Unlisted banks	9,325	1.11	1.77	29.58	16.62	20.95	12.34	5.05	10.40	3.58	8.25

Table 4.4 – Bank performance and income diversification by bank category
The table shows descriptive statistics for the bank performance and income diversification variables for different sample bank subsets. Sample banks are either categorized by bank type, bank size or stock exchange listing. Bank type differentiates between commercial banks, co-operative banks, savings banks, and investment banks. The classification of bank size is based on total assets. Small banks (large banks) are defined as the 25% smallest (25% largest) banks in the entire sample of banks with respect to total assets at time t. Medium-sized banks are banks with total assets in the second and third quartile. Listed banks are banks that are listed on the stock exchange. All data are sampled on an annual frequency and cover the period from 2007 to 2014. For a detailed description of the bank performance and income diversification variables we refer to Table 4.1.



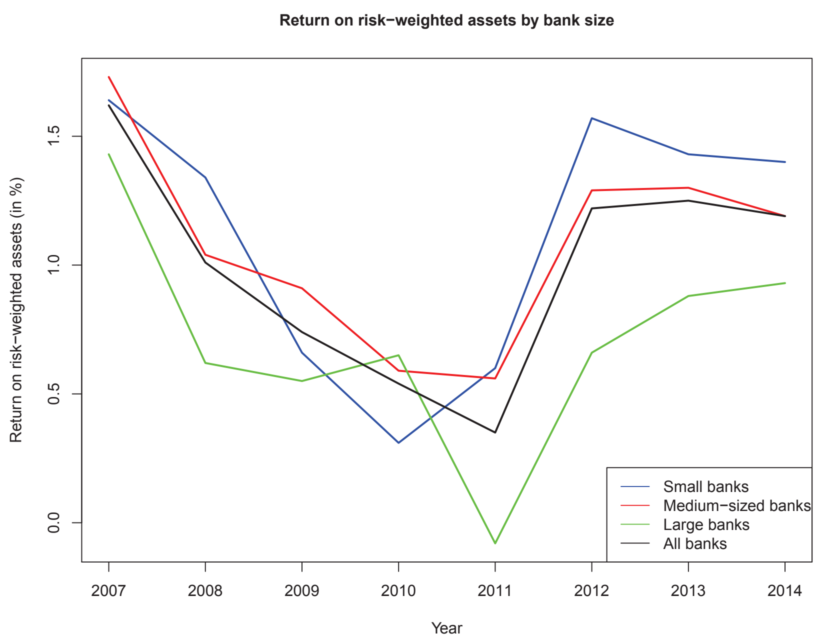


Figure 4.2 – Return on risk-weighted assets
The figure presents the trend of the return on risk-weighted assets by bank type and bank size. The *return on risk-weighted assets* is defined as the ratio of operating profit over total risk-weighted assets expressed in percentage terms. Bank type differentiates between commercial banks, co-operative banks, savings banks, and investment banks. The classification of bank size is based on total assets. Small banks (large banks) are defined as the 25% smallest (25% largest) banks in the entire sample of banks with respect to total assets at time t. Medium-sized banks are banks with total assets in the second and third quartile. The time series of observations cover the period from 2007 to 2014. All data are obtained from Bankscope.

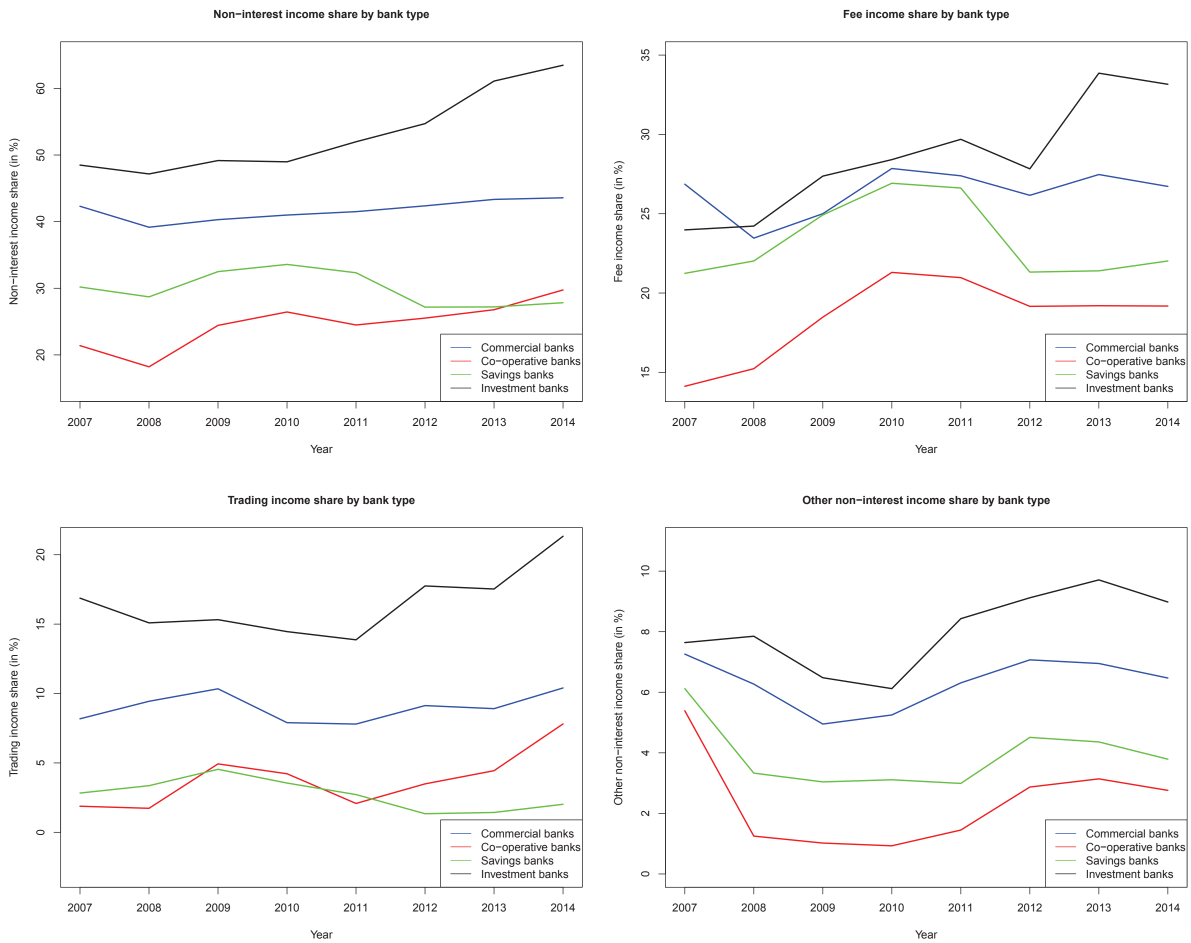


Figure 4.3 – Bank type and income diversification
The figure presents the time trend of the non-interest income share and its subcomponents fee income share, trading income share, and other non-interest income share for different types of banks covering the period from 2007 to 2014. Sample banks are either classified as commercial banks, co-operative banks, savings banks, or investment banks. The *non-interest income share* represents the share of non-interest income in total operating income. Non-interest income is the sum of fee income, trading income, and other non-interest income. The *fee income share*, *trading income share*, and *other non-interest income share* are the shares of fee income, trading income, and other non-interest income in total operating income. All time series are expressed in percentage terms. The data are obtained from Bankscope.

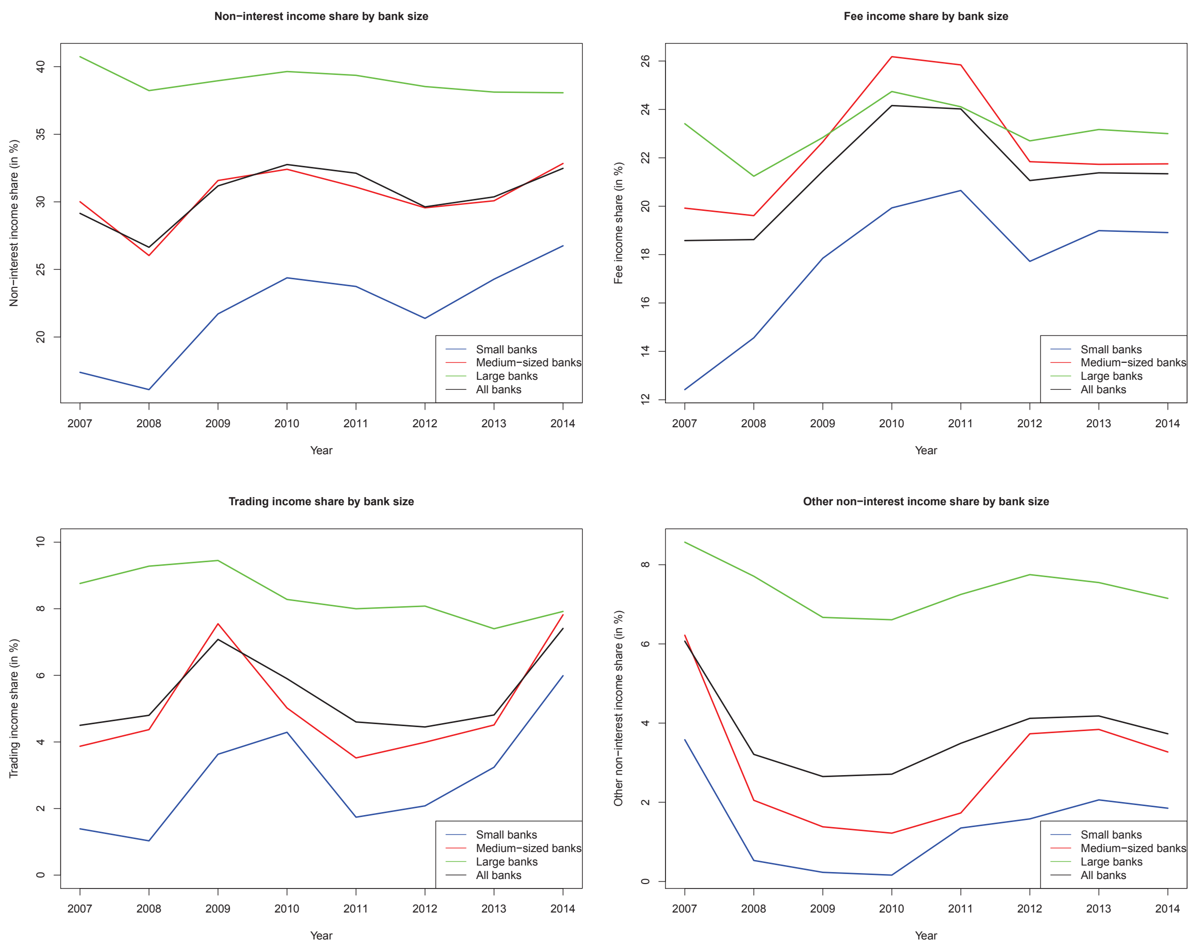


Figure 4.4 – Bank size and income diversification
The figure presents the time trend of the non-interest income share and its subcomponents fee income share, trading income share, and other non-interest income share for small, medium-sized, and large banks covering the period from 2007 to 2014. The classification of bank size is based on total assets. Small banks (large banks) are defined as the 25% smallest (25% largest) banks in the entire sample of banks with respect to total assets at time t. Medium-sized banks are banks with total assets in the second and third quartile. The *non-interest income share* represents the share of non-interest income in total operating income. Non-interest income is the sum of fee income, trading income, and other non-interest income. The *fee income share*, *trading income share*, and *other non-interest income share* are the shares of fee income, trading income, and other non-interest income in total operating income. All time series are expressed in percentage terms. The data are obtained from Bankscope.

Figure 4.2 shows the time trend of the return on risk-weighted assets assorted by bank type and bank size. Not surprisingly, the RoRWA variable decreases for each subsample after the onset of the International Financial Crisis in 2007. Returns are lowest at the height of the European Sovereign Debt Crisis in 2011. Over time, however, the risk-adjusted returns of commercial banks and investment banks seem to be more cyclical than those of co-operative banks and savings banks.

Figures 4.3 and 4.4 additionally present the time trends of the four income diversification measures NII share, fee income share, trading income share, and other NII share for the different subsets of the categories bank type and bank size, respectively.

The NII share of commercial banks and investment banks is higher throughout the sample period than for co-operative banks and savings banks. The same holds true for the other income diversification variables. Most important though, the diversification measures' trajectories of each bank type seem to move in tandem. Figure 4.4 underlines these results except for the trend of the trading income share. Interestingly, small and medium-sized banks have significantly increased their trading income share since 2011 if compared to large banks.

4.3.5 Estimation method

We estimate and explore the impact of income diversification on bank performance using the following linear regression specification:

$$Y_{i,t} = \alpha + \beta Y_{i,t-1} + \gamma DIV_{i,t} + \sum_{b=1}^{B} \delta_b X_{i,t}^{b} + \sum_{m=1}^{M} \zeta_m X_{i,t}^{m} + \sum_{t=1}^{T} \lambda_t TF_t + u_i + \epsilon_{i,t}, \quad (4.4)$$

where subscript i denotes the institution ($i = 1, 2, ..., 2, 374$) and t indicates the time period ($t = 2007, 2008, ..., 2014$). $Y_{i,t}$ is bank i's risk-adjusted performance measure RoRWA at time t and $DIV_{i,t}$ represents any of the four income diversification measures NII share, fee income share, trading income share or other NII share. Furthermore, the $X_{i,t}^{b}$'s represent a set of bank-specific control and dummy variables, the $X_{i,t}^{m}$'s a set of macroeconomic controls, and the TF_t's capture the time fixed effects. U_i is the unobserved bank-specific fixed effect and $\epsilon_{i,t}$ the remaining idiosyncratic error term. The coefficient α denotes the intercept of the regression.

We additionally include the one period lag of the dependent variable $Y_{i,t}$ among the regressors in order to account for the possibility of endogenous performance persistence. We estimate Equation 4.4 using the two-step system GMM (generalized method of moments) approach developed by Arellano and Bover (1995) and Blundell and Bond (1998).

The system GMM estimation technique has two major advantages. First, the system GMM allows us to treat all explanatory variables as endogenous and uses their lagged values as their instruments, which is especially helpful given the fact that we can easily expect reverse causalities between bank performance and income diversification.

For example, although the non-interest income share determines a bank's performance pattern, a bank could also change its business model and hence its non-interest income share due to prior underperformance. We therefore treat all bank characteristics as endogenous. The macroeconomic control variables are expected to be exogenous, however. Second, the system GMM approach deals with the problem of unobservable heterogeneity across banks by creating a matching equation of the first differences of all variables (i.e., by using the technique of first differencing).

Since the two-step system GMM estimation technique produces downward biased standard errors (Blundell and Bond, 1998), we use a finite sample correction in line with Windmeijer (2005). We test the validity of the system GMM instruments using the Hansen's J test statistic of overidentifying restrictions, with the $H0$ hypothesis that the instruments are exogenous. Furthermore, we report the Arellano and Bond (1991) test statistic for first- and second-order autocorrelation in the error terms.

4.4 Empirical evidence

In the following, we empirically explore the dependence structure between banks' non-interest income shares and their risk-adjusted performance patterns. As a starting point, Table 4.5 reports the results of regressions with the return on risk-weighted assets as the dependent variable and the non-interest income share as the explanatory variable of special interest. All regressions are estimated applying standard error clustering at the bank level. The coefficients' standard errors are given in parentheses and the abbreviation $L.$ indicates the one period lag of the corresponding variable.

Regression (1) reveals that a diversification into non-interest related activities significantly increases the average bank's risk-adjusted return measure RoRWA, supporting the existence of economies of scope. We find no evidence that bank size is significantly positively related to bank performance, which is in line with the descriptive statistics of Table 4.4. That is to say, we are unable to find evidence for potential economies of scale. Banks with higher capital ratios, nevertheless, tend to have higher risk-adjusted returns. This finding supports Berger (1995), who shows that better capitalized banks disproportionately benefit from lower funding costs.

	Return on risk-weighted assets						
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L.RoRWA	0.240 ***	0.237 ***	0.236 ***	0.267 ***	0.141 ***	0.252 ***	0.238 ***
	(0.035)	(0.035)	(0.037)	(0.034)	(0.032)	(0.035)	(0.035)
NII share	0.032 ***	0.032 ***	0.029 ***	0.029 ***	0.030 ***	0.031 ***	0.031 ***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)
Assets	0.013	-0.056	0.027	0.040	0.002	-0.026	-0.011
	(0.046)	(0.060)	(0.046)	(0.048)	(0.040)	(0.064)	(0.053)
Capital ratio	0.074 **	0.084 ***	0.089 ***	0.072 ***	0.030	0.067 **	0.074 **
	(0.029)	(0.031)	(0.027)	(0.028)	(0.026)	(0.028)	(0.030)
Asset growth	-0.000	0.002		0.004	-0.000	0.000	0.000
	(0.006)	(0.006)		(0.006)	(0.005)	(0.006)	(0.006)
Loan growth			0.003				
			(0.005)				
Loan loss reserves	-0.153 ***	-0.148 ***	0.148 ***	-0.152 ***	-0.218 ***	-0.157 ***	-0.150 ***
	(0.022)	(0.026)	(0.024)	(0.020)	(0.024)	(0.022)	(0.022)
Overhead costs	-0.860 ***	-0.812 ***	-0.871 ***		-0.012	-0.782 ***	-0.889 ***
	(0.177)	(0.190)	(0.181)		(0.145)	(0.177)	(0.178)
Personnel costs				-0.384			
				(0.298)			
Nonpersonnel costs				-1.019 ***			
				(0.278)			
Net interest margin	1.417 ***	1.430 ***	1.364 ***	1.235 ***	0.714 ***	1.393 ***	1.422 ***
	(0.148)	(0.150)	(0.157)	(0.135)	(0.143)	(0.149)	(0.147)
Liquid assets	0.007	0.006	0.006	0.006	0.009	0.007	0.008
	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.009)	(0.009)
Nondeposit funding					-0.012 ***		
					(0.003)		
Cost income ratio					-0.054 ***		
					(0.005)		
Investment bank						0.191	
						(0.233)	
Savings bank						-0.266 **	
						(0.124)	
Co-operative bank						-0.459 **	
						(0.224)	
Listed							0.203
							(0.188)
GDP growth	0.124 ***	0.120 ***	0.113 ***	0.125 ***	0.152 ***	0.108 ***	0.125 ***
	(0.032)	(0.035)	(0.031)	(0.031)	(0.031)	(0.032)	(0.032)
GDP per capita	0.005	-0.097 **	0.003	0.006	-0.003	-0.000	0.006
	(0.007)	(0.048)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)
Inflation	0.086 *	0.150 ***	0.078 *	0.073 *	0.157 ***	0.089 **	0.084 *
	(0.044)	(0.046)	(0.046)	(0.042)	(0.040)	(0.045)	(0.044)
Interest rate	-0.129 ***	-0.091 ***	-0.144 ***	-0.101 ***	-0.066 **	-0.145 ***	-0.132 ***
	(0.030)	(0.033)	(0.030)	(0.027)	(0.027)	(0.032)	(0.030)
Country fixed effects	No	Yes	No	No	No	No	No
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Test for AR(1) (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Test for AR(2) (p-value)	0.603	0.735	0.618	0.586	0.750	0.593	0.598
Hansen test (p-value)	0.335	0.299	0.020	0.133	0.018	0.293	0.269

Table 4.5 – Non-interest income share and the return on risk-weighted assets

Table 4.5 – continued:
The figures are estimated from annual sample bank characteristics and annual macroeconomic data from euro area countries covering the period from 2007 to 2014. All regressions feature the return on risk-weighted assets (RoRWA) as the dependent variable. *RoRWA* is defined as the ratio of operating profit over total risk-weighted assets expressed in percentage terms. *L.* indicates the one period lag of the corresponding variable. For a description of the explanatory variables we refer to Table 4.1. The regressions are estimated using the two-step system GMM methodology with the Windmeijer (2005) finite sample correction. The estimation method is described in more detail in Section 4.3.5. All bank performance and income diversification variables as well as all bank-specific control variables are treated as endogenous. For all above regressions we apply clustered standard errors at the bank level. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant. ***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels. The Hansen test refers to the difference-in-Hansen tests statistic of exogeneity of the instruments in GMM dynamic model estimation (H0: instruments are exogenous). AR(1) and AR(2) refer to the Arellano-Bond test that the average auto-covariance in residuals of order one and two, respectively, is zero. For the ease of exposition we suppress the regressions' intercepts.

Furthermore, an increase in the level of banks' loan loss reserves is significantly negatively associated with bank performance. A poor loan portfolio quality thus decreases profitability. In contrast, not surprisingly, higher net interest margins and GDP growth rates increase a bank's RoRWA. We cannot find evidence that the growth rate of total assets acts as a driver of the bank performance measure.

Regression (2) contains the same explanatory variables as Regression (1) but includes country fixed effects to control for differences between the sample bank countries that are not captured by our macroeconomic control variables and Regression (3) substitutes the asset growth rate with the loan growth rate in order to control for the effect of bank growth. In Regression (4) we split the variable overhead costs into its components personnel costs and nonpersonnel costs to get a better impression about the underlying drivers of the former costs efficiency variable. Our regression results on the effect of the non-interest income share remain unaltered. The loan growth rate cannot explain differences in the level of banks' RoRWA either. It is worth mentioning, however, that the overhead costs efficiency variable is mostly driven by nonpersonnel costs. In contrast, the variable personnel costs is insignificantly related to aggregate bank performance.

In Regression (5) we additionally include the bank-specific control variables nondeposit funding and cost income ratio. The estimates show that banks with a higher share of wholesale funding are less profitable than banks funded mainly by customer deposits. The same relation holds true for the cost income ratio. The inclusion of the variables has no effect on the economic significance of the income diversification measure. However, the controls capture the explanatory power of the capital ratio, which becomes insignificant.

Finally, Regressions (6) and (7) add the bank-specific dummy variables investment bank, savings bank, co-operative bank, and listed to the regression equation. These variables enable us to analyze whether a bank's legal framework has an influence on its performance. Furthermore, the bank type might influence the degree to which banks can profit from the diversification into non-interest income activities. For example, one could expect investment banks to better utilize the benefits of economies of scope.

The data show that we cannot find evidence that investment banks and banks with a stock exchange listing exhibit, all else being equal, risk-adjusted performance patterns that are significantly different from those of the average bank. We do find, however, that both savings banks and co-operative banks do not lift their full performance potential when compared to the average sample bank. Nevertheless, the inclusion of the former dummy variables does not change the circumstance that banks can significantly boost their return on risk-weighted assets by increasing their non-interest income share.

In a next step, we examine the separate impact of the subcomponents of the non-interest income share on banks' risk-adjusted performance measure RoRWA. Table 4.6 contains the estimates and is structured as follows. Regression (1) again depicts the non-interest income share as the dependent variable of interest and Regressions (2), (3), and (4) feature the fee income share, trading income share, and other non-interest income share as the dependent variable of interest. All regressions include the bank type dummy variables investment bank, savings bank, and co-operative bank.

The results demonstrate that an increase in the fee income share coincides with an increase of the dependent variable RoRWA. The relation is significant at the 5% confidence level. Likewise, increasing a bank's share of trading income enhances its return on risk-weighted assets. Yet, the economic significances of both diversification measures differ substantially. Whereas a one unit increase in the trading income share increases a bank's RoRWA by 0.028 percentage points, a one unit increase in the fee income share only increases a bank's RoRWA by 0.015 percentage points. In other words, banks, on average, can boost their performance twice as much by relatively expanding their trading activities instead of trying to expand their relative income from fees and commissions.

Regression (4) of Table 4.6 further reveals that a bank's other non-interest income share is negatively related to its risk-adjusted performance pattern. The coefficient of the other NII share variable is significant at the 10% level. A relative increase in non-core banking activities thus reduces the average bank's profitability. This finding indicates that financial institutions should primarily focus on fee generating and trading activities when expanding into non-interest revenue streams since the benefits of the other non-interest income share are rather disadvantageous.

	Return on risk-weighted assets			
Variable	(1)	(2)	(3)	(4)
L.RoRWA	0.252 ***	0.296 ***	0.269 ***	0.275 ***
	(0.035)	(0.037)	(0.039)	(0.038)
NII share	0.031 ***			
	(0.007)			
Fee share		0.015 **		
		(0.006)		
Trading share			0.028 ***	
			(0.008)	
Other NII share				-0.029 *
				(0.016)
Assets	-0.026	-0.015	-0.013	-0.015
	(0.064)	(0.066)	(0.077)	(0.068)
Capital ratio	0.067 **	0.058 ***	0.054 *	0.068 ***
	(0.028)	(0.023)	(0.029)	(0.025)
Asset growth	0.000	0.005	-0.003	0.000
	(0.006)	(0.006)	(0.007)	(0.006)
Loan loss reserves	-0.157 ***	-0.106 ***	-0.164 ***	-0.121 ***
	(0.022)	(0.020)	(0.025)	(0.021)
Overhead costs	-0.782 ***	-0.600 ***	-0.534 ***	-0.685 ***
	(0.177)	(0.175)	(0.187)	(0.173)
Net interest margin	1.393 ***	0.900 ***	1.179 ***	0.936 ***
	(0.149)	(0.123)	(0.148)	(0.128)
Liquid assets	0.007	0.017 **	0.009	0.014
	(0.009)	(0.008)	(0.010)	(0.010)
Bank type controls	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Test for AR(1) (*p*-value)	0.000	0.000	0.000	0.000
Test for AR(2) (*p*-value)	0.593	0.451	0.529	0.402
Hansen test (*p*-value)	0.293	0.284	0.365	0.060

Table 4.6 – Baseline results: The non-interest income share and its subcomponents
The figures are estimated from annual sample bank characteristics and annual macroeconomic data from euro area countries covering the period from 2007 to 2014. All regressions feature the return on risk-weighted assets (RoRWA) as the dependent variable. *RoRWA* is defined as the ratio of operating profit over total risk-weighted assets expressed in percentage terms. *L.* indicates the one period lag of the corresponding variable. The label *bank type controls* includes the dummy variables investment bank, savings bank, and co-operative bank and the label *macro controls* refers to the macroeconomic control variables GDP growth, GDP per capita, inflation, and interest rate. For a description of the explanatory variables we refer to Table 4.1. The regressions are estimated using the two-step system GMM methodology with the Windmeijer (2005) finite sample correction. The estimation method is described in more detail in Section 4.3.5. All bank performance and income diversification variables as well as all bank-specific control variables are treated as endogenous. For all above regressions we apply clustered standard errors at the bank level. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant. ***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels. The Hansen test refers to the difference-in-Hansen tests statistic of exogeneity of the instruments in GMM dynamic model estimation (H0: instruments are exogenous). AR(1) and AR(2) refer to the Arellano-Bond test that the average auto-covariance in residuals of order one and two, respectively, is zero. For the ease of exposition we suppress the regressions' intercepts and the coefficients of the bank type and macro control variables.

4.5 Extended analysis and robustness tests

In this section, we present an extended regression framework to further analyze the effects of the different income diversification measures and discuss the results of a number of robustness tests, which indicate that the economic significances that we find in our baseline regression analysis are robust.

We extend our regression analysis to identify the differences between a diversification into fee income, trading income, and other non-interest income in more detail. For this reason, we first expand Equation 4.1 by total assets:

$$RoRWA_{i,t} = \frac{\textit{operating profit}_{i,t}}{\textit{risk-weighted assets}_{i,t}} \times 100 = \frac{\dfrac{\textit{operating profit}_{i,t}}{\textit{total assets}_{i,t}}}{\dfrac{\textit{risk-weighted assets}_{i,t}}{\textit{total assets}_{i,t}}} \times 100, \tag{4.5}$$

where the numerator of the second fraction is the return on assets and the corresponding denominator the relative riskiness of a bank's total assets. With these definitions in mind, we are able to evaluate the effects of the main components of the non-interest income share on banks' profit and risk figures in isolation. Table 4.7 reports the results and is organized as follows. Regressions (1) to (3) feature the ratio of operating profit over total assets as the dependent variable and regressions (4) to (6) feature the ratio of risk-weighted assets over total assets as the dependent variable. Both ratios are expressed in percentage terms. To adequately analyze the relationship between the fee income share, trading income share, and other non-interest income share and the riskiness of total assets, we additionally make use of three different control variables that proxy for a bank's balance sheet structure. These variables are *gross loans*, defined as the ratio of total gross loans over total assets, *derivatives*, the ratio of on-balance-sheet derivatives over total assets, and *non-earning assets*, which is the share of non-earning assets to total assets. Gross loans, derivatives, and non-earning assets are all expressed in percentage terms.

The fee share in Regression (1) is seen to obtain a coefficient that is positive and statistically significant. In contrast, Regression (4) shows that fee generating activities do not provide explanatory power for the ratio of risk-weighted assets over total assets. An increase in the fee income share thus increases a bank's profitability but does not substantially change its riskiness per unit of total assets. These results are in line with expectations, as the income of fees and commissions should not affect the measures risk-weighted assets and total assets. Quite the contrary, an increase of the fee income share should increase a bank's RoRWA as long as the additional revenues from fees and commissions exceed the additional expenses and costs from a possible cross-subsidization.

The trading income share exhibits significant explanatory power for both the return on assets and the riskiness of a bank's total assets. That is to say, increasing the trading income share results in an increase in banks' profitability patterns and a decrease in their risk profiles (see Regressions (2) and (5)). The regression results of Table 4.7 thus support our finding that diversifying into trading income disproportionately increases the average bank's RoRWA when compared to a relative increase of its fee generating activities. Our findings, though, depend on the adequateness of banks' risk-weighted assets as a measure of their underlying credit risk, market risk, and operational risk. In particular, one possibility why trading activities disproportionately increase institutions' RoRWA could be due to the fact that the determination of regulatory capital for trading activities was incorrectly specified over the sample period. In fact, the International Financial Crisis revealed that major banks' trading books were insufficiently backed by regulatory capital, prompting supervisors in the European Union to increase the capital requirements for market risk in 2010.

We cannot find evidence that the isolated effect of the other non-interest income share variable on the return on assets is significantly different from zero. The relation between the former diversification measure and a bank's riskiness of total assets is positive but also insignificant.

Next, our summary statistics revealed that bank size has a substantial effect on banks' income diversification pattern. I.e., the non-interest income share significantly differs for small, medium-sized, and large banks, with small banks being less and large banks being most diversified. This fact may indicate that the relationship between a bank's non-interest income activities and its profitability depends on bank size. Therefore, we split our sample of banks into three subsets based on bank size and rerun our baseline regressions for each subset. The classification of bank size is based on total assets. In line with the category definitions of Table 4.4, small banks are defined as the 25% smallest banks in the entire sample of banks with respect to total assets at time t and large banks are defined as the 25% largest banks with respect to total assets at time t. Medium-sized banks are banks with total assets in the second and third quartile.

We further control for the possibility of nonlinearities between the income diversification measures and banks' return on risk-weighted assets by including squared terms of the diversification measures non-interest income share, fee income share and trading income share. Table 4.8 reports the results. To be more specific, Panel A of Table 4.8 features the regression results for small sample banks, Panel B for medium-sized sample banks, and Panel C for large sample banks.

	Operating profit/total assets			RWA/total assets		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
L.Dependent	0.169 ***	0.162 ***	0.163 ***	0.746 ***	0.755 ***	0.733 ***
	(0.021)	(0.021)	(0.022)	(0.033)	(0.031)	(0.033)
Fee share	0.009 **			-0.007		
	(0.004)			(0.027)		
Trading share		0.010 ***			-0.082 ***	
		(0.003)			(0.031)	
Other NII share			0.003			0.051
			(0.005)			(0.048)
Assets	0.033 *	0.027	0.030	-0.238	-0.380	-0.262
	(0.019)	(0.019)	(0.019)	(0.281)	(0.323)	(0.293)
Capital ratio	0.041 ***	0.047 ***	0.049 ***	0.442 ***	0.340 ***	0.481 ***
	(0.008)	(0.008)	(0.008)	(0.120)	(0.118)	(0.121)
Asset growth	0.006	0.004	0.006 *	-0.114 ***	-0.118 ***	-0.109 ***
	(0.004)	(0.003)	(0.003)	(0.026)	(0.026)	(0.025)
Loan loss reserves	-0.070 ***	-0.094 ***	-0.069 ***	-0.115	-0.050	-0.136
	(0.009)	(0.011)	(0.009)	(0.108)	(0.116)	(0.104)
Overhead costs	-0.324 ***	-0.275 ***	-0.275 ***			
	(0.066)	(0.060)	(0.060)			
Net interest margin	0.507 ***	0.553 ***	0.472 ***			
	(0.059)	(0.050)	(0.053)			
Liquid assets	0.005 *	0.004	0.004	-0.032	-0.024	-0.047
	(0.003)	(0.003)	(0.003)	(0.086)	(0.077)	(0.077)
Gross loans				0.085	0.081	0.093
				(0.080)	(0.071)	(0.070)
Derivatives				-0.031	0.025	-0.037
				(0.076)	(0.072)	(0.070)
Non-earning assets				0.051	0.034	0.015
				(0.098)	(0.089)	(0.092)
Bank type and macro controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Test for AR(1) (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
Test for AR(2) (p-value)	0.552	0.671	0.561	0.209	0.192	0.250
Hansen test (p-value)	0.000	0.000	0.000	0.745	0.829	0.883

Table 4.7 – Fee, trading, and other NII share and the RoRWA: An extended analysis
The figures are estimated from annual sample bank characteristics and annual macroeconomic data from euro area countries covering the period from 2007 to 2014. The table is organized as follows. Regressions (1) to (3) feature the ratio of operating profit over total assets as the dependent variable and regressions (4) to (6) feature the ratio of risk-weighted assets (RWA) over total assets as the dependent variable, both expressed in percentage terms. *L.Dependent* indicates the one period lag of the dependent variable. *Gross loans* is the ratio of total gross loans over total assets and *derivatives* is defined as on-balance-sheet derivatives divided by total assets. *Non-earning assets* is the ratio of non-earning assets over total assets. Gross loans, derivatives, and non-earning assets are expressed in percentage terms. For a description of the other explanatory variables we refer to Table 4.1. The label *bank type controls* includes the dummy variables investment bank, savings bank, and co-operative bank and the label *macro controls* refers to the macroeconomic control variables GDP growth, GDP per capita, inflation, and interest rate. The regressions are estimated using the two-step system GMM methodology with the Windmeijer (2005) finite sample correction. The estimation method is described in more detail in Section 4.3.5. All bank performance and income diversification variables as well as all bank-specific control variables are treated as endogenous. For all above regressions we apply clustered standard errors at the bank level. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant. ***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels. The Hansen test refers to the difference-in-Hansen tests statistic of exogeneity of the instruments in GMM dynamic model estimation (H0: instruments are exogenous). AR(1) and AR(2) refer to the Arellano-Bond test that the average auto-covariance in residuals of order one and two, respectively, is zero. For the ease of exposition we suppress the regressions' intercepts and the coefficients of the bank type and macro control variables.

Independent of bank size, the non-interest income share is significantly positively related to the risk-adjusted performance measure RoRWA. That is, small, medium-sized, and large banks can all enhance their performance figures by increasing their non-interest income activities. However, differences between the bank size categories become evident when focusing on the subcomponents of the income diversification measure. Small banks are able to significantly increase their return on risk-weighted assets by diversifying their revenue streams into fee generating and trading activities. Both coefficients are significant at the 5% confidence level and of similar magnitude. Nevertheless, the diversification of small banks' revenue streams into trading income generating activities cannot be easily realized in practice. The implementation of new trading desks, especially for banks that have not been engaged in trading in the past, comes at very high costs and needs supervisory permission. Small banks could, however, without the need to establish own trading desks, participate from the advantages of an increased trading income share by setting up co-operation models with specialized financial institutions. The other non-interest income share variable is negatively related to risk-adjusted bank performance.

In contrast, for medium-sized and large banks, only the fee income share adds significant explanatory power to the dependent variable RoRWA. The trading income share is insignificantly related to the latter. As a consequence, increasing these banks' trading activities, on average, should not substantially enhance their performance patterns. One reason for this finding might be the fact that, in contrast to small banks, medium-sized and large banks already exhibit optimal trading income ratios. An increase of the former would then not increase aggregate profitability. Furthermore, Table 4.4 indicates that small banks have, relatively to the other bank size categories, much lower trading income shares than fee income shares, suggesting that they are not operating at their optimal trading income mixture. Finally, we are unable to find evidence that diversifying into other non-interest income activities is disadvantageous for medium-sized and large banks.

We also examine whether our baseline results are driven by the possibility that only particular types of banks profit from (or disproportionately profit from) a diversification into non-interest income generating activities. For example, the positive and significant relationship between the average bank's fee income share and trading income share may be predominantly driven by investment banks or listed banks that already exhibit the highest non-interest revenue streams and thus are likely to be better and more sophisticated at utilizing the benefits of economies of scope. In order to control for this particular issue, Panel A of Table 4.9 features the baseline regression results including the interaction of the regressions' corresponding income diversification variable with the dummy variable investment bank (e.g. *NII share* $*$ *investment bank*) and Panel B of Table 4.9 features the baseline regression results including the interaction of the regressions' corresponding income diversification variable with the dummy variable listed (e.g. *NII share ∗ listed*).

The results of Regression (1) show that the interaction terms do not significantly affect the relationship between banks' aggregate non-interest income share and their risk-adjusted performance patterns. However, differences between investment banks and listed banks and the other sample banks become evident when shifting the focus to the fee income share. The positive relation between fee generating activities and a bank's return on risk-weighted assets is predominantly driven by the bank type interactions of Regression (2). The coefficient of the fee income share in Panel A turns out to be only slightly significant at the 10% confidence level and the coefficient of the fee income share in Panel B becomes insignificant altogether. That is to say, after controlling for the different type of banks, the evidence that non-investment banks and non-listed banks can increase their RoRWA by relatively increasing their business related to fees and commissions seems to be less clear-cut, whereas investment banks and listed banks excel at utilizing economies of scope resulting from fee generating activities.

In contrast, Regression (3) reveals that an increase in the trading income share is still beneficial for all types of banks. We do not find evidence that only investment banks or listed banks can increase their return on risk-weighted assets by relatively increasing their trading income streams. The results for the other non-interest income share are similar. We do not find divergent results for the different types of banks. On average, increases in the share of other non-interest income reduce a bank's return on risk-weighted assets.

As primary robustness checks, we consider whether our findings are robust to using alternative measures of the non-interest income share variable. In order to do so, we follow De Jonghe et al. (2015) and construct one income diversification measure based on the Herfindahl-Hirschman index and one diversification measure based on Laeven and Levine (2007). The first one, denoted *Div(HHI)*, is defined as:

$$Div(HHI) = 1 - \left(\frac{NII_{i,t}}{NII + II_{i,t}}\right)^2 - \left(\frac{II_{i,t}}{NII + II_{i,t}}\right)^2, \tag{4.6}$$

where NII denotes the non-interest income and II the interest income. Both variables are defined as described in Section 4.3.2. The measure can attain a maximum value of 0.5 if non-interest income and interest income each account for exactly 50% of total operating income (perfect diversification) and a minimum value of 0 if there is no diversification at all, i.e., total operating income is exclusively generated by non-interest income or interest income.

Panel A – small banks

	Return on risk-weighted assets						
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L.RoRWA	0.169 ***	0.152 ***	0.199 ***	0.216 ***	0.226 ***	0.238 ***	0.216 ***
	(0.052)	(0.050)	(0.056)	(0.057)	(0.054)	(0.059)	(0.056)
NII share	0.030 ***	-0.017					
	(0.007)	(0.016)					
NII share ∗ NII share		0.001 ***					
		(0.000)					
Fee share			0.024 **	-0.003			
			(0.011)	(0.015)			
Fee share ∗ Fee share				0.000			
				(0.000)			
Trading share					0.020 **	0.007	
					(0.009)	(0.015)	
Trading share ∗ Trading share						0.000	
						(0.000)	
Other NII share							-0.033 *
							(0.019)
Bank type controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank and macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Test for AR(1) (*p*-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Test for AR(2) (*p*-value)	0.259	0.182	0.339	0.318	0.273	0.252	0.255
Hansen test (*p*-value)	0.489	0.272	0.136	0.593	0.650	0.682	0.618

Panel B – medium-sized banks

	Return on risk-weighted assets						
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L.RoRWA	0.236 ***	0.230 ***	0.234 ***	0.245 ***	0.215 ***	0.209 ***	0.268 ***
	(0.057)	(0.054)	(0.064)	(0.060)	(0.062)	(0.065)	(0.060)
NII share	0.030 ***	-0.027					
	(0.011)	(0.024)					
NII share ∗ NII share		0.001 **					
		(0.000)					
Fee share			0.018	-0.045			
			(0.013)	(0.029)			
Fee share ∗ Fee share				0.001 ***			
				(0.000)			
Trading share					0.010	0.030	
					(0.010)	(0.021)	
Trading share ∗ Trading share						-0.000	
						(0.001)	
Other NII share							0.004
							(0.022)
Bank type controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank and macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Test for AR(1) (*p*-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Test for AR(2) (*p*-value)	0.250	0.246	0.234	0.277	0.258	0.273	0.182
Hansen test (*p*-value)	0.611	0.679	0.694	0.338	0.780	0.744	0.761

Table 4.8 – Income diversification and bank size (continued on the next page)

Panel C – large banks

	Return on risk-weighted assets						
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L.RoRWA	0.265 ***	0.221 ***	0.226 ***	0.222 ***	0.259 ***	0.243 ***	0.271 ***
	(0.047)	(0.050)	(0.049)	(0.051)	(0.046)	(0.050)	(0.049)
NII share	0.033 ***	0.124 ***					
	(0.012)	(0.031)					
NII share ∗ NII share		-0.001 ***					
		(0.000)					
Fee share			0.034 **	0.050			
			(0.013)	(0.033)			
Fee share ∗ Fee share				-0.000			
				(0.001)			
Trading share					0.017	0.037	
					(0.013)	(0.023)	
Trading share ∗ Trading share						-0.000	
						(0.000)	
Other NII share							-0.010
							(0.013)
Bank type controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank and macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Test for AR(1) (*p*-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Test for AR(2) (*p*-value)	0.380	0.484	0.396	0.427	0.310	0.313	0.289
Hansen test (*p*-value)	0.728	0.971	0.196	0.057	0.132	0.504	0.267

Table 4.8 – Income diversification and bank size
The figures are estimated from annual sample bank characteristics and annual macroeconomic data from euro area countries covering the period from 2007 to 2014. The table is organized as follows. Panel A features the baseline regression results for small sample banks, Panel B for medium-sized sample banks, and Panel C for large sample banks. The classification of bank size is based on total assets. Small banks (large banks) are defined as the 25% smallest (25% largest) banks in the entire sample of banks with respect to total assets at time t. Medium-sized banks are banks with total assets in the second and third quartile. All regressions feature the return on risk-weighted assets (RoRWA) as the dependent variable. *RoRWA* is defined as the ratio of operating profit over total risk-weighted assets expressed in percentage terms. *L.* indicates the one period lag of the corresponding variable and *variable ∗ variable* illustrates the use of an interaction term. The label *bank type controls* includes the dummy variables investment bank, savings bank, and co-operative bank and the label *macro controls* refers to the macroeconomic control variables GDP growth, GDP per capita, inflation, and interest rate. *Bank controls* indicates that the bank-specific control variables assets, capital ratio, asset growth, loan loss reserves, overhead costs, net profit margin, and liquid assets are used in the regression analysis. For a description of the explanatory variables we refer to Table 4.1. The regressions are estimated using the two-step system GMM methodology with the Windmeijer (2005) finite sample correction. The estimation method is described in more detail in Section 4.3.5. All bank performance and income diversification variables as well as all bank-specific control variables are treated as endogenous. For all above regressions we apply clustered standard errors at the bank level. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant. ***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels. The Hansen test refers to the difference-in-Hansen tests statistic of exogeneity of the instruments in GMM dynamic model estimation (H0: instruments are exogenous). AR(1) and AR(2) refer to the Arellano-Bond test that the average auto-covariance in residuals of order one and two, respectively, is zero. For the ease of exposition we suppress the regressions' intercepts and the coefficients of all control variables.

Panel A – income diversification benefits and investment banks

	Return on risk-weighted assets			
Variable	(1)	(2)	(3)	(4)
L.RoRWA	0.244 ***	0.286 ***	0.272 ***	0.284 ***
	(0.036)	(0.037)	(0.036)	(0.039)
NII share	0.031 ***			
	(0.007)			
NII share ∗ investment bank	-0.002			
	(0.010)			
Fee share		0.011 *		
		(0.007)		
Fee share ∗ investment bank		0.024 **		
		(0.011)		
Trading share			0.033 ***	
			(0.007)	
Trading share ∗ investment bank			-0.020	
			(0.021)	
Other NII share				-0.032
				(0.021)
Other NII share ∗ investment bank				0.002
				(0.031)
Bank type controls excl. investment bank	Yes	Yes	Yes	Yes
Bank and macro controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Test for AR(1) (*p*-value)	0.000	0.000	0.000	0.000
Test for AR(2) (*p*-value)	0.617	0.502	0.573	0.362
Hansen test (*p*-value)	0.128	0.287	0.177	0.164

Panel B – income diversification benefits and stock exchange listing

	Return on risk-weighted assets			
Variable	(1)	(2)	(3)	(4)
L.RoRWA	0.248 ***	0.285 ***	0.271 ***	0.269 ***
	(0.036)	(0.036)	(0.039)	(0.037)
NII share	0.032 ***			
	(0.007)			
NII share ∗ listed	0.003			
	(0.007)			
Fee share		0.010		
		(0.007)		
Fee share ∗ listed		0.023 ***		
		(0.007)		
Trading share			0.027 ***	
			(0.007)	
Trading share ∗ listed			0.007	
			(0.018)	
Other NII share				-0.036 **
				(0.018)
Other NII share ∗ listed				0.027
				(0.031)
Bank type controls	Yes	Yes	Yes	Yes
Bank and macro controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Test for AR(1) (*p*-value)	0.000	0.000	0.000	0.000
Test for AR(2) (*p*-value)	0.556	0.472	0.503	0.376
Hansen test (*p*-value)	0.065	0.375	0.475	0.047

Table 4.9 – Income diversification and the impact of investment banks and listed banks

Table 4.9 – continued:
The figures are estimated from annual sample bank characteristics and annual macroeconomic data from euro area countries covering the period from 2007 to 2014. The table is organized as follows. Panel A features the baseline regression results including the interaction of the regressions' corresponding income diversification variable with the dummy variable investment bank and Panel B features the baseline regression results including the interaction of the regressions' corresponding income diversification variable with the dummy variable listed. All regressions feature the return on risk-weighted assets (RoRWA) as the dependent variable. *RoRWA* is defined as the ratio of operating profit over total risk-weighted assets expressed in percentage terms. *L.* indicates the one period lag of the corresponding variable and *variable ∗ variable* illustrates the use of an interaction term. The label *bank type controls* includes the dummy variables investment bank, savings bank, and co-operative bank and the label *macro controls* refers to the macroeconomic control variables GDP growth, GDP per capita, inflation, and interest rate. *Bank controls* indicates that the bank-specific control variables assets, capital ratio, asset growth, loan loss reserves, overhead costs, net profit margin, and liquid assets are used in the regression analysis. For a description of the explanatory variables we refer to Table 4.1. The regressions are estimated using the two-step system GMM methodology with the Windmeijer (2005) finite sample correction. The estimation method is described in more detail in Section 4.3.5. All bank performance and income diversification variables as well as all bank-specific control variables are treated as endogenous. For all above regressions we apply clustered standard errors at the bank level. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant. ***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels. The Hansen test refers to the difference-in-Hansen tests statistic of exogeneity of the instruments in GMM dynamic model estimation (H0: instruments are exogenous). AR(1) and AR(2) refer to the Arellano-Bond test that the average auto-covariance in residuals of order one and two, respectively, is zero. For the ease of exposition we suppress the regressions' intercepts and the coefficients of all control variables.

The second measure, denoted *Div(LL)*, is defined as:

$$Div(LL) = 1 - \left| \frac{non\text{-}interest\ income_{i,t} - interest\ income_{i,t}}{non\text{-}interest\ income_{i,t} + interest\ income_{i,t}} \right|. \tag{4.7}$$

Regressions (1) and (2) of Table 4.10 report the estimates. Both regressions feature the ratio of operating profit over total risk-weighted assets as the dependent variable. The results using the former diversification measures rather than the non-interest income share variable are very similar to our previous findings. An increase in a bank's income diversification significantly increases its return on risk-weighted assets and thus improves aggregate bank performance. The income diversification variables Div(HHI) and Div(LL) are significant at the 5% and 1% confidence level, respectively.

We also test if a change in the risk-adjusted performance measure's definition may alter our regression results. For this reason we redefine a bank's return on risk-weighted assets as the ratio of net income over total risk-weighted assets. That is to say, the risk-adjusted performance measure now additionally captures the effect of the income statement items non-recurring and non-operating income and expenses.

	Operating profit/RWA		Net income/RWA			
Variable	(1)	(2)	(3)	(4)	(5)	(6)
L.Dependent	0.254 ***	0.251 ***	0.255 ***	0.291 ***	0.283 ***	0.295 ***
	(0.037)	(0.040)	(0.036)	(0.037)	(0.037)	(0.040)
Div(HHI)	0.637 **					
	(0.297)					
Div(LL)		1.129 ***				
		(0.387)				
NII share			0.032 ***			
			(0.006)			
Fee share				0.024 ***		
				(0.006)		
Trading share					0.025 ***	
					(0.006)	
Other NII share						-0.034 ***
						(0.013)
Assets	-0.097	-0.072	0.034	0.069	0.035	0.046
	(0.078)	(0.081)	(0.054)	(0.061)	(0.063)	(0.064)
Capital ratio	0.111 ***	0.102 ***	0.095 ***	0.085 ***	0.084 ***	0.087 ***
	(0.028)	(0.029)	(0.026)	(0.023)	(0.024)	(0.025)
Asset growth	0.011 *	0.007	0.006	0.008	0.005	0.007
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Loan loss reserves	-0.133 ***	-0.144 ***	-0.102 ***	-0.050 ***	-0.103 ***	-0.053 ***
	(0.021)	(0.023)	(0.017)	(0.015)	(0.018)	(0.016)
Overhead costs	-0.867 ***	-0.818 ***	-0.641 ***	-0.578 ***	-0.446 ***	-0.584 ***
	(0.186)	(0.184)	(0.144)	(0.140)	(0.140)	(0.147)
Net interest margin	0.841 ***	1.100 ***	0.877 ***	0.520 ***	0.649 ***	0.455 ***
	(0.132)	(0.139)	(0.126)	(0.098)	(0.110)	(0.103)
Liquid assets	0.009	0.013	0.007	0.014 **	0.007	0.012 *
	(0.009)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)
Bank type and macro controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Test for AR(1) (*p*-value)	0.000	0.000	0.000	0.000	0.000	0.000
Test for AR(2) (*p*-value)	0.217	0.419	0.985	0.969	0.924	0.852
Hansen test (*p*-value)	0.600	0.354	0.222	0.004	0.197	0.002

Table 4.10 – Different measures of income diversification and RoRWA
The figures are estimated from annual sample bank characteristics and annual macroeconomic data from euro area countries covering the period from 2007 to 2014. The table is organized as follows. Regressions (1) and (2) feature the ratio of operating profit over total risk-weighted assets (RWA) as the dependent variable and replace the NII share variable with the variables Div(HHI) and Div(LL). Regressions (3) to (6) feature the ratio of net income over total RWA as the dependent variable. The dependent variables are expressed in percentage terms. *L.Dependent* indicates the one period lag of the dependent variable. *Div(HHI)* is a measure of income diversification based on the Herfindahl-Hirschman index and *Div(LL)* is a income diversification measure based on Laeven and Levine (2007). For a description of the other explanatory variables we refer to Table 4.1. The label *bank type controls* includes the dummy variables investment bank, savings bank, and co-operative bank and the label *macro controls* refers to the macroeconomic control variables GDP growth, GDP per capita, inflation, and interest rate. The regressions are estimated using the two-step system GMM methodology with the Windmeijer (2005) finite sample correction. The estimation method is described in more detail in Section 4.3.5. All bank performance and income diversification variables as well as all bank-specific control variables are treated as endogenous. For all above regressions we apply clustered standard errors at the bank level. Standard errors are given in parentheses. The regression coefficients are assigned asterisks if they are statistically significant. ***, **, and * denotes significance at the 1%-, 5%-, and 10%-confidence levels. The Hansen test refers to the difference-in-Hansen tests statistic of exogeneity of the instruments in GMM dynamic model estimation (H0: instruments are exogenous). AR(1) and AR(2) refer to the Arellano-Bond test that the average auto-covariance in residuals of order one and two, respectively, is zero. For the ease of exposition we suppress the regressions' intercepts and the coefficients of the bank type and macro control variables.

Regressions (3) to (6) of Table 4.10 show the estimates. Our results do not change substantially. Regression (3) reveals that a diversification into non-interest related activities significantly increases the average bank's risk-adjusted return measure, supporting the existence of economies of scope. Furthermore, we again find that both the fee income share and the trading income share are significantly positively related to bank performance. Both variables are significant at the 1% confidence level. However, the magnitudes of the effects of the fee income share and the trading income share on the dependent variable net income over risk-weighted assets do not differ anymore. The former has a regression coefficient of 0.024 percentage points and the latter a coefficient of 0.025 percentage points. Regression (6) provides further evidence that an increase in banks' other non-interest income share is disadvantageous for their aggregate performance patterns. This time the relationship is significant at the 1% level, supporting the view that income diversification is only beneficial if it is based on core banking activities.

4.6 Conclusion

In this paper, we analyze how banks' income diversification affects their risk-adjusted performance patterns on the basis of a broad representative sample of euro area banks covering the period from 2007 to 2014. We measure a bank's profitability employing the variable return on risk-weighted assets and proxy for income diversification by calculating the shares of non-interest income, fee income, trading income, and other non-interest income in total operating income.

Our empirical analysis reveals that a diversification into non-interest related activities significantly increases banks' return on risk-weighted assets, supporting the existence of economies of scope. That is, an increase in both the fee income share and the trading income share increases the average bank's risk-adjusted performance pattern. Yet, the economic significances of both diversification measures differ substantially. On average, banks can boost their performance twice as much by relatively expanding their trading activities instead of trying to expand their relative income from fees and commissions. We additionally find evidence that diversifying into other non-interest income activities is disadvantageous for a bank's profitability. The latter is in line with the point of view that income diversification is only beneficial if it is based on core banking activities.

We conduct a number of robustness tests, which indicate that the economic significances that we find in our baseline regression analysis are fairly robust. However, we also find that the relation between non-interest income diversification and aggregate bank profitability is substantially driven by bank type and bank size. Especially investment banks and banks with a stock exchange listing excel at utilizing economies of scope resulting from fee generating activities, whereas the evidence that other type of banks can actually increase their return on risk-weighted assets by relatively increasing their business related to fees and commissions is less clear-cut.

The effect of the trading income share on banks' return patterns is not distorted by the bank type identifiers, but depends on bank size. Small banks are able to significantly increase their return on risk-weighted assets by diversifying their revenue streams into trading activities. Nevertheless, the diversification of small banks' revenue streams into trading income generating activities cannot be easily realized in practice. The implementation of new trading desks, especially for banks that have not been engaged in trading in the past, comes at very high costs and needs supervisory permission. Small banks could, however, without the need to establish own trading desks, participate from the advantages of an increased trading income share by setting up co-operation models with specialized financial institutions.

In contrast, for medium-sized and large banks, the trading income share is insignificantly related to risk-adjusted bank profitability. As a consequence, increasing these banks' trading activities, on average, should not substantially enhance their performance patterns, suggesting that medium-sized and large banks already exhibit optimal trading income ratios.

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